IT-supported Occupational Self-Management to Promote Sustainable Productivity and Psychological Well-Being

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I dedicate this work to my beloved Raphael: You make me appreciate who I am and the depth of feeling I have for you spurs me on to bring out the best in me.

Abstract

Technological advances in recent decades and the shift to knowledge-intense work offer individuals wide personal and professional freedom regarding time, space, and task definition. At the same time, large self-responsibility and flexibility in modern work life can lead to high working pressure and requires the workforce to manage themselves effectively. Overtaxing workers' self-management competencies can result in work behaviors through which they actively risk their health. Thus, supporting individuals' self-management steadily grows in importance, especially to promote sustainable productivity and psychological well-being in this area of tension. The complexity of self-management behaviors and the reference to highly individual situations leave a need for personalized but scalable approaches to support.

Digital solutions can be an effective means for the integration of assistance into everyday life. The increasing use of various mobile devices and unobtrusive sensors enables new kinds of individual tracking and personalized feedback. However, there is a lack of research addressing digital assistance for self-management regarding the challenges of modern work life. This dissertation fills this gap and investigates how technology can especially contribute to self-manage sustainable productivity and psychological well-being. It provides an overview on the design space relevant for the construction of such systems assisting the workforce in their occupational self-management and showcases application areas. A series of contributions investigates various important aspects in engineering occupational self-management systems. The complex subject matter with its interdisciplinary nature spanning research traditions of several disciplines led to a large variety of methods used. An architecture is presented that conceptualizes a context-aware system integrating several data sources, analyses, and feedback options along with descriptions of implementation options of such a system in form of a technical infrastructure. Furthermore, human energy is presented as a key variable in occupational self-management regarding the challenges the workforce faces in these times. In this direction, especially the support in human energy self-management as prototypical instance of possible self-management assistance systems is investigated. An evaluation of the energy self-management approach has shown a positive effect of the technological assistance on the individual. Future research could deepen the understanding in this direction.

Kurzfassung

Die technologischen Fortschritte der letzten Jahrzehnte und die Verlagerung hin zu wissensintensiver Arbeit bieten dem Einzelnen große persönliche und berufliche Freiheit in Bezug auf Zeit, Raum und Aufgabenstellung. Gleichzeitig kann die große Eigenverantwortung und Flexibilität im modernen Arbeitsleben zu einem besonderen Arbeitsdruck führen und verlangt von den Arbeitnehmern ein effektives Selbstmanagement. Eine Überforderung der Selbstmanagementkompetenzen von Erwerbstätigen kann zu einem aktiv die Gesundheit gefährdenden Arbeitsverhalten führen. Daher gewinnt die Stärkung des individuellen Selbstmanagements immer mehr an Bedeutung, insbesondere um in diesem Spannungsfeld nachhaltige Produktivität und psychisches Wohlbefinden zu fördern. Die Komplexität von Selbstmanagement-Verhaltensweisen und der stark individuelle Situationsbezug erzeugen einen Bedarf an personalisierten, aber skalierbaren Ansätzen zur Unterstützung.
Digitale Lösungen können hierbei wirkungsvolles Mittel zur Einbettung von Unterstützungsmaßnahmen in den Alltag sein. So erlaubt die zunehmende Verbreitung mobiler Geräte und unauffälliger Sensoren neue Formen des individuellen Trackings und personalisierten Feedbacks. Allerdings fehlt es an Forschung, die sich mit digitaler Unterstützung des Selbstmanagements in Bezug auf die Herausforderungen des modernen Arbeitslebens befasst. Die vorliegende Dissertation füllt diese Lücke und untersucht, wie Technologie insbesondere zum Selbstmanagement für nachhaltige Produktivität und psychisches Wohlbefinden beitragen kann. Sie gibt einen Überblick über den Gestaltungsraum, der für die Konstruktion solcher Systeme zur Unterstützung von Erwerbstätigen bei ihrem beruflichen Selbstmanagement relevant ist, und zeigt Anwendungsbereiche auf. In einer Reihe von Beiträgen werden verschiedenste Aspekte bei der Konstruktion von Systemen des betrieblichen Selbstmanagements untersucht. Die komplexe, interdisziplinäre Thematik, die Forschungstraditionen mehrerer Disziplinen einbezieht, führte zu einer Vielzahl von verwendeten Methoden. Es wird eine Architektur vorgestellt, die ein kontextsensitives System konzeptualisiert, das verschiedene Datenquellen, Analysen und Feedbackoptionen integriert, sowie Implementierungsmöglichkeiten eines solchen Systems in Form einer technischen Infrastruktur beschrieben werden. Darüber hinaus wird die menschliche Energie als Schlüsselvariable des beruflichen Selbstmanagements im Hinblick auf die Herausforderungen heutiger Arbeitskräfte vorgestellt. In diesem Sinne wird insbesondere die Unterstützung des Energie-Selbstmanagements als prototypisches Beispiel für mögliche Selbstmanagement-Assistenzsysteme vertieft untersucht. Im Rahmen einer Evaluierung des Energie-Selbstmanagement-Ansatzes konnte eine positive Wirkung der technologischen Unterstützung auf die Individuen festgestellt werden. Zukünftige Forschung sollte das Wissen in dieser Richtung weiter vertiefen.

Contents

List of Figures

List of Tables

Part I

Synopsis

1 Introduction

"The need to mange oneself is [...] creating a revolution in human affairs."

- Drucker (2005) -

1.1. Motivation

Encouraging effective employee self-management is beneficial to organizations in several respects (Manz and Sims, 1980).
The outstanding importance of managing oneself in the work context has already been emphasized decades ago regarding the shift away from routine work towards knowledge-intensive work, with which it is a necessary prerequisite for productivity and excellence (Drucker, 1999, 2005). In addition to this success-oriented perspective, self-management has gained crucial relevance with regard to the dynamics of work for even more areas since, especially for individuals' well-being, balance in life, and their interplay also with performance (Graf, 2019). This is due to "a wide range of economic, technological, sociocultural and corporate developments" (Graf, 2019, p. 12, translated), which have bright, but also dark sides.
Technology can facilitate work or even minimize the need for involvement of humans, especially for physically strenuous jobs, and with this, reduced the need for manual labor (Näswall et al., 2008). As a result, in industrialized countries there is a shift from manufacturing and manual types of jobs to service provision and white-collar work with higher education. For manual work, the task is always clear and routine steps can be taken focusing on speed and uniformity, while the tasks in knowledge-intense work have to be defined individually (Drucker, 1999). In particular, knowledge tasks are often labor-intensive requiring time e.g. to think or communicate (Palvalin et al., 2013). Such vague tasks leave employees with a large self-responsibility to determine at what point a goal is appropriately completed, which may be especially stressful under time pressure (Näswall et al., 2008). In contrast to manual work, planning the time needed for intellectual work is difficult, possibly leading to miscalculations resulting in higher work intensity (Rau, 2012). The precarious situation in this direction is apparent from representative study results in Germany. For example, around a quarter of employees stated a few years ago that they were frequently or very frequently unable to accomplish their workload, and for one in three, the workload even increased in comparison to the previous year (DGB-Index Gute Arbeit, 2019). Worth special mention in this context, necessary quality reductions due to an unmanageable workload are reflected as particularly intensive strains (DGB-Index Gute Arbeit, 2015).

The autonomy that is essential to fulfill knowledge-intense jobs well (Drucker, 1999) can be provided through another notable development in the working world, which is flexibility. Over the last forty years, flexible work forms have emerged, primarily targeted at raising productivity and work engagement among employees (Dettmers et al., 2016). These forms range from flexible work times to mobile or remote work. Together with the advances in information technology, the changes in work types make work more independent giving employees theoretically more opportunities (Näswall et al., 2008). Telework and ICT-based mobile work provide employees with additional autonomy with regard to how, when, and where they do their jobs, which is seen as a key characteristic of this work forms and can be positive for their work-life balance (Eurofound, 2021). However, flexible work forms entail their own challenges and can also lead to an imbalance between different roles (Näswall et al., 2008). They offer autonomy, but in return require employees in the first place to manage themselves[1] effectively (Dettmers et al., 2016).

When confronted with high work demands, the greater freedom in one's work can be perceived as an obligation to handle higher workloads, also called the autonomy paradox (Eurofound, 2021). This is also due to the fact that commitment is seen an important characteristic for knowledge jobs (Davenport, 2005) and also welcomed to an excessive degree in some professional subcultures (Kalimo, 1999). Autonomous work is hardly subject to external regulation; instead, employees are encouraged to behave like entrepreneurs, making the achievement of goals subject to their own dedicated alignment with performance indicators in their personal interest (Dettmers et al., 2016; Krause et al., 2012). A term also used in this context of high individual involvement is the subjectification of employment (Moldaschl, 2002). Subject and labor are no longer considered separately, but individual potentials and scope for subjective action gain relevance (Sauer, 2012). Classical concepts of management get replaced by outcome-oriented, indirect leadership (Krause et al., 2012). Often, performance targets are increased accordingly on success, and the significance of mental loads at work continues to grow. Most notably, failure to achieve work goals is considered a personal inadequacy by the employees in the context of high individual involvement (Dettmers et al., 2016).

Against this background, mental load due to work pressure in self-responsible, complex work comes in a new form and with different effects, although the same pressure already existed in routine work (Böhle, 2010). Indeed, today's working conditions with autonomous and flexible jobs foster self-endangering work behavior, as progressively increasing demands can overtax employees' resources and self-management[1] competencies (Dettmers et al., 2016). This can result in an increase in these individual work behaviors actively risking their health (Dettmers et al., 2016; Krause et al., 2012). Such behaviors include, for example, presenteeism, working long hours to a high extent, and foregoing recovery breaks or vacation (Krause et al., 2012). Work and non-work is no longer clearly separated, not only in regard to space and time, but also in terms of social networks (Allvin, 2008). All this can lead to being constantly available and unable to relax. According to results of the Sixth European Working Conditions Survey, 45 % of workers carried out work in their free time in order to meet work demands (Eurofound, 2017). More than every fifth worker did

[1]originally self-leadership, see Section 2.3 for a differentiation

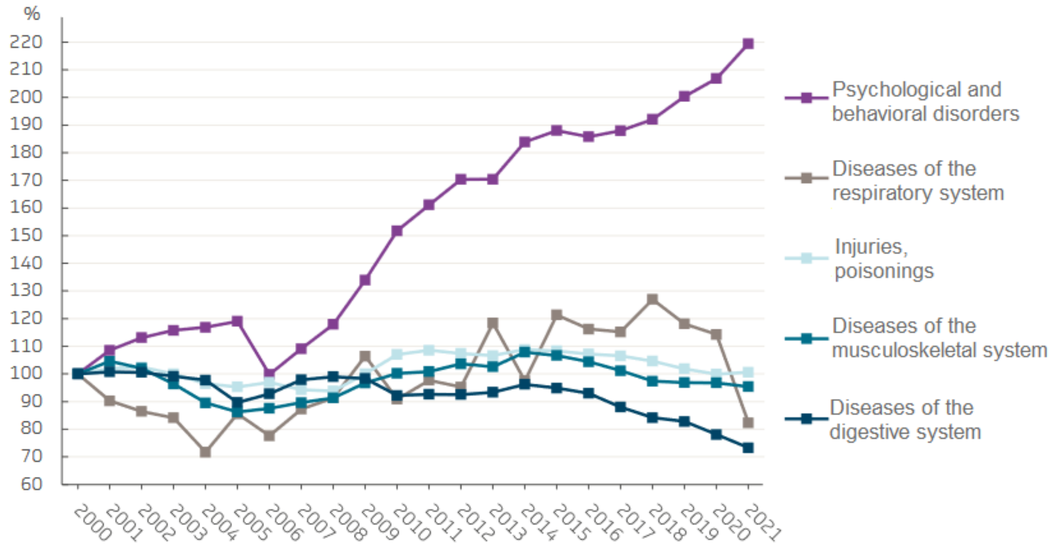

Figure 1.1.: Relative change of absenteeism due to incapacity to work according to diagnostic groups between the years 2000 and 2021; working persons with membership in the health insurer Techniker Krankenkasse; adopted from Techniker Krankenkasse (2022)

this several times a month or even on a daily basis.
Even if such coping behaviors help to fulfill work goals, they are not sustainable as they have negative effects on health and well-being and threaten the ability to work in the long-term (Dettmers et al., 2016). Any strain, even positively associated, must be compensated for in the longer term by recovery in order to prevent negative consequences, such as illnesses caused by exhaustion (Rau, 2012) (also referred to as energy depletion (Kalimo, 1999)). Therefore, recovery is of central importance (Rau, 2012). However, as a result of the developments described above, there is increasingly an imbalance between work strain and recovery, e.g., due to insufficient non-working time between periods of strain or ruminating about work at night. It is noteworthy that work-related loads have a particularly strong impact on recovery in most cases compared to other loads. For instance, poor sleep is predominantly caused by work-related problems (Techniker Krankenkasse, 2017). The problem of exhaustion states is meanwhile accumulating (Rau, 2012) and with this, mental health in the context of work has become even more a hot topic. Worldwide, mental health problems are a major contributor to the overall burden of disease and are particularly concentrated in the working population (James et al., 2018). As can be seen from Figure 1.1, in Germany as an example, incapacity to work due to psychological and behavioral disorders increased drastically since the last two decades according to numbers from a health insurer (Techniker Krankenkasse, 2022). Thus, mental health problems possibly lead to a loss of human capital (James et al., 2018) and as such, are not only a problem to individual quality of life, but also for the competitiveness of organizations. And even before disorders arise, stress can have negative effects on work performance (Leka et al., 2003). However, increasing work overload is

predicted for the future, e.g. due to further rise in mobile work (Kauffeld et al., 2022b). Maintaining at the same time workforce productivity and especially also recovery is thus a major challenge to be tackled (Reinke and Düvel, 2022).
Despite the various risks described above, which are associated with freedoms and self-responsibility of work, this is clearly not intended to imply that such work forms are detrimental in principle and that a return to traditional work forms would be preferable (Peters, 2014). Relying on individual potentials and subjective action gives employees meaningfulness beyond an earning purpose (Sauer, 2012). Furthermore, for organizations, flexibilization and digitization are central topics anyway (Eilers et al., 2017; Lott and Ahlers, 2021) and autonomy is essential for productive knowledge work (Drucker, 1999). While many employees are concerned that flexible working will interfere too much with their private lives, fixed working hours are nevertheless no longer attractive, especially for the younger generation, and most employees want to work in a self-determined way (Kugler, 2020). They expect digitization to provide increasing opportunities to work more flexibly and location-independent (Cloots, 2020). Ideally, this freedom can lead to better compatibility with other areas of life and better health (Lott and Ahlers, 2021). For example, flexible working offers more options when it comes to the need to nurse relatives and care for children, in particular given the increase in two-earner households, where both partners' jobs have to be taken into account. As a result, employees do indeed wish for more freedom to deal with such challenges.
However, it is not at all the case that new freedoms *automatically* have a positive effect, but on the contrary - it is essential to work out how to use the new freedoms in a positive way (Peters, 2014). Consequently, "the digital transformation and a growth in flexible working will make us healthier and more productive, *if properly managed*" (BARMER and Universität St. Gallen, 2020)[2]. In this regard, organizations are responsible to take measures ensuring appropriate work design (Sandrock and Stahn, 2017, p. 4). If risks cannot be completely eliminated by the organization, it is first and foremost necessary to take measures to improve working conditions and thus, address the loads instead of the employees first. An exemplary essential measure is that the workload must be adjusted in such a way that it can be accomplished in the usual working time (Eurofound, 2021; DGB-Index Gute Arbeit, 2019; Kalimo, 1999; Sandrock and Stahn, 2017, p. 2). A further example more specific to highly self-responsible work is that, in combination with it, especially a corresponding high level of control or authority should be granted (Näswall et al., 2008; Lott and Ahlers, 2021; Sauer, 2012; Sandrock and Stahn, 2017, p. 13), which has been pointed out as a crucial benefit for self-employed to the consequences of job demands (Hessels et al., 2017).
Nevertheless, self-endangering work behavior may still occur, if self-management[1] competencies of workers are exceeded (Dettmers et al., 2016). Forms of indirect leadership with the associated entrepreneurial interest of employees actually can lead to their non-compliance to regulations promoting health, if these could impair their success (Krause et al., 2012; Sauer, 2012; Peters, 2014). The autonomy paradox can then be induced by the employees themselves, e.g., when people with pronounced am-

[2]freely translated from the original „Richtig gemanagt werden uns der digitale Wandel und das Mehr an flexibler Arbeit gesünder und leistungsfähiger machen."

bition or perfectionism struggle to set limits (Eurofound, 2021; Scharnhorst, 2012). This is even more significant against the background of existing personnel shortages with the resulting increase in workload (DGB-Index Gute Arbeit, 2019) and characteristics of knowledge jobs like handling the information flood (Kalimo, 1999; Palvalin et al., 2013). Organizations can unfortunately barely ensure that all potential (psychological) risks are entirely eliminated, which is why support should also be given in the enhancement of competencies and awareness should nevertheless be created among employees (Sandrock and Stahn, 2017, p. 20).

In light of all the above, one competency stands out in particular for enhancement and is more topical than ever before - "[m]ore than ever, entrepreneurs as well as their employees need to develop their self-[management][1] skills to be able to use the responsibility and decision-making authority that comes with the autonomy" (Klösel, 2022, p. 262). Self-management subsumes all efforts of a person to influence the own behavior in a targeted manner[3] (König and Kleinmann, 2014, p. 649) and direct decision making (Frayne and Geringer, 2000). With this, it is especially important in highly self-responsible work (Kleinmann and König, 2018). While everyone exercises self-management to some degree, it is not necessarily functional or effective (Manz and Sims, 1980; Frayne and Geringer, 2000). For instance, the underlying decision making can be dysfunctional, e.g. when setting too high goals (Manz and Sims, 1980). It is estimated that in 2030 effective self-management will be imperative due to more remote work (Kauffeld et al., 2022b). As self-management is learned and can be enhanced (Frayne and Geringer, 2000), it is thus desirable to build strong self-management competencies. Effective self-management can not only prevent negative aspects associated with self-responsible work, but, as alluded to in the beginning, also foster various desired factors like productivity (Drucker, 1999) and excellence (Drucker, 2005). In this direction, self-management is furthermore necessary to lead others (Luthans and Davis, 1979), it promotes motivation and well-being (Greinert, 2020), and its training even achieves further transfer effects on other variables that are not explicitly trained, such as mental strength (Kamp et al., 2020).

Continuing training on self-management belongs to person-related measures that can be implemented by companies for occupational health and safety (Sandrock and Stahn, 2017, p. 20). In contrast to measures of condition-oriented prevention mentioned earlier, person-related measures aim to equip the workforce with enhanced skills or competence and are classified as behavior-oriented prevention (Michel and Hoppe, 2022). However, many companies lack a holistically oriented, sustainable perspective, thus failing to recognize the importance of self-management to their business success (Zaugg, 2019). While enhancing employee self-management could be seen as an investment for the future, a focus on short-term efficiency hinders developments in that direction (Manz and Sims, 1980). An underlying problem might also be that occupational health management requires additional personnel and financial resources (Kauffeld et al., 2022a). The digitization and connected recent laws in Germany, though, enable the establishment of health management in companies of different sizes, as well as financial support from health insurers. In addition,

[3]Translated from the original: „Unter Selbstmanagement verstehen wir (als Arbeitsdefinition) alle Bemühungen einer Person, das eigene Verhalten zielgerichtet zu beeinflussen"

offering digital solutions to employees as part of workplace health promotion initiatives provides various potential benefits, both for the company and the individual user (Hoppe et al., 2022). Digital solutions are cost-effective for companies because the solutions are highly scalable to be deployed across the board and also eliminate travel and trainer costs when face-to-face contact is no longer mandatory. Their use is flexible in terms of space and time and could therefore achieve increased usage among employees. The possibility of interactive or playful design formats could also provide greater motivation for use. Most notably for the recipient, digital solutions distinguish themselves through the possible individualization of the content for each participant, and app-based solutions in addition through the fact that they can even serve as support in the daily setting in real time.

1.2. Problem Statement and Relevance

Against earlier assumptions, people do not make optimal decisions in their own interest (Hsee and Hastie, 2006). While self-management in terms of regulating oneself is key for humans and related to health and success (Voigt, 2017), according to Luthans and Davis (1979, p. 43):

> *"self-management skills should not be taken for granted".*

Fortunately, self-management skills can be raised through training (Frayne and Geringer, 2000). As described previously, digital solutions in general can be a beneficial means for training. Even more, information technology (IT) can not only motivate to execute self-management (Li and Vogel, 2021), but even develop independent self-management competence among users and, beyond that, continue to support (Lehrer et al., 2021). Li and Vogel (2021) state in their review with focus on digital health education, however, that there is:

> *"insufficient work on addressing self-management challenges via digital technology".*

This dissertation is premised on the consideration that this is not only true for health self-management, but even more for self-management in a more holistic view - i.e. in the work at hand, considering well-being for health promotion in combination with productivity-related factors that are essential for the work context. While there are numerous articles trying to tackle productivity-related problems, especially in the area of task and time management (cf. e.g. Azvine et al. (2000); Berry et al. (2011); Yorke-Smith et al. (2012); Geetha et al. (2018)), information systems research has just begun to bring together the promotion of productivity and well-being (e.g. John et al. (2023)). Most notably, even such recent approaches are lacking consideration of the overall self-management context, which might be an important basis to develop tools effective in tackling the challenges of the modern working world outlined above. Thus, it is highly relevant to connect research on occupational self-management like Manz and Sims (1980) and Graf (2019) with such on technology for individual use, e.g. for tracking and engaging with personal data (cf. e.g. Li et al. (2010); Rapp and Cena (2016); Kersten-van Dijk et al. (2017)). Related research and the terms used are as manifold as self-management is complex. For instance, related research on technology to measure and manage personal states like stress or flow is quite diverse and still under research, e.g. Sharma and Gedeon (2012); Rissler et al. (2017a). By aiming to utilize technology to support individuals in facing the challenges of the modern working world, all this scattered knowledge needs to be assembled with a focus on assisting occupational self-management. On this basis, research has to be conducted to craft the occupational self-management context into technology and decide which variable(s) are to be supported in order to promote sustainable productivity and psychological well-being. Up to now, it is unclear how this can be achieved and in which ways it actually contributes to self-management.

1.3. Aim of the Research

IT-based assistance for self-management is important against the background of highly self-responsible work discussed above, in order to ensure that the individuals' work behavior is not self-endangering, but actually uses the available freedoms as positively as possible for the individual and the entire organization in a long-term perspective. Thus, taking into account individual well-being, productivity is to be promoted in a targeted yet sustainable manner, i.e., under less mental strain by considering individual resources. The overarching research question in this thesis is therefore:

How to provide technological assistance to enhance individuals' occupational self-management?

In order to address this question, the main objectives of this dissertation are:

i) to investigate how scattered knowledge from different disciplines can be connected to create artifacts enhancing occupational self-management,

ii) to explore relevant components and features of occupational self-management systems, and

iii) to determine and showcase how to promote sustainable productivity and psychological well-being in combination through the assistance.

1.4. Research Design and Outline of the Dissertation

This dissertation contributes to the scientific knowledge base through a series of twelve peer-reviewed articles. Each article provides insights on an important aspect in engineering occupational self-management systems and has its specific subordinate research questions and implications. The applied methods were chosen according to the respective research questions targeted through the certain research endeavour. The complex subject matter of this dissertation with its interdisciplinary nature spanning research traditions of several disciplines led to a large variety of methods used, which underpins the inherent challenges and associated special value of the dissertation. Throughout the research, according to one aim of the dissertation, it has become apparent that an outstanding umbrella variable to promote together sustainable productivity as well as psychological well-being through self-management is human energy that also reflects the continuum of strain and recovery (cf. energy depletion mentioned in Section 1.1). However, managing personal energy is such a recent and innovative topic that suggestions made for engineering occupational self-management systems in this dissertation are not yet transferable to it in larger parts, e.g. because sensor measurements are missing so far. Thus, the research process has followed two streams mainly in the end. The first is about engineering systems for occupational self-management from a more general and holistic view, proposing a concept and implementation options from compiling more established, but deficiently interconnected research fields. The second stream presents the special case of assisting energy self-management.

According to this, the dissertation consists of three parts. Part II and Part III present the series of published articles separated according to the two mentioned streams, while the first and thus current part elucidates the overall theme of the thesis and describes how the publications contribute to it to build the large overall research project. Part I next continues with elaborating highly relevant terms of the thesis, namely productivity, health and well-being, and self-management in Chapter 2. Chapter 3 presents details on the research focus, process, methods, and results. Especially, a thematic categorization of the research results with their interrelations is given. In Chapter 4, the limitations and impact of the dissertation are discussed, potential future work is outlined, and the work is concluded.
Part II has the overall theme of engineering systems for assisting occupational self-management. In that part, eight publications are presented. These can be classified as concerning preliminary analysis, sustainable productivity support, concept, and technical infrastructure. Part III comprises the special case of assisting in energy self-management, represented through four publications. In this, thematic categories are constructing and proving a research study design with prototypic character for assisting people in their individual energy management as well as developing the energy assistance in the direction of the general idea of engineering systems for occupational self-management.

2 Background and Research Context

In light of the challenges in modern work life, the self-management assistance focused in this dissertation is intended to enable *sustainable* productivity of the workforce that is thus in balance with health in terms of promoting psychological well-being. This chapter deals with these central terms guiding the dissertation, namely productivity, health and well-being, and self-management. Along with this, it underpins the underlying philosophy of the research demanding a human-centered approach.

2.1. Workforce Productivity

The term productivity was originally coined by the manufacturing sector, which emphasized the quantity of input and output (Drucker, 1999). Thus, following the classical understanding of productivity in business administration, the term can be understood as the ratio of input to output with a focus on quantity (Wöhe et al., 2013):

$$Productivity = \frac{Quantitative\,Output}{Quantitative\,Input}$$

The output then means the production volume, while the input represents the quantitative use of production factors, such as human labor hours, but also machine hours or material consumption quantities. However, the equation above can only be used meaningfully as long as only one type of production factor has to be considered, since mixing several types together as a single sum no longer yields any meaning. That is why, in practice, partial productivity metrics are more often used instead of the above equation. For example, as a possible point of reference for assessing the performance of individual employees, labor productivity can be determined as follows (Wöhe et al., 2013):

$$Labor\,Productivity = \frac{Number\,of\,Similar\,Operations}{Working\,Hours}$$

The rational behind such efforts to quantify productivity is especially the optimization of processes. For the manual worker, the approach for better productivity was to analyze each motion related to a task and record physical effort and time needed (Drucker, 1999). This uncovers unnecessary movements to be eliminated and has shown that even traditionally cherished procedures often are superfluous.
However, changes in the working world (cf. Section 1.1) demanded for novel perspectives in looking at productivity. Drucker already stated 1999:

> *"Still, in developed countries, the central challenge is no longer to make manual work more productive — after all, we know how to do it. The central challenge will be to make knowledge workers more productive."*

According to Davenport (2005), “knowledge workers have high degrees of expertise, education, or experience, and the primary purpose of their jobs involves the creation, distribution, or application of knowledge”. The term *primary purpose* here is important, because many knowledge-intense jobs also include more or less manual work. The surgeons, for example, have to utilize their specialized knowledge for diagnosis and decision making, but the operation itself is repetitive manual work as long as there are no unexpected complications (Drucker, 1999). Addressing productivity in this regard is difficult due to the complexity of knowledge work and the various factors influencing the productivity (Laihonen et al., 2012). What is required to make knowledge work productive is almost the opposite as for manual work (Drucker, 1999). The largest difference lies in the fact that in manual work the task is always clear and the main question is how to optimize the routine steps involved in it. In contrast, the tasks or their proportion have to be defined individually in knowledge-intense work. Nurses, for example, can see their primary role as either providing patient care or serving physicians. It is crucial for their productivity to assist the chosen task and prevent them from being interfered with by non-nursing activities such as paperwork or answering telephone calls. Thus, knowledge jobs in general have to be (re-)structured in a way that allows for the intended contribution.

Furthermore, in knowledge jobs the input, transformation to output, and output itself are often intangible (Laihonen et al., 2012). In addition, with the increase in knowledge-intensive work, quality has become at least as important as quantity (Drucker, 1999; Laihonen et al., 2012). In most cases the quality is even the most important aspect of the output before asking for the quantity, whereas in manual work a certain minimum quality has to be fulfilled while focusing on the quantity (Drucker, 1999). For example, teachers are evaluated on how high-quality their teaching is and not primarily on the number of students. In this direction, knowledge work typically includes some services in the output, which is why customer satisfaction plays also a role (Laihonen et al., 2012).

The described complex nature of knowledge work poses challenges for assessing the productivity of the workers, because traditional quantity-focused metrics are typically inappropriate (Laihonen et al., 2012). In this context, the difference between efficiency and effectiveness is also worth emphasizing, whereby, for example, a focus on time efficiency can even be a hindrance, for instance in collaboration (Graf, 2019, p. 230). Many factors that influence knowledge worker productivity are qualitative, for example self-management (Laihonen et al., 2012). Palvalin et al. (2017) demonstrate in their study that self-management skills of the individuals are an important means to increase the quality and quantity of output in knowledge work. Other examples of qualitative factors influencing the productivity of knowledge workers are their innovation capability and personal factors like satisfaction and motivation (Laihonen et al., 2012). Also workers themselves perceive factors like their emotional or physical state and enjoyment or significance of the tasks as important for their productivity (Kim et al., 2019). In line with this, numerous literature sources associate individual well-being with higher productivity, e.g. Wright and Cropanzano (2000), Mishra and Venkatesan (2022), Lyubomirsky et al. (2005), Johnson et al. (2017), and Diener and Seligman (2004). Along these lines, the research in this dissertation strives to support productivity implicitly through technology assistance for self-management and well-being as drivers of productivity that are at the same time relevant to workers' individual quality of life. With this, it is intended to support productivity in a sustainable way, taking into account benefits for both, the individuals and the organizations.

2.2. Health and Well-Being

This dissertation is especially motivated by the critical developments in work-related mental health. Although the term health is thus relevant and considered in the following, health is indirectly targeted in this dissertation in terms of promoting well-being as a basis of health. Both terms are described in the following.

2.2.1. Health

Health is not a clearly defined construct, although there have been numerous attempts to define it (Franzkowiak and Hurrelmann, 2022). Its description ranges from more comprehensive but not rigorously derived circumscriptions to definitions confined to specific contexts. Further contemporary and multidisciplinary useful definitions are subject of ongoing considerations. Originally and still widely used is the definition in distinction to disease associated to medical purposes. From this traditional, medical perspective, health is defined as the absence of disease (Boorse, 1977), and thus health and disease are simplified as alternative dichotomous states (Franzkowiak and Hurrelmann, 2022). From the sociological and functional perspective, health denotes the ability to perform in a physical and social sense. This perspective already includes physical and mental balance at least and adaptation to changing environmental conditions. An even broader description of health that does not claim to be a scientific derived definition, but is particularly relevant in health promotion, is provided by the preamble to the 1948 constitution of the World Health Organization (WHO). The WHO states to remain firmly committed to the principles set out in the preamble to the Constitution and lists them also on their webpage (World Health Organization, 2022). In one of the principles they describe health in the following way:

> *"Health is a state of* ***complete physical, mental and social well-being*** *and not merely the absence of disease or infirmity."*

In a study of the German health insurer BARMER it is stated that the German healthcare system focuses on physical and mental health so far (BARMER and Universität St. Gallen, 2020). They define physical health as comprising "the physical condition in full range between mere absence of disease to fitness level" and the mental health as "a state of psychological well-being in which a person can realize his or her full potential, cope with the normal stresses of life, work productively, and contribute to his or her community." Social health adds the aspect of social well-being to the health continuum. As in the WHO description of health, well-being represents an integral part of the terminology and is also a focal point in this PhD thesis. Thereby, the term "complete well-being" in the WHO description is to be understood in the sense of encompassing the different dimensions rather than as a

demand for a perfect state, which is hardly achievable (Franzkowiak and Hurrelmann, 2022). In this context, health and illness are rather to be seen as fluid in a continuum in which more or less healthy and sick parts of well-being can exist simultaneously (Franzkowiak, 2022). Furthermore, objective as well as subjective states play a role for this continuum.
Thus, other definitions try to describe health relative to ways of handling it. According to Hurrelmann and Richter (2013), health refers to the state of well-being, in which a person is physically, mentally, and socially in harmony with the own possibilities and goals as well as the respective given internal and external living conditions.

> Huber et al. (2011) conceptualize *"health as the **ability** to adapt and **to self manage**"* in the face of lifelong change.

Especially the last description highlights the importance of self-management that promotes balance in life. Background on self-management as a central aspect of this thesis is described in Section 2.3.

2.2.2. Well-Being

Similar to the different perspectives for specifying the term health, there are different, partly conflicting terms and approaches defining well-being. The following descriptions are not meant to be exhaustive, but to clarify and delimit the use of the term in this dissertation. Same as in the WHO health definition above, some authors affirm that well-being can be divided into physical, mental or psychological, and social well-being (Grant et al., 2007; Johnson et al., 2017; Singh and Gautam, 2023). Then, physical well-being refers to bodily health, functioning, and the subjective experiences with these (Grant et al., 2007). Social well-being is about "the appraisal of one's circumstance and functioning in society" (Keyes, 1998). It includes, among others, a sense of belonging to communities and society. Psychological well-being comprises, for example, persons' experiences of positive emotions, satisfaction, and meaning in life (Singh and Gautam, 2023). However, a variety of further dimensions of well-being, like the intellectual or financial, are proposed in the literature (cf. e.g. Table 1 in Pincus (2023)). The varying concepts of well-being could be due the different demands on the definition and measurement of the construct (World Health Organization, 2013). Drawing on demands for general and objective indicators, well-being can be seen as a composite of observable components, such as education and income. In contrast, well-being can also be defined "as a concept in itself", typically referring to subjective experiences of people. The different perspectives might additionally be due to synonymous uses of the terms well-being, wellness, and quality of life (cf. Ciziceno (2022)), where a differentiated use could add clarification.
Pincus (2023) emphasizes that from the tradition of social psychology well-being is a latent construct, which means it is inherently subjective. For its definition, a distinction has to be made to exogenous factors. Such factors as finances may then rather be an input to a person's subjective evaluation of the well-being state, but should not be used to define well-being. Other dimensions from literature, like emotional well-being, may be subordinate concepts of the psychological construct.

In contrast to earlier mentioned literature, the author points out that well-being as a higher-level construct and all its components have to be psychological.

> Well-being as psychological construct can then be defined as the *"optimal psychological functioning and experience"* (Ryan and Deci, 2001).

Thus, in psychology, the general term well-being or wellness is typically used for the subjective, psychological construct, while the terms subjective well-being and psychological well-being partly refer to more specific sub-constructs due to historical roots (cf. e.g. Ryan and Deci (2001); Donaldson et al. (2015)), which is outlined in the following. Meanwhile, there is largely a consensus that well-being as psychological construct is multidimensional with two prominent aspects, namely a hedonic and a eudaimonic (Ryff et al., 2021; Donaldson et al., 2015; Ryan and Deci, 2001). While hedonic well-being mainly is concerned with happiness, eudaimonic well-being focuses on human potential (Ryan and Deci, 2001). The prevalent assessment instrument in the hedonic approach are scales of so-called subjective well-being (SWB), which were also dominant generally for well-being in psychology for a long time. SWB focuses on three components, namely positive affect, negative affect, and life satisfaction (Diener, 1984). However, it has been shown that the hedonic view alone does not explain well-being to a sufficient degree (Ryan and Deci, 2001; Johnson et al., 2017; Ryff, 1989). Some pleasurable activities might, for example, have negative impact on the person's life (Ryan and Deci, 2001). The eudaimonic approach to well-being takes this into account by referring to deeper values that are less short-lived. In this direction, Ryff (1989) defined "six dimensions of psychological well-being" in contrast to extant indexes of SWB. The defined dimensions are self-acceptance, positive relations with others, autonomy, environmental mastery, purpose in life, and personal growth. With this, the term psychological well-being is often used interchangeable with Ryff's six dimensions tapping into eudaimonic well-being (cf. e.g. Donaldson et al. (2015); Ryan and Deci (2001)), although she may not have intended to narrow the term in this way, as is apparent from her designation of earlier measures as "reigning measures of psychological well-being" (Ryff, 1989). Supporting this assumption, in a recent publication (Ryff et al., 2021), she describes psychological well-being by taking into account both eudaimonic and hedonic aspects, among others.

The dissertation at hand uses the term (psychological) well-being following this overarching perspective including the different aspects. In particular, with the emphasis on energy self-management in large parts of the research to target the continuum of strain and recovery at work (cf. Section 13.1.2), experiences like feeling vigorous and vital (Quinn et al., 2012) play an outstanding role in this dissertation. As these were already classified hedonic (Ryff et al., 2021) or eudaimonic (Ryan and Deci, 2001), it is reasonable to not restrict the proposed self-management assistance to one of these perspectives. Assistance in energy self-management emerged to be of utmost importance in the context of the modern work problems, especially because states of energy depletion are accumulating in the workforce with negative consequences for individuals and whole organizations (cf. Section 1.1). At the same time, enhancing energetic well-being serves not only as a means to prevent negative consequences, but even to promote desirable outcomes for both the individuals and the organizations they work for (cf. Section 13.4.1). Feeling vigorous is furthermore part of the WHO-5 Well-Being Index, a valid 5-item well-being questionnaire (Topp et al., 2015), highlighting the relevance of energy experiences in the overall well-being continuum.

As the proposed assistance is intended for the work context, it is worth mentioning some examples of how work can also contribute positively to well-being and not only well-being to work. Work can give structure and meaning (Greinert, 2020). Especially with high individual involvement and based on individual potentials, work can give employees meaningfulness beyond an earning purpose (Sauer, 2012). It can benefit the workforce in psychosocial terms, shape their development, and generate positive experiences of achievement (Greinert, 2020). Human needs such as feeling competent and appreciated, realizing the own potential, and gaining knowledge can be satisfied through work, which enhances well-being (Sirgy, 2012). However, in order to ensure that highly self-responsible work does not result in overstraining, so that such needs can actually be met, it is important to strengthen self-management competencies of the workforce (Greinert, 2020). The term self-management is elaborated in the following section. In summary, promoting well-being is beneficial for the workforce as well as the organization (Johnson et al., 2017) or even indispensable in these times (Mishra and Venkatesan, 2022) and should become central to organizations (Diener and Seligman, 2004).

2.3. Self-Management

As the previous sections have shown, self-management is essential for a healthy and productive life (cf. particularly Sections 1.1, 2.1, and 2.2.1). It is even referred to as a core competence in today's working world (Graf, 2018). In the literature it is diverse, how self-management is defined and what areas belong to it. Thus, this section is concerned with important terms and definitions around self-management.

The term self-management originates from behavior therapy and was coined by Frederick H. Kanfer (Graf, 2019, p. 10). As a therapeutic approach, it differs from the classical understanding of the therapist as the sole expert and emphasises the patient's active role in directing the own life (Kanfer et al., 2012, Ch. 1). The central theme is to enable patients to take responsibility for themselves, so that they can pursue their goals autonomously in the future, in harmony with their everyday lives. To this end, a key is to promote the client's ability to direct his or her behaviour in relation to self-set goals, which means to promote the so-called *self-regulation* or its special case *self-control* described later on.

Based on the original term from the field of therapy, the term self-management has been transferred to various other contexts. As a result, the way how self-management is defined exactly and what the areas of interest are, is described differently in the literature, especially according to the field of work (Graf, 2019, p. 9-10). Examples would be the medical, psychology or management literature. Still underlying most of the aforementioned different streams, however, are self-regulation and self-control. Self-regulation and its special case, self-control, denote those mental processes by which persons can direct their behavior with respect to their self-imposed goals (Kanfer et al., 2012). In daily life, humans automate many habitual behaviors, which can be a great relief. Sometimes, though, these automatisms are interrupted, for example by obstacles, uncertainties, or conflicts. At such an interruption, self-regulation takes over. This is, if a mismatch between a current and a desired state is detected (Voigt, 2017). However, self-regulation can also be stimulated from outside in order to change existing automatisms (Kanfer et al., 2012). In contrast to automated behavior, self-regulation requires controlled cognitive processes of information processing, as well as continuous attention to one's own behavior, its (possible) consequences, and external influences by the situation. Basically, information about one's own behavior is collected, the situation is evaluated against standards, and consequences for the behavior are explored, possibly until personal standards are reached and a normal flow of behavior can be resumed. The involved "systematic data gathering about one's own behavior" is mentioned by Manz and Sims (1980) as a self-management technique, called self-observation, which can proactively be used to develop self-management behavior. It is one of the techniques chosen to be directly supported by the self-management assistance described in this dissertation. Instead of the aforementioned modification of behavior, the conditions of the behavior can also be modified (Kanfer et al., 2012, p. 29). In order to regulate the frequency of certain behaviors, Manz and Sims (1980) describe two further techniques to actively develop self-management behavior. The first, incentive modification, comprises reinforcement of behavior through rewarding oneself as well as the opposite, namely punishing oneself for certain behavior. The other one and also second of the techniques to be directly supported by the intended self-management assistance is stimulus control, also listed as cueing strategies. It is the "gradual limiting of discriminative stimuli that precede maladaptive behavior while simultaneously increasing exposure to stimuli evoking more desirable behavior" (Manz and Sims, 1980).

Regarding the processes of self-regulation, the special case of self-control comes into play when there are at least two alternative behaviors that are in conflict with each other (Kanfer et al., 2012, p. 35-36). This can be the case when a decision has to be made at a point in time, or, far more demanding, when a temptation has to be resisted or an adverse condition has to be endured over a longer period of time. Thus, self-control means that, compared to the usual behavior, controlling behaviors with an originally lower probability of occurrence are used, causing the usual behavior controlled thereby to occur less frequently. The motivation must be high enough for the exertion of self-regulation, because the related mechanisms consume resources and may be perceived demanding (Voigt, 2017). In the context of this dissertation, this could be seen as an important reason for technological support in motivation. Summarizing, according to Kanfer and colleagues, processes of self-regulation are the fundament for understanding self-management (Kanfer et al., 2012). For detailed discussions on self-regulation theories and facets see also Voigt (2017) and Karoly (1993). However, pursuing goals in harmony with everyday life cannot only be achieved by adjusting behavior, but alternatively, goals can be adjusted, both can be aligned, or a complete reorientation can take place (Kanfer et al., 2012, p. 43). While goal striving is widely regarded as an integral part of self-regulation, goal formation and implementation are not (Voigt, 2017). Important overall self-management skills besides self-control are thus, among others, also goal clarification and goal setting (Kanfer et al., 2012, Ch. 1). Manz and Sims (1980)

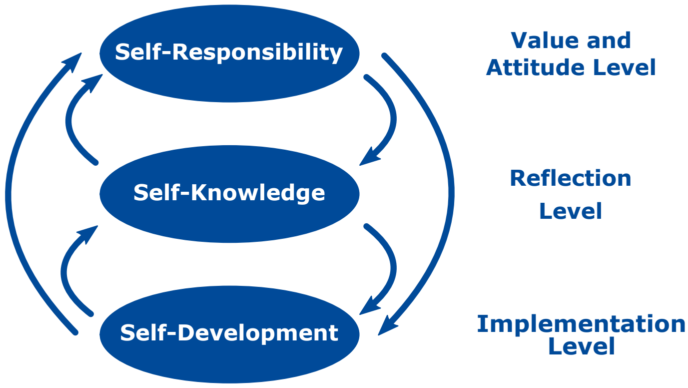

Figure 2.1.: Dynamic core model of self-management competence, adapted from Graf (2019, p. 61)

describe specifying goals as a further technique to develop self-management.
As mentioned earlier, the term self-management has been transferred from the field of therapy to various other contexts. The work at hand focuses on organizational contexts, taken up, for example, by Manz and Sims (1980), Frayne and Geringer (2000), König and Kleinmann (2014), Kleinmann and König (2018), and Graf (2019). There are various definitions of self-management in this context. According to Frayne and Geringer (2000), for example:

> "[S]elf-management is an effort by an individual to exert control over certain aspects of his or her decision making and behavior".

Graf (2019, p. 10-12) provides a table with a small overview of further definitions and proposes an own comprehensive definition:

> *"Self-management competence comprises the willingness and ability to direct one's own life in a self-responsible manner and to shape it in such a way that capability, readiness to perform, well-being, and balance are strengthened and maintained in the long term."* (adapted from German)

While Graf (2019, p. 11) decided to use the terms self-management and self-leadership synonymously in her book to simplify matters, self-leadership is usually defined more broadly. In contrast to self-management that is mainly focused on behavioral influence, self-leadership additionally includes cognitive and intrinsically motivating strategies that target, for example, beliefs and thought patterns (Stewart et al., 2011). These are not considered in the research at hand. A further distinction is to be made is between self-management and stress management. Self-management aims to prevent stress, while stress management is mainly concerned with stress coping, e.g. through relaxation techniques (Kleinmann and König, 2018, p. 7).
The approach to self-management assistance in this dissertation is based on the dynamic core model of self-management competence by Graf (2019), which is shown in Figure 2.1. The three building blocks on the different levels reflect the dynamic process in the development of self-management competence, where the different levels influence each other (Graf, 2019, Ch. 4). The building block *self-responsibility* on the *value and attitude level* concerns meaning in life and the development of a guiding

model. On this level, the focus is on taking responsibility for personal needs and values. This level is only indirectly targeted by the planned self-management assistance. The building block *self-knowledge* on the *reflection level* represents knowledge gain about the own potentials, resources, load factors, and problems. This level involves reflecting on thoughts, emotions, and behaviors, as well as identifying strengths and necessary changes in life. Furthermore, goal formation is assigned to this level. Along the last building block *self-development* on the *implementation level*, personal needs and development goals are translated into actions. Self-development concerns the proactive direction of life in line with personal strengths, conceptions, and needs. Each building block can contribute as an input to the advancement of another, or can itself be reinforced by input from the other levels.

3 Contributions

This dissertation's core contribution is a series of twelve peer-reviewed articles, each providing insights on an important aspect in engineering occupational self-management systems. The chapter at hand first explains the overall research focus that permeates the dissertation. Subsequently, the logical structure throughout the contributing articles is pointed out by means of a thematic categorization. The third section summarizes the research contents and findings of each article together with the research questions and corresponding methods.

3.1. Research Focus

Digital technology supporting self-management challenges is an under-researched topic (cf. Section 1.2). This dissertation tackles this gap by investigating technological assistance for self-management. It focuses on a life domain, where self-management even evolved to a necessary precondition for sustaining well-being and productivity, namely the work life (cf. Section 1.1). While private life necessarily influences well-being and productivity at work, the focal point of this thesis is on assistance that targets the severe challenges in modern work contexts. With this, some self-management domains frequent in the literature, e.g. patient self-management for managing diseases like diabetes, are excluded. Instead, managing the own resources in a healthy way during work is central. The assistance is intended especially for the part of the workforce that has higher degrees of autonomy, as this requires more self-management (Drucker, 1999) and at the same time is what makes it possible in the first place to decide self-responsibly on alternatives or implement new behavioral strategies as it is intended with the assistance. This share of the workforce includes, in particular, employees with larger portions of knowledge-intense tasks and also self-employed.

The scope of the assistance is broadly shown in Figure 3.1. It is intended for a *Person* in the *Work Context*, but for personal use or use as part of corporate health promotion initiatives. The focus of the *Self-Management Assistance* is on supporting the person in achieving professional goals with special respect for the personal resources. For this purpose, the assistance *measures* the situation through self-tracking of the person in the work context. The self-management support is oriented to the model according to Graf (cf. Section 2.3) by including the reflection level from a broader perspective and the implementation level for self-development. The level of values and attitudes is not included for direct support, but as per the model it is influenced by the other levels and is thus indirectly supported. Following this approach, the system shall provide (1) *Self-Reflection Support* as well as

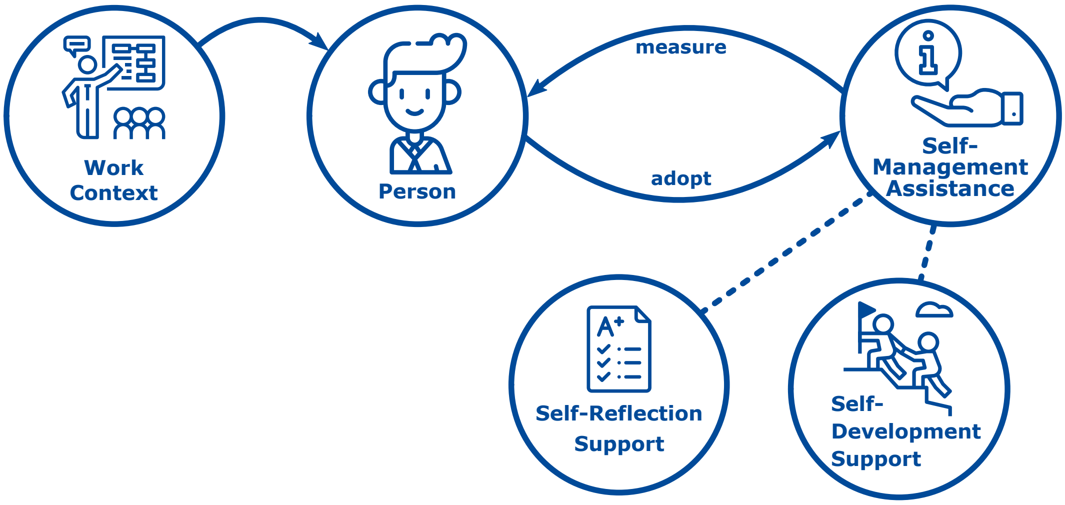

Figure 3.1.: Scope of the self-management assistance

(2) *Self-Development Support.* The support is intended to facilitate and even enrich the utilization of self-management strategies that promote self-reflection and self-development, especially self-observation and cueing strategies (cf. Section 2.3). Self-observation as the systematic gathering of data about oneself is the strategy at the heart of the self-reflection support, which is intended to provide information about the data measured by the assistance system to reflect upon it. During busy working days, observations can be tedious and error-prone without assistance. Technology adds value beyond automation, for example, to back up assumptions with objective data (John et al., 2023), uncover unexpected insights (Pammer and Bratic, 2013; Meyer et al., 2019), and trigger reflection (Halttu and Oinas-Kukkonen, 2017), thus, it helps re-interpreting a situation (Rapp and Tirassa, 2017), "fostering insight, increasing self-control, and promoting positive behaviors" (Baumer et al., 2014). Based on the information provided for self-observation, corresponding goals can be defined. Thus, observation data can be used to trigger and inform goal specification as another self-management strategy in self-reflection support. When observations are compared to goals or standards, achievements can be identified, but also discrepancies between a current and a desired state, for which necessary steps for change can be derived. An identified discrepancy can lead to active action for approaching a target state (Burkert and Sniehotta, 2009). However, a meta-analysis has revealed that there is a large gap between intentions for action and actual implementation (Sheeran, 2002). In some of the analyzed studies, even more than half of the participants with positive intentions nevertheless failed to take action. Thus, the self-development support is intended to help the user to act and implement changes. To achieve this, an emphasis is placed on the cueing strategies of self-management, in which the frequency of exposure to stimuli that elicit (un)desirable behavior is altered. Implementation examples are recommendations, e.g. for work breaks, or automatic countermeasures like blocking certain websites (Meyer et al., 2019). With the self-management assistance provided overall, the person may thereupon *adopt* self-management behaviors, self-reflect and develop beneficial behaviors. Through

regular measurement, changes are reflected in the assistance, so that adoption cycles can take place. The assistance shall follow a holistic approach, targeting as core variables well-being and productivity that are often seen in contrast, but can profit each other (cf. Chapter 2) and in view of developments in the world of work (cf. Section 1.1) should be given joint attention.

3.2. Research Structure and Procedure

There are three objectives specified for this dissertation that serve the overall research question (cf. Section 1.3). Objective 1 concerns the connection of scattered knowledge and is fulfilled throughout all parts of the work at hand. Objective 2 aiming at an conceptual and technical exploration is addressed in particular by Part II on **engineering occupational self-management systems**. Objective 3 for the combined promotion of well-being and sustainable productivity is already present in Part II, but specifically addressed in Part III on **assisting in energy self-management**, as human energy turned out as an outstanding umbrella variable to promote both matters through self-management assistance. Table 3.1 illustrates the logical structure throughout both parts with its contributing articles by means of a thematic categorization. The themes shown with their corresponding chapters are outlined in the following.

Eight publications deliver results for the objective of **engineering occupational self-management systems**. Chapter 5 to 7 explore the basis for a design space by means of a preliminary analysis. Therein, the first theme is *quantifying the self*. Quantification through self-tracking is a necessary prerequisite and core element for the data basis in IT-supported self-management and thus, it was essential to investigate and systematize persons' objectives in self-tracking. Different objectives might lead to different needs, e.g. for data collection and analyses. The research revealed valuable insights into which interests in self-observation can be met with a self-management assistance and how to tailor systems to the corresponding needs. The second theme is *stress-sensitive systems as role models*. In contrast to systems supporting self-management, leveraging technology in the context of stress is a more established field of research that serves as an inspiration regarding feasible measurements, analyses, and feedback. While much existing research is focused on the measurement and management of stress reactions already present, the research presented in this dissertation is also concerned with potentials for prevention. Thus, it goes beyond simply addressing stress that has already occurred. Both chapters included in this theme examine IT support to manage and, even more, to prevent stress. Preventing stress is in line with the self-management perspective, in which a person influences the own behavior according to long-term consequences that typically avoids stress emergence (cf. Section 2.3). The research in the first chapter of this theme, Chapter 6, is focused on work-induced stress and stress-sensitive systems at work, like the acceptance of different data collection methods at the workplace. It revealed, among others, that data should be processed mainly for personal use even in an organizational context and that integrating self-assessments into measurement might be highly appreciated and relevant. Therefore, the research presented in Chapter 7 targets personal stress management and delves deeper into people's

Table 3.1.: Structure and theme of the contributing articles

Part	**Theme**	**Chapter**
Part II: Engineering Occupational Self-Management Systems	Quantifying the Self	*Chapter 5*: Self-Tracking Objectives
	Stress-sensitive Systems as Role Models	*Chapter 6*: Stress-Sensitive IT-Systems at Work
		Chapter 7: Combining Automation and Self-Assessments for Stress Management
	Supporting Sustainable Productivity	*Chapter 8*: Measures and Tools for Personal Productivity Management
		Chapter 9: Requirements and Opportunities for Smart To-do Lists
	Envisioned Systems	*Chapter 10*: Smart Self-Management Concept
	Technical Infrastructure	*Chapter 11*: The Data Perspective for Smart Self-Management
		Chapter 12: Architectural Concept for a Wearable Recommendation System
Part III: Assisting in Energy Self-Management	Human Energy Diary Studies	*Chapter 13*: A Pictorial Scale of Human Energy and Application Opportunities
		Chapter 14: Human Energy Diary Studies with Personalized Feedback
		Chapter 15: Evaluation of Energy Feedback: Randomized Controlled Trial
	Sensor Measurement for Human Energy	*Chapter 16*: The Relationship between Levels of Energy and Blood Glucose

preferences for using self-assessments as data collection method. It is especially directed towards early steps to mitigate stress, just before stress reactions really arise, by examining all stages of stress emergence together with coping strategies, then synthesized into a framework for IT-support.
Building on the preliminary investigations, research was conducted to adapt and complement this foundation for a broad-based self-management assistance that covers an even larger and innovative field. The chapters of the theme on *supporting sustainable productivity* explore the design space regarding a smart assistance in productivity management with an integration of well-being aspects. Therein, Chapter 8 elucidates potentials from research and practice. It presents a consolidated overview on publications concerned with productivity-related parameters unobtrusively measurable through technology and elaborates people's usage of conventional self-tracking and self-management tools. As heart rate variability (HRV) is a surprisingly prominent and versatile measure for the personal state in sustainable productivity management, e.g. for the cognitive performance, it is considered highly relevant for an occupational self-management assistance besides measures for the work context. Furthermore, the research elucidated a regular use of applications for a better organization, especially an email application or calendar, but surprisingly also to-do lists. This provides an opportunity for the extension of such productivity tools taking into account the personal state like the current cognitive performance. Working off to-dos is strongly connected to personal task and time management, important for the pursuit of professional goals and therefore considered part of the design space for engineering occupational self-management systems. Accordingly, Chapter 9 presents initial requirements regarding advanced features for to-do lists that assist in task and time management. However, it has shown that with extensions of productivity tools, the focus is mainly on work facilitation. As such, most frequently in the requirements was the demand for intelligent task creation, e.g. based on textual descriptions. It was necessary to investigate the design space more in the direction of an own concept that focuses on the self-management challenges outlined in the previous section.
Thus, Chapter 10 to 12 comprise conceptual and technical suggestions for holistic self-management assistance systems. Therein, one theme is about the *envisioned systems*. Chapter 10 representing this theme proposes a concept towards self-management assistance based mainly on sensor information for unobtrusive and objective measurement. It presents possible components and their relations, from relevant data to assistance, along with descriptions of implementation options. Because it was decided to focus the concept on innovative, automatic, and objective data collection methods, self-assessments were not included explicitly, but are still intended as a valuable complement in IT-supported self-management.
The other theme is about the *technical infrastructure* along the lines of the proposed concept. Chapter 11 focuses on the data collection perspective illustrating how various sensors and devices can work together collecting certain data for self-management assistance. Especially physiological data are considered very important for integrating objective information about well-being into the self-management assistance, but in the investigation on stress at work mentioned earlier, neurophysiological measuring methods were comparatively less accepted than other methods. In

order to get a first impression of the acceptability of the envisaged data in the specific context of self-management support, the architecture proposed in the chapter is complemented with a survey study with the premises of asking for the willingness to share concrete data instead of the agreement to certain measuring methods and focusing on self-management as a preventive approach instead of pointing to stress states. The initial insights show promise for the potential of incorporating objective data on well-being aspects, while the use of location data seems controversial in this sample. Chapter 12 generalizes and complements the data collection perspective for self-management assistance into a generic architecture for wearable reflection and recommendation systems. It has been paid attention to a modular structure with loose coupling of the components. The end-user devices smartwatch, smartphone, and personal computer are central elements to sense, display, and interact using the system. The architecture henceforth distinguishes between these central end-user devices and additional data sources, comprises a complex server-side, and proposes access of the system via a web browser.

While the presented exploration of the design space open up a wide range of possibilities for self-management assistance systems, it has emerged from all the investigations that the well-being aspect should be the explicit focus of management in order to address the described challenges in the work context, as opposed to work facilitation approaches in which well-being is rather a secondary consideration. The question remained, what exactly should then be the target variable to be self-managed, observed and influenced, with the help of technology. Human energy revealed to be an outstanding variable to consider both, psychological well-being and sustainable productivity. However, assistance for energy self-management is still in its infancy. A major leap has been made with the contributions in this dissertation to pave the field for the development of evidence-based energy self-management tools. Four publications deal with the focus of **assisting in energy self-management**. Because human energy is such an innovative topic, rigor had to be hedged by using established psychological assessment methods and conducting further research on possible assistance instead of aiming directly at the development of an end-user tool based on the concept proposed earlier. In this, Chapter 13 to 15 describe the construction and proving of a research study design with feedback for participants that functions as a prototype for energy self-management tools. These chapters are subsumed under the theme *human energy diary studies*, as diary studies were the chosen research instrument. They help to regularly gather data about peoples' situation by daily self-reports. This is especially relevant here, as there is no established automatic measurement instrument like sensors for the targeted phenomenon yet. For the purpose of time-efficient self-reports, Chapter 13 proposes and validates a single-item pictorial scale as well as it describes the utility of regular energy assessments for technology-assisted human energy management. The pictorial scale is the core element of tracking in the prototypical studies with feedback for participants. Chapter 14 describes the prototypical design and implementation of such studies with feedback. The feedback is generated for each participant based on the individual self-reports and shows in particular the person-specific energy curves, characteristics of workdays, and correlations between various behaviors and personal energy that manifested during study participation. Findings support the need for personal-

ized feedback, because energy curves and strongly correlated factors demonstrated high variance between persons. Chapter 15 presents an evaluation of the energy feedback. Participants tended to enjoy the feedback and to find it useful, which is important for the motivation to use the intended energy self-management tool. Even more, a significant increase in persons' energy upon receiving the feedback was detected. Demonstrating positive effects of the feedback is a critical step towards evidence-based tools for effective energy self-management assistance.
The iteratively improved study designs are based solely on self-assessments. Thus, the last theme is about a possible *sensor measurement for human energy*, which represents the development of the energy prototype towards the general idea of engineering systems for occupational self-management using automatic measures. The respective Chapter 16 investigates the glucose concentration in the blood of persons as a possible predictor of their experienced energy level, because glucose is described a central resource of human energy. A sensor-based measure would reduce the burden for measurement, add an objective perspective, and provide enough data points to enable comprehensive analyses like energy forecasts. However, the results suggest that glucose fluctuations can be primarily attributed to meals and do not appear to be appropriate as a measure of experienced energy.

3.3. Research Results, Questions, and Methods

In this section, the contributing articles' contents and corresponding insights are presented with the underlying research questions and accordingly used research methods. As stated in the introduction (Section 1.4), the research endeavor presented here applied a large variety of methods due to the complex, interdisciplinary topic it targets. Each publication contributing to this dissertation uses proper methods that were chosen according to the respective research questions of the articles. The section is structured according to the two parts and corresponding themes that were presented in Table 3.1. An overview of the research questions and methods used in the individual contributions is given for each of the two parts at the beginning of the respective subsection.

3.3.1. Engineering Occupational Self-Management Systems

This subsection summarizes the contents and insights of Part II focusing on important components and features in the light of the overall thesis aim. The research questions and corresponding methods for chapters in that part are presented in Table 3.2.

Quantifying the Self (Chapter 5)

For the design of personal assistance systems that build on a self-tracking data basis, individual purposes for the tracking should be considered to provide valuable insights and tailored features to the user. However, knowledge regarding possible purposes of self-tracking is scattered among various works. Thus, the chapter on *Self-Tracking Objectives* collects and analyzes people's self-tracking objectives through a systematic literature review (Kitchenham and Charters, 2007) and proposes a systemati-

Table 3.2.: Research questions and main methods for Part II

Chapter	Research Questions	Main Methods
Chapter 5	• What are people's objectives of self-tracking practices? • How can these objectives be systematized?	– Systematic Literature Review – Conceptual-Deductive Analysis
Chapter 6	• What is the acceptance of different stress-related measuring methods? • For which purposes is the processing of stress-related data accepted? • What is the preferred feedback for a stress-sensitive system? • What is the preferred interaction mode with a stress-sensitive system?	– Argumentative-Deductive Analysis – Survey
Chapter 7	• Which dimensions are relevant to measure according to the stages of stress emergence? • How to support coping in the different stages? • What is peoples' situation and preferences to use certain features of an intended system regarding the three stages?	– Conceptual-Deductive Analysis – Survey
Chapter 8	• Which productivity factors that are unobtrusively measurable through IT are described in research? • What prerequisites in the form of data sources are already given in practice through the usage of conventional tools? • What are major obstacles and drivers for the use of conventional applications for self-tracking and -management?	– Systematic Literature Review – Survey
Chapter 9	• What advanced approaches for personal task and time management are desired in improved IT-supported to-do lists?	– Interviews – Content Analysis
Chapter 10	• How can context-aware systems contribute positively to workers' self-management? • How to construct systems from different components that assist self-management ?	– Conceptual-Deductive Analysis
Chapter 11	• How to connect the various data collection tools for self-management support? • What is the willingness to provide data according to their category?	– Prototyping – Survey
Chapter 12	• How to conceptualize and implement an architecture for a recommendation system tailored to occupational self-management?	– Argumentative-Deductive Analysis – Prototyping

zation (cf. Figure 5.2) through a conceptual-deductive analysis (Wilde and Hess, 2007). Most analyzed articles investigate the motivations, practices, or cultures of people using self-tracking, but a small part also considered, e.g., how users can be extrinsically motivated to use self-tracking devices or why users stop tracking. In systematizing the purposes, it became apparent that the objectives for which people possibly want to use technology to quantify themselves are manifold and complex.
In the context of this dissertation especially relevant are elements of the found categories *information*, *health*, and *achievement*. They illustrate that there actually is an intrinsic interest in tracking data for purposes intended in the research at hand and that using technology can be a relief in this regard. It is possible that several purposes apply at the same time. The categories health and achievement fit to the overarching themes of the intended self-management assistance, namely well-being and productivity. Examples for purposes of the category *health* are reducing stress and finding a balance. Purposes in the category *achievements* target optimizing efficiency through observations of the time use and improving performance. The category *information* provides more concrete hints about what features might be important to implement in self-management assistance. With purposes in this category, people hope to recognize previously invisible aspects of their life or gain evidence and confidence. In this direction, technology is considered neutral and more reliable than instinct or tradition and can also provide higher levels of detail. People found that they misjudged aspects and that self-tracking can help them test hypotheses. They want to observe their current status, developments over time, or identify correlations and patterns. These are purposes that are explicitly targeted in the proposed concept of engineering occupational self-management systems and in the presented showcase of assisting in energy self-management. Thus, the integration might appeal persons following these purposes. In contrast to fears sometimes expressed to the author of this dissertation in research discussions about reduced autonomy and control through technology, one purpose mentioned in the literature was an increase in exactly this control through better opportunities for informed choices and further features of self-tracking tools, such as plans, comparison to goals, or reminders. Some people also exclusively want to understand aspects of their life, without a need for change. For this type of users, it might be desirable that corresponding features of an assistance system like reminders are optional.
The literature describes that intrinsic motivation is a factor of utmost importance, because the supply of extrinsic motivation can mainly strengthen an intrinsic motivation already present. Therefore, found purposes directed towards an external target, e.g. the comparison to others or the receipt of discounts, are considered subordinate for the intended assistance. Even more relevant is to strengthen internal purposes that provide intrinsic motivation.

Stress-sensitive Systems as Role Models (Chapter 6 and 7)

This theme includes two chapters investigating assistance to manage and even prevent stress. The chapter on *Stress-Sensitive IT-Systems at Work* is focused on work-induced stress, data collection methods at the workplace, and the use of the data in an organizational context. It is becoming increasingly important for companies to mitigate work-induced stress in order to maintain employee health and avoid productivity losses. While research is concerned with utilizing technology for stress measurement and more rarely also stress management, preferences of workers to manage stress with the help of IT were largely unknown. However, for stress-sensitive systems to be successful and useful, taking into account the willingness of people to utilize certain measurement methods and system feedback is a necessary precondition. Thus, the contribution of the article is to describe implementation options for stress-sensitive systems through an argumentative-deductive analysis (Wilde and Hess, 2007) and to present findings regarding the acceptance, feasibility, and preferences of workers from a survey (Boxill et al., 1997). The survey was conducted with a sample of 103 participants. The results regarding measuring methods, purposes of data processing, system feedback, and interaction with the system can inspire the design of self-management assistance systems, because approaches possibly overlap. Stress detection data examined fall into the categories neurophysiological, communication, documents and calendar, and self-assessment. Furthermore, a prominent device to monitor various (stress-related) data is the smartphone that can provide, among others, data about ambient noises or steps taken. It was, thus, also chosen integral to support self-management. Self-assessment by questionnaire is the most accepted and feasible data collection method in the sample, followed by the utilization of calendar, document, and then communication data. Neurophysiological measuring methods are the least accepted, while still accepted by at least one third of the participants. In regard to smartphone data, the data connection and then the step counter are most accepted in the sample, while just about one third of the answering participants ($n = 76$) would agree to utilizing running apps and GPS position.

The purpose of data processing most accepted with nearly 80 % of the participants agreeing is for personal use, e.g. to receive personal feedback on working habits. Also the improvement of the work organization, e.g. through changing the task distribution, is accepted by many of the participants, while feedback about a person's workload to other people is chosen acceptable by less than one third of the participants. Furthermore, preferences regarding feedback were examined. Feedback about the current state was chosen desirable by more participants than feedback about predicted future states. The delivery should be in a decent way to comply with the private nature of information and also to avoid disturbance in the workflow. A suggestion in the responses that was followed later in the concept for self-management assistance was to use a smartwatch for feedback, which might not only provide a decent way for feedback delivery, but was also found very useful to combine sensor measurement and feedback in one device. A stress-sensitive system could provide information or recommendations either upon request or proactively and it could even execute countermeasures autonomously. The survey revealed that a vast proportion of the participants prefer to retain control by solely requesting assistance or approving proactively recommended actions. Nearly 70 % chose the semi-automated mode, which informs the user proactively, but takes action only after approval. Thus, such systems should mainly empower users and leave the final decisions to them, although higher perceived stress levels seem to lead to a higher desire for automation.

Complementary to the previously described investigation, the chapter on *Combining Automation and Self-Assessments for Stress Management* targets IT support for personal stress management more holistically and in the direction of preventive self-management by examining the different stages of stress emergence and correspondingly possible assistance. A conceptual deductive analysis (Wilde and Hess, 2007) is used to present a framework demonstrating dimensions relevant to an IT support for stress measurement and coping based on the three pillars of stress emergence, namely stressors, cognitive appraisal, and stress reactions (cf. Table 7.1). Based on this, it is proposed to use a combination of automatic, objective measurements with subjective self-assessments on stress-relevant topics in order to strengthen early stress prevention and provide tailored recommendations with a higher chance of being adopted. Furthermore, people's situation and preferences along the framework elements are examined through a survey (Boxill et al., 1997), taking in particular a closer look at self-assessments as a data collection method that can target the individual appraisal of a situation, which is decisive for stress emergence. Cognitive appraisal is, thus, also relevant for the self-management assistance, although not that crucial as in stress management. The IT support for self-management as preventive approach is primarily intended to avoid stressors and especially to strengthen resources, which in turn counteract an appraisal of the situation as dangerous.

The survey yielded a sample of 111 participants. The topics of the questionnaire are the presence of stressors, the acceptance and frequency of self-assessments, the willingness to utilize automatic stress recognition, as well as coping strategies used and the desire for IT-supported stress management. Stressors that are stated most stressful and occurring frequently are lack of sleep, noise, above average work, and too many appointments. Self-management assistance could help reduce such stressors, which is why the respective data is part of the concept and infrastructure described in the next themes. The survey results furthermore indicate that answering different types of stress-related questions would be quite accepted depending on the time required, while it might be a good choice to still let users decide which topics are allowed. Regarding the number of questions in self-assessments and the time to spend on them, short questionnaires could be carried out daily or weekly, while extensive questionnaires are deemed acceptable rather at long intervals. Although many of the participants would provide smartphone data for stress recognition, ensuring that data analysis is performed only locally on the device is a requirement for about half of the respondents. This underlines that data protection and privacy are essential for any system handling personal data and that local storage and processing, if possible, might be a good option for such systems to create more trust.

No clear trend is apparent for the willingness to adopt recommendations from a personal stress management system. Ideally the acceptance of recommendations should be tested in the future using a concrete prototype. Regarding the interaction with such a system, the results confirmed the findings of the first stress-related study, according to which an assistance system should take measures only after the user's consent. One participant indicated in a final free text field the desire for a provision of the collected data for self-reflection. This is in line with the intended self-management assistance, in which support for self-reflection is an integral component as described in the next theme.

Supporting Sustainable Productivity (Chapter 8 and 9)

This theme comprises two chapters concerned with smart assistance in productivity management that considers well-being aspects and integrates with conventional tools related to work productivity. The chapter on *Measures and Tools for Personal Productivity Management* first examines through a systematic literature review (Webster and Watson, 2002) productivity factors from research that are unobtrusively measurable through technology. Then, potentials and constraints from practice regarding IT-supported personal productivity management are determined through a survey study (Boxill et al., 1997) on the usage of conventional self-tracking and self-management tools. It provides insights on the data sources already available through tools in use as well as on the major obstacles and drivers for the use.
Collecting data can help people to observe factors that influence them and their personal productivity during work. Knowledge about the state of these factors can help people to better cope with challenges. When automatic measurements during work are deployed for data collection, they should not disturb the people in their work. Thus, the focus of the literature review was on measurement procedures that work unobtrusively and provide a seamless integration into everyday life. Articles had to describe the connection between data that is sensed unobtrusively and productivity factors of workers in order to be included for review. The search and exclusion process resulted in 32 relevant publications. In order to provide a systematic overview on the literature, the approach of creating a concept matrix was chosen, in which the literature sources examined were mapped to concepts identified through the literature analysis (cf. Table 8.1). The concepts identified are divided into three categories, namely objectives of investigation (i.e. measurement, data analysis, or prediction), productivity factors that are subjects of consideration (e.g. cognitive performance or happiness), and parameters used for state detection regarding the productivity factors (e.g. heart rate variability, physical activity, or PC interaction). The literature review features a considerable variety of parameters that can be measured for the promotion of sustainable productivity, i.e. considering various factors related to well-being that influence individual productivity at work. Although there is a wide spectrum of parameters considered for state detection, heart rate variability (HRV) is a surprisingly prominent parameter that can be used in a variety of contexts. Thus, HRV is considered highly relevant for an occupational self-management assistance.
In practice, measurements and assistance should not complicate existing work routines. Potentials and constraints arise from the already available data sources in terms of conventional tool usage (e.g. fitness tracker, digital calendar) and motives of people to use tracking and management tools. The survey study that examined this yielded a sample of 556 participants with complete records. The majority of the participants frequently used electronic devices for professional and private purposes on a regular basis, in particular personal computers and smartphones. About 94 % of the participants use a smartphone several times a day for private purposes and still about 45 % at least once a day for occupational purposes. As personal computers are mainly valuable for an occupational self-management assistance to add information on work activities or interact with the assistance during work, for these only the professional use is relevant. They are used at least once a day by about 63 % of the

participants for occupational purposes. In contrast, smartwatches are used only by 15 % of the participants for private purposes and even more rarely for professional purposes. However, this might change due to technical advancements and the growing market. Regarding the frequency of self-tracking and self-management activities via tools, a list of possible features was provided for both. An exploratory factor analysis of the responses showed that the used applications can be clustered to three factors of self-tracking, namely health-related, habits, and affect as well as three factors of self-management, namely organization, goals, and avoid distraction. For both, some applications could not be assigned to cluster and form the “Oher Apps”-category (e.g. time tracking). For self-tracking, the health-related applications to track physical activity show the highest frequencies of use in the sample, while the use of applications for a better organization is very common in the self-management activities. These comprise the use of an email application, calendar, notes, or to-do lists. As expected, email and calendar applications are used frequently. However, it was surprising that a high percentage of people regularly uses notes and to-do lists. This could build a good basis to integrate new features in the direction of the intended self-management assistance, such as a prioritization of items on a to-do list according to the current cognitive performance of the user. Thus, it was decided to conduct further research in that direction and investigate requirements for intelligent to-do lists as described in the second chapter of this theme. Finally, predictors of application use were examined with a focus on attitudes towards technology and personality traits. The analysis revealed that negative attitudes towards information and communication technology (ICT) contribute to explain why at least some users may refrain from using the opportunities of ICT, while personality traits like proactive personality and perfectionism contribute to explain why some individuals use self-tracking and self-management applications more frequently. In addition, age was found to be negatively related to application use, and no differences were found between genders.

The chapter on *Requirements and Opportunities for Smart To-do Lists* investigates advanced features for personal task and time management in to-do lists. As there is little research regarding the requirements for intelligent task and time management tools like to-do list, the chapter presents a preliminary requirements catalog based on scientific literature, a review of state-of-the-art tools using a major product weblog, and results from semi-structured in-depth interviews with employees (Misoch, 2015). It was decided to merge requirements from scientific prototype descriptions and those identified by inspecting descriptions of state-of-the-art tools as requirements from tool analysis spanning existing and possibly upcoming tools. The different requirements identified were clustered and ordered through content analysis (Mayring and Fenzl, 2014) into a requirements catalog in the form of a mind map (cf. Figure 9.1). The literature was consulted in order to incorporate the current state of research regarding intelligent features. In summary, there are advancements in regard to intelligent task creation, task planning and context-sensitive reminders. They form requirements together with the results of what current tools developed outside scientific research offer. In order to get first insights what employees consider as important features, interviews were conducted with a small sample of five professionals from the IT industry. The interviewees were asked questions about their current methods

for time and task management, whether they could imagine using applications that solve such tasks in an intelligent way, and what functions these applications should have. Furthermore, they were asked for visionary future features they envision to use.
Overall, requirements in the catalog fall into five broad categories: task management, tracking, reminder, preference management, and cross-cutting requirements. The demand for intelligent support in task creation (e.g. based on textual descriptions, e-mails, or from voice messages) as part of the task management category was mentioned by far most frequently in the interviews together with the tool analysis. Throughout the research it became clear that with the extension of conventional tools, work facilitation stays in the focus. Well-being aspects could be integrated, but might be considered secondary by users in this context. Thus, it was decided to regard tasks of a to-do list as a possible data source for self-management assistance, but conceptualize self-management systems independently and focused on self-management challenges with a reflection and development stage.

Envisioned Systems (Chapter 10)

While digital solutions can be a beneficial means for training, supporting people deal with self-management challenges of the modern working world from a holistic self-management perspective is an under-researched topic. Thus, the chapter on the *Smart Self-Management Concept* provides a contribution towards the design space of self-management assistance that is based on sensor information. First, the vision is illustrated by a fictional scenario in order to sketch the envisioned systems independent from technology choices and constraints. This vision changed throughout the dissertation from systems being rather directive and pervasive to systems focused on empowerment at work. Through a conceptual-deductive analysis (Wilde and Hess, 2007), an architecture for technological assistance is proposed (see Figure 10.1) to contribute positively to workers' self-management and inform the future design of concrete assistance systems. It presents possible components and their relations, from data sources (*Devices and Sensors*), through relevant information that can be gathered from these (*Data and Analytics*), to assistance (*Feedback*), along with descriptions of implementation options.
For a seamless, low-disturbance integration into work life, the concept aims for an unobtrusive data collection mainly without user intervention, i.e. via sensors (here: hardware or software that senses context). Hardware components proposed as data sources are wearables and smartphones, personal computers, and indoor positioning devices. They can contribute through body sensors (e.g. for heart rate), software sensors (e.g. for files and appointments), and location sensors (e.g. for proximity to rooms). The smartphone and the smartwatch as the most commonly used smart wearable are considered central as they have various built-in sensors and can provide information on a person's well-being essential in the self-management assistance, while they are also very useful in mobile contexts for data collection as well as feedback and are often already in use or can at least be integrated easily in daily life. They also corroborated as core devices throughout the further research process. In contrast, location sensors and therewith indoor positioning devices were rather discarded later on. While they could complement the context data, they have

no longer been considered integral, when aiming at a union of well-being and productivity, and showed rather low acceptance (cf. next theme). The data gathered would be stored and then used in data analytics for aggregation, history analyses, pattern detection, etc. Already in this concept, the use of a time series database was thought of, which was later implemented as described in the next theme on the technical infrastructure. Proposed components in data analytics for higher-level information are analysis of time-consuming activities, workload, biological rhythms, and the productivity status. As human energy has been found later on to be a highly valuable variable for the union of well-being and productivity, it should be an integral part for data analytics in future concepts for self-management assistance and examined especially in the interplay to the other variables.

The self-management assistance is intended to support the workforce in self-reflection as well as self-development. Thus, one option is to present the user insights from data analyses for reflection in kind of a dashboard. This is also the approach that was mainly followed in the later research on assisting in energy self-management, because it can empower and educate the user without being directive and patronizing. On the other hand, taking necessary steps for change can be quite challenging and thus, another option is encouraging the user to take action by providing recommendations on carrying out or omitting activities in order to serve prevention. In this direction, an assistance system can recommend next actions or tasks, breaks and relaxation, it can warn for goal conflicts, and provide scheduling assistance. Based on the preliminary investigation on stress-sensitive systems, this assistance could be provided on request or proactively, which could be made configurable according to personal preferences. Furthermore, the proposed components for data collection are intended to be complemented by questionnaires presented to the user on the smartphone or computer in order to take into account subjective appraisal. A prototypical implementation of system components was planned, based on which the implementation options should be evaluated, and subsequently adjusted or extended. The next theme presents the step towards this aim.

Technical Infrastructure (Chapter 11 and 12)

Both chapters included in this theme focus on the necessary technical infrastructure along the lines of the previously described concept. Prototyping (Wilde and Hess, 2007) is underlying both investigations and still ongoing due to the complexity of the proposed infrastructure. The chapter on *The Data Perspective for Smart Self-Management* focuses on the composition of the data collection tools and complements it with insights from a survey study (Boxill et al., 1997) on the willingness of people to provide the envisaged data. The initial data collection architecture (cf. Figure 11.1) contains relevant devices and exemplary data as well as the connections between the devices and to a database. Thus, it illustrates how various sensors and devices can work together to collect data for the support of individuals during their workday. The central hub is a smartphone that collects data from various sensors, especially those built into a smartwatch. Furthermore, a computing device like a laptop or tablet can capture software-based work. Data from the smartphone and computing device are sent via internet to a database.

Due to the personal nature of the data to be processed, the willingness to share the data for assistance is a crucial prerequisite. The survey that resulted in 39 complete data sets addressed the data categories body, software, and location. In this sample, the majority of participants would provide at least some body and software data, but nearly half of the participants would not provide any of the questioned location data. In contrast, the willingness to share data on the body, especially steps, heart rate, and physical activity, is relatively high. Although more extensive research should be done in this regard in the future, ideally on a less theoretical basis using a prototype of the intended assistance, this is a promising sign in terms of possibilities for incorporating objective data on well-being. About one quarter of the participants used the option to describe in a free-text field their concerns about data collection, which were almost entirely about privacy and data protection concerns. This is in line with the insights gained trough the studies on stress-sensitive systems. As suggested there, one participant expressed interest in assistance, if data would be collected only locally without access possibilities for others. The feasibility of a local solution depends, however, on various aspects, like computing power and memory of the devices used as well as communication options between different devices. For research purposes and based on the current technical possibilities, it was decided to retain the use of non-local structures as described in the next chapter of this theme.

The chapter on an *Architectural Concept for a Wearable Recommendation System* generalizes and complements the previously described composition of data collection tools into a generic architecture for reflection and recommendation systems for self-management focused on a mobile context. The provision of personal insights and recommendations should raise awareness for potential well-being and productivity issues among users and encourage them to take action promoting a balance between different aspects of their work-life. The proposed architecture (cf. Figure 12.1) is developed through an argumentative-deductive analysis (Wilde and Hess, 2007) based on the literature on wearable devices and different types of data, related work on architectures and frameworks, and motivational scenarios sketched exemplarily. Equal to the previously described composition of data collection tools, the architecture shall enable the collection of data from various sources and integrates smartwatch, smartphone, and the personal computer as central elements that also enable interaction. In addition, it distinguishes between these end-user devices and additional data sources. Computational expensive tasks shall be outsourced to components with larger computational capacities to save energy on devices with low battery capacity like the smartwatch that is integral for the wearable recommendation system. The architecture adds to the composition of data collection tools a complex server-side with capabilities not only for different data storage, but also for analyses, generation of recommendations, and management. Furthermore, an access of the system via web browser complements the architecture. The architecture features the key advantage of a modular structure with loose coupling of the components. This makes it possible to develop and adapt the components independently of each other without the risk of losing the functionalities of other components. As such, adding further sensors to the system or adapting algorithms for the recommendations would not force an update of the software on the end-user devices. Since it is a major challenge to provide recommendations specifically suited to the individual as well as the situation, the architecture also covers the aspect of user feedback on recommendations to allow for tailoring the recommendations to the user's needs. In summary, the architecture consists of four areas:

1. *End-user Devices*: Smartwatch, smartphone, and personal computer are not only able to sense context, but also to display information and provide interaction, e.g. to intervene through recommendations, to give feedback on recommendations, to answer self-assessment questionnaires, or to interact with the self-reflection dashboard.

2. *Further Data Sources*: Any reasonable further data source could be integrated. This provides the possibility to consider sensor data by a variety of additional sources besides the end-user devices.

3. *Server-Side*: It serves for storing and processing data as well as for the management of the system. While a time-series database is dedicated to store the sensor data, a relational database is responsible for storing all other data, like the list of recommendations, user feedback on recommendations, and user settings. Based on data from both databases, a recommendation system generates the recommendations. A management and reporting system manages the user configurations and processes the data stored in both databases, e.g. to provide analyses of data over time for the user.

4. *Access via Browser*: The system should be accessible via HTTPS using a common browser in order to let the user change settings or access the self-reflection dashboard.

Due to the complexity of such systems implementing the architecture, separate prototypes evolved so far for parts towards the presented ideas. The core elements of a wearable recommender are the smartwatch coupled with the smartphone, the databases, and the recommender system. The ongoing work on an instantiation of the core elements is briefly described in the chapter, while other developed prototypes have already also proven valuable as stand-alone tools. See for these Chapter 15 regarding effective feedback generated solely based on self-assessments and Fellmann et al. (2023) for a desktop tracker and software. The advancement and fusion of the prototypes is still subject to ongoing research and development.

3.3.2. Assisting in Energy Self-Management

This subsection summarizes the findings of Part III with respect to the overall aim of the thesis. The presented research emphasizes the united support of well-being and productivity through the showcase of energy self-management assistance. Research questions and corresponding methods for each chapter in that part are presented in Table 3.3. To ensure rigor, the research connected to human energy is based on validated self-assessment methods, because so far there are no other measures for this umbrella construct. All chapters in this part therefore use experience sampling methods to keep track of individual everyday experiences (Gabriel et al., 2019) with daily electronic diaries. An iterative approach was chosen to first research effective assistance based on the electronic diaries before aiming at the development in the direction of the envisioned concept.

Table 3.3.: Research questions and main methods for Part III

Chapter	Research Questions	Main Methods
Chapter 13	• How to measure human energy with a valid single-item scale? • What are application cases of the short scale in technology-assisted energy management?	– Experience Sampling – Argumentative-Deductive Analysis
Chapter 14	• How to design and implement diary studies with personalized feedback on individual energy trajectories? • What are challenges, learnings, and the perception of participants?	– Prototyping
Chapter 15	• How effective are energy diaries with personalized feedback for improving individual energy? • What is the evaluation in terms of perceived enjoyment and usefulness?	– Randomized Controlled Trial – Survey
Chapter 16	• Can humans' glucose concentration serve as an objective measure of human energy?	– Field Study

Human Energy Diary Studies (Chapters 13 to 15)

This theme includes three chapters focused on energy diaries as a digital tool for enhancing self-management of energetic well-being. The theme comprises investigations on self-assessments of human energy and related aspects, the provision of personalized feedback for energy self-management, and the evaluation of the approach.

The chapter on *A Pictorial Scale of Human Energy and Application Opportunities* introduces human energy as a highly relevant construct reflecting well-being in terms of individual resources. A high level of human energy corresponds to high levels of subjective vitality and low levels of fatigue. The individual resource status changes through processes of strain and recovery during work and should be actively managed. This is not only important in order to prevent energy depletion of the workforce, but also to promote innovation, creativity, and productivity in organizations. In order to capture momentary levels of human energy in a short way, a single-item pictorial scale was developed. The chapter presents the validation of the scale through an experience sampling study. Having a valid measure of human energy is an essential prerequisite for assistance in energy self-management and thus, an updated version of the scale is also the basis of the research in the remaining three chapters described in the following. Of particular interest to this dissertation, furthermore the utility of regular energy assessments for technology-assisted energy management is elaborated in this chapter through an argumentative-deductive analysis (Wilde and Hess, 2007). The application cases described for the individual level reflect the targeted research that was subsequently implemented as presented in the next chapters of this theme.

The developed pictorial scale draws on the metaphor of charging or depleting batteries to describe the ups and downs in a person's energetic resources. The initial version validated here represents five battery icons to choose from, which range from exhausted to full of energy (cf. Figure 13.1). The focus of the presented validation study was to examine the association between answers to the battery scale and to established verbal scales of subjective vitality and fatigue as prototypical indicators of human energy. The experience sampling study was conducted with a sample of 57 working persons. It spanned 12 consecutive days with three electronic self-reports of the momentary energy level per day measured through the pictorial scale as well as through the mentioned verbal scales. It has been proven that the battery scale provides a reliable and valid broad assessment of momentary human energy, as it is highly correlated with ratings of subjective vitality and fatigue. Hence, it is a valid tool to track trajectories of individual energy over time and with its brevity even down to the course of a day. As proposed in the chapter, digital tools offer the possibility to automatically analyze and visualize the tracked data in order to provide insights into individual patterns and further support personal energy management through IT-supported triggers. Personalized feedback should be generated that helps to determine, for example, individual energetic peaks and troughs or (de)energizing activities. The remaining chapters of this theme present the implementation and evaluation of such personalized energy feedback.

As assistance for energy self-management is such an innovative topic and not much is known about individual patterns of energy, knowledge-oriented research on human energy was combined with design-oriented examinations by conducting electronic diary studies that at the same time provide comprehensive and personalized feedback for participants. Based on three energy diary studies with a total of 74 participants, the chapter on *Human Energy Diary Studies with Personalized Feedback* proposes a prototypical design and implementation of such studies with feedback. The presented implementation of the self-assessment procedure and the feedback generated for each participant based on the individual self-reports functions as a prototype for energy self-management tools (Wilde and Hess, 2007). The chapter describes the corresponding infrastructure based on a study framework and open-source software tool called formr and provides examples for feedback generation. Furthermore, it provides insights from the conducted studies regarding participant perceptions, technical challenges, and lessons learned.The focus of the feedback generation is to utilize rich visualizations of individual data in order to provide tailored information that empower the workforce to understand personal patterns. In particular, the generated feedback reveals the person-specific energy curves, characteristics of workdays, and correlations between various behaviors and personal energy that manifested during the study. Figures 14.3 to 14.6 present the proposed feedback graphs generated with formr for each participant. For reflection purposes, the participants are asked, for example, in the beginning to estimate their daily energy pattern using an updated version of the battery scale (cf. Figure 14.2) for different times of a day. This estimated curve is then shown in the feedback in comparison to the actual mean daily energy curve during participation. As the provision of feedback is intended to empower the workforce to improve their energy self-management, a quite important graph is the one showing a selection of factors with the strongest

correlations to a person's energy, which means that these factors could have a major influence on the energy level for the specific person. An example would be a negative correlation of energy with time in meetings. Determining such influencing factors is valuable in order to proactively enhance (promote positive correlates) the own energy level or prevent a decrease (restrict negative correlates). An important finding from conducting these studies is that energy curves and strongly correlated factors can vary greatly from person to person (cf. Figure 14.7), which supports the need for individual feedback versus rather general recommendations. An essential lesson learned for the design of the assistance is that the assessed factors to be correlated with energy should be actionable, meaning that the person should be able to change the factor, as it is typically with behavioral strategies. Based also on positive responses from study participants about the possible impact of energy feedback, it was decided to use the feedback as an intervention and examine the psychological effects of receiving personalized energy feedback.
This approach is described by the chapter on the *Evaluation of Energy Feedback: Randomized Controlled Trial*. More specifically, the chapter combines an evaluation of the energy feedback in terms of perceived enjoyment and usefulness with an evaluation of actual changes in assessed energy as a result of the feedback. The evaluation of the feedback effects is a decisive step towards evidence-based tools for effective energy self-management assistance. In order to evaluate the effectiveness of energy feedback for improving individual energy, the proposed study design was adapted to enable using the method of a randomized controlled trial (Kang et al., 2008). While certain aspects of the study design, such as the experience sampling assessments and personalized feedback reports based on these, were retained similarly, the process was especially adapted in that participants were randomly assigned to one of two groups - intervention or waitlist. Both groups received feedback, but at different points in time in order to control confounding factors. The intervention group received a personalized feedback report already in the middle of the study period as an intervention and again at the end, while the waitlist group only got feedback at the end of the study. Furthermore, this time momentary and daily self-reports on workdays were combined with weekly retrospective surveys that encompassed a selection of the daily captured variables referring to the past week. Perceived enjoyment and usefulness of the feedback, on the other hand, were examined through a survey at the end of the study (Boxill et al., 1997), after both groups received their final feedback reports. This complex study was conducted with a sample of 136 employees from diverse occupational contexts. There were four consecutive weekly surveys that started on the weekend preceding the experience sampling assessments on workdays. For the experience sampling part, the participants provided up to four daily self reports across the ten workdays of two consecutive workweeks. The experienced energy was examined all four times a day, while influencing factors like taking micro-breaks, imagining successful performance, or making a to-do list were examined once a day. Based on this data, the intervention group already received feedback after five workdays, while both groups received feedback after the full ten workdays, i.e. at the end of week 2. The final weekly questionnaire that served as follow-up at the end of week 3 combined a weekly retrospective survey with an exploration of the participants' perception of the personalized feedback. The 101 persons,

who participated to rate the perceived enjoyment and usefulness of the feedback reports tended to enjoy the feedback and to find it useful. Most importantly for the effectiveness of the feedback, a comparative analysis of changes in the experienced energy between the two groups upon receiving feedback was performed. While it is possible to look at the experience sampling data or at the weekly self-reports for this, the focus of the chapter is on analyzing the weekly self-reports. It is possible with these to examine energy trajectories across all four weeks comparing the two groups. In fact, a significant increase in energy upon receiving the feedback was detected, i.e. for the intervention group at the end of week 1 and for the waitlist group at the end of week 2, that last over the remaining period of the study (cf. Figure 15.5). This means that both groups gained immediate benefits from receiving the energy feedback. The significant transition effect can be interpreted in terms of a causal effect, suggesting that the receipt of the energy feedback is associated with upward shifts in energy. This is an excellent result that opens up promising opportunities for technology-assisted energy self-management.

Sensor-Measurement for Energy (Chapter 16)

As an physiological measure to determine human energy levels would benefit self-management assistance, the chapter on *The Relationship between Levels of Energy and Blood Glucose* investigates through a field study (Palvia et al., 2004), whether humans' glucose levels serve as such a measure. In the literature, glucose is considered one of the main energy resources and is thus a subject of measurement relevant for investigation. The presented study examines whether self-reported energy and continuous glucose data or their diurnal patterns correlate during everyday life. Experienced energy was measured 10 times on each workday through the earlier proposed battery scale, while glucose concentrations were tracked every 5 minutes by a continuous glucose monitoring system. The study was conducted over a period of 10 days with a sample of 12 healthy participants working at least 30 h a week. The results of the examination show a mixed picture. No statistically significant linear or nonlinear relationship could be determined between energy and glucose trajectories, even if time-lagged effects were assumed or a 1-hour mean value of the glucose level was used instead of an exact value (cf. Table 16.2 to 16.3 and Figure 16.4). In contrast, analyses on the correlations of diurnal patterns, peculiarities in certain situations such as glucose peaks, and differences by gender indicate that some connections exist and further studies could contribute to a deeper understanding of the relationship between glucose levels and perceived energy. However, overall the results suggest that glucose fluctuations can be primarily attributed to meals leading to multiple increases and decreases during the day, while the experienced energy seems to be a limited resource, rather refilled by sleep and controlled during the day by relaxation and (work) strain. Therefore, other physiological measures should be investigated to determine a suitable sensor measurement for human energy.
The study confirmed results from earlier investigations in that diurnal patterns of human energy vary considerably between subjects. In addition, the findings suggest that human energy patterns, similar to glucose levels, vary between women and men. In this direction, technology-based self-management should strive to provide tailored support that enables a comprehensive understanding of oneself.

4 Discussion and Conclusions

As complex, self-responsible, and flexible work has become increasingly prevalent, strong self-management skills are essential to take advantage of the upsides and master the downsides of such work forms (cf. Section 1.1). When individuals' self-management competence is exceeded, they are at risk of proactively engaging in self-endangering work behaviors and could even ignore health promotion regulations. Organizations are therefore not only responsible to take measures ensuring appropriate work design, but should also take care that their employees can acquire or enhance the required skills to use the freedoms of self-responsible work forms in a positive way. Properly managed, this will have a positive impact to both, individual well-being and overall sustainable productivity. Digital solutions are highly scalable and cost-effective for companies as well as flexible in use for employees. This dissertation addresses digital assistance for self-management regarding the challenges of modern work life and investigates how technology can contribute especially with this to sustainable productivity and psychological well-being.

4.1. Discussing the Results

Digital prevention for fostering mental well-being is often conceptualized without considerations of the work context. However, the increasing challenges regarding the imbalance between work strain and recovery cannot be ignored. Furthermore, according to Li and Vogel (2021), many "studies fail to explain how IT enables effective health education". The research presented in this dissertation brings together knowledge from several disciplines to pave the way for effective digital tools with an overall self-management perspective as theoretical grounding. It explores the large and innovative field on how personalized occupational self-management systems that foster well-being in productive work should be engineered. While the research is based on established fields, like personal informatics and digital interventions, it comprehensively connects the various strands of research with a base in psychological theory and expands the knowledge base with an innovative concept for a new class of assistance for use in the work context. With the novelty of this topic and the critical need to take care of individual concerns of self-management in an occupational context, a broad approach using various research methods was chosen to explore the diverse aspects of the topic. This creates a sound basis to account for the aspect of usefulness when engineering occupational self-management assistance. The dissertation presents relevant components and desired features of measurement, analysis, and feedback of occupational self-management assistance. Addressing the need to take care of individual concerns regarding self-management assistance in an occupational context, the work deduces potentials and challenges

from literature and presents insights from several empirical investigations for the integration of people's perception on assistance features in the subsequent research. For example, rather semi-automatic systems are desired that leave the control to the users. Very important is also the data processing only for personal use, as privacy and data protection are essential for a system handling personal data. Moreover, integrating self-assessments into measurement were found to be quite accepted and relevant. Self-assessments were then used as the sole basis in the presented showcase of assisting in energy self-management. While self-assessments were originally used to this extent mainly due to lack of sensor measurements, they appeared to be a good means of making the personal condition more salient to the user. However, complementing the energy prototype with further components from the proposed architecture is still regarded highly relevant, because it reduces the burden for measurement, adds an objective perspective, and provides considerably more data points to enable comprehensive analyses like complex patterns of interactions or energy forecasts. Building on the modular structure of the generic technical architecture proposed, an extension would be quite flexible in scope.
There are also certain feedback features implemented in the showcase, based on findings of a previous investigation. Relevant for feedback are, for example, the current status, developments over time, or correlations and patterns, all of which have been implemented in the energy feedback. Tailoring the assistance to such user objectives as discovered with the different presented investigations might motivate for use and empower for the desired knowledge gain, leading to effective digital tools. In this, it might be important to provide solution-focused insights for the users, so that they can constructively reflect on necessary steps instead of remaining in the attempt to understand their situation (Grant et al., 2002). The energy self-management approach implemented does this by providing actionable feedback in the form of correlations of the individual energy with used behavioral strategies and characteristics of the work days. Thus, users receive highly individualized, directed feedback.
The initial evaluation of the energy self-management prototype underlines, based on the positive effects found on individual energy, the value of the extensive exploration undertaken on various aspects of digital solutions for occupational self-management. A major leap has been made with this, as it is not self-evident that tracking tools achieve such results. A recent, year-long, in-the-wild study with smart rings showed: even though participants declared changes in sleep habits as a result of wearing the ring, they could not improve their sleep quality according to the ring data (R. Nolasco et al., 2023). The authors conclude that many existing self-tracking tools lack actionable feedback or information on how to gain insights from the data.

Theoretical and practical implications. The implications arising from the presented research are multifaceted:

- Conceptual and technical implementation options are proposed for reflection and recommendation systems in the context of occupational self-management together with the provision of diverse insights on how such assistance systems should be engineered. This provides a foundation for the development of effective digital tools with different core variables that are relevant in the context of fostering well-being or productivity. Thus, developers of tracking tools can utilize the presented knowledge to build new tools or integrate additional components and features in their tools. Based on results from this dissertation, a desktop tracker was implemented following the idea of a software sensor as proposed in the conceptual architecture and integrating well-being aspects through self-assessments(Fellmann et al., 2023).

- Self-assessments appeared to be valuable as a complement in digital self-management tools. They are quite accepted, provide the opportunity to integrate the person's subjective perception, and possibly serve as additional trigger for reflection. Therefore, it should be considered for which parts of the tracking it might be useful to integrate self-assessment.
- It has emerged from the investigations that, in order to address the described challenges in the work context, health education should be the explicit focus of occupational self-management assistance as opposed to a focus on work facilitation in the form of support for task and time management or other areas relating more to efficiency. Raising the awareness and understanding of the workforce for the development of their individual well-being during and through their work therefore appears to be particularly important. Information on individual well-being as well as on the work or work behaviors have to be part of such an occupational self-management assistance.
- Successful digital cueing through reminders or recommendation might require an intention for change. Thus, it should be combined with opportunities for reflection.
- Human energy revealed to be an outstanding variable to consider both, psychological well-being and sustainable productivity. Based on this insight, innovative digital tools can be developed that create benefits for employees and organizations. The combined benefit might be an incentive for organizations to integrate such tools into their workplace health promotion.
- The human energy studies demonstrated a high variance between persons energy curves and strongly correlated factors. These findings support the need for personalized feedback rather than just one size-fits-all recommendations in health promotion. Digital solutions are key for highly personalized, but scalable health promotion initiatives. Thereby, actionable feedback about interrelations should be provided in order to foster self-development.
- The found positive effect of the energy feedback is a critical step towards an evidence-based tool for health promotion. Employees can use the tool to learn about their energy patterns and enhance their energetic resources. An evidence-based tool could allow health insurers to promote its use and would thus facilitate access to it.
- The proposed battery scale can be used in even more contexts, as practitioners in various domains can integrate it as needed in their work context. Social services, for example, is a domain with major challenges regarding mental strain and related health problems. A social service company from Rostock

integrated the battery assessment in their documentation system for reflection purposes.

4.2. Limitations and Future Work

Each of the twelve contributions has its own limitations described in the corresponding chapters. Overall, these relate to restrictions in the scope of literature analyses, lack of representative samples in empirical studies, and pending maturity of prototypical implementations. However, valuable insights could be generated regarding the diverse aspects of the large and innovative field on how occupational self-management systems should be engineered. While parts of the technical infrastructure proposed for engineering self-management systems have already been implemented, completion is still ongoing. In particular, the development of recommendations and the parts of the infrastructure responsible for delivering them are the subject of future work. Furthermore, the level of attitudes and values of the self-management model is not considered so far. Because all three levels with their interaction are important, future research could investigate integrating aspects as described by Huldtgren et al. (2014). It also needs further exploration whether the link between reflection and development support should be designed in a way where users themselves choose which development support they want to receive based on the reflection data delivered or in an automated way based on, e.g. health promoting standard ranges.
Many promising opportunities for future work are noticed for the prototypical energy diaries with feedback. So far, they have only been implemented in the form of a research infrastructure. It would be desirable to develop the energy approach as an independent tool, e.g. as an app. Instead of rare feedback reports, the app could provide a dashboard that shows feedback to the user at any time. A relevant shortcoming of the current form of energy feedback is that only simple correlations for energy with other factors are calculated. Time-lagged effects are not taken into account, for example. This could even lead to wrong conclusions by the users. Thus, complex analyses of the data should be researched and implemented, considering time-lagged effects, but possibly also complex interaction patterns or trends. In addition, further studies should be conducted to deepen the knowledge on the effects of the energy feedback. For example, observing the effects over longer time periods would be important. In this regard, it would be highly relevant to investigate, if a tool for burnout prevention could be developed based on the energy approach. Burnout is associated with a lack of energy and thus might be recognizable through energy measurements. Taking into account that a prevention or early warning system would be used in the long-term, finding a sensor-based measure for human energy is also still relevant. While blood glucose has not proven to be an appropriate measure, heart rate variability as a quite versatile measure for the personal state could be examined alternatively. The inclusion of physiological data could help uncover relationships underlying energetic activation that are not already apparent from introspection alone.

4.3. Conclusion

Self-management is a crucial workforce competence in order to keep a healthy balance in the context of the ever growing demand for autonomous work behavior. The dissertation at hand explores how to engineer digital solutions to provide assistance in self-management at work. Thereby, it comprehensively connects scattered knowledge from several disciplines to conceptualize support for self-reflection and self-development of individuals in organizational contexts. An innovative approach based mainly on automatically tracked data is proposed. With this, relevant components and desired features of measurement, analysis, and feedback of occupational self-management assistance are presented. Furthermore, the combined promotion of psychological well-being sustainable productivity is investigated and as a result, energy self-management assistance is proposed and demonstrated. Due to the novelty and complexity of the topic, a broad approach using various research methods was chosen to explore the diverse aspects of the topic. The thesis contributes multifaceted insights on conceptual and technical implementation options useful for developers of digital tools for self-reflection and self-development. Furthermore, the implemented energy self-management approach demonstrates assistance of employees in gaining knowledge about their individual patterns of energy in the work context. This is realized through the provision of feedback based on individual self-assessment data. A randomized controlled trial revealed immediate positive effects of the personalized energy feedback on individual energy. With this, the research contributes to evidence-based digital solutions that tackle the increasing imbalance of work strain and recovery. The development of the energy prototype towards the proposed general idea of engineering systems for occupational self-management will multiply the possibilities to deliver assistance.

An essence of the work is that well-being should be taken even more into focus, while connecting it to the context of work. Approaches that focus mainly on facilitating work try to tackle high workload with efficiency, but lack empowering people to manage the underlying challenges. Empowerment turned out as a core target for IT-supported self-management. This is due to the fact that self-management is so strongly based on the individual, e.g. individual desires and fears. Even intelligent technology might not be able to adapt to all the needs of a person. With empowerment the individual retains and even increases control. The associated learning might be more sustainable and desired by people. Furthermore, intrinsic motivation was found to be of utmost importance. Thus, the assistance might be most effective when supporting the implementation of intentions already formed or the formation of new intentions. Overall, an assistance should be engineered in a way that supports the individual in a sovereignty-preserving manner that stimulates personal growth.

Part II

Engineering Occupational Self-Management Systems

5 Self-Tracking Objectives[1]

Abstract. With the ongoing spread of smart devices, self-tracking increasingly finds its way into everyday use. Even a community has formed around it, called the "Quantified Selfers". A pivotal question to further develop appropriate tools tailored to people's needs in the future is: For what purposes do people try to systematically track their data digitally? This question is fundamental as different goals of tracking might lead to different needs and requirements, e.g. in terms of the collected data or the provided data analyses. Since knowledge regarding the purposes of self-tracking is scattered among various works, we provide a consolidated overview through a systematic literature review. In contrast to frequently mentioned health-related purposes, there are a lot less apparent purposes that are connected, for example, to a community, awareness, or life experiences. We present our systematization of the purposes as frame for consideration in future developments and research.

5.1. Introduction

In the era of *datafication*, there is data and statistics on almost everything. Also individuals collect data about themselves, e.g. to draw conclusions about their lifestyle and to adapt their behavior accordingly (Sharon and Zandbergen, 2017). However, the collection of data about oneself is not a new phenomenon. Only the technical means to support it arose later and continue to develop. So-called *self-monitoring* as an assessment procedure for behavior change was documented already nearly 40 years ago. Self-monitoring means that a person notices a certain behavior relevant for the own assessment goal and creates a record on it. Self-monitoring was thus found a valuable means in order to e.g. identify targets for a therapy or monitor a therapy's progress, because some behaviors may not be obvious to the person in any situation, but can be assessed in the person's everyday life. Nevertheless, the accuracy of such self-monitoring can vary according to situational factors and

[1] The content of this chapter has already been published as follows:
Lambusch, F.; Fellmann, M.; Rosenau, C.; Gember, A. (2021): On the Diversity of Self-tracking Purposes: Systematizing the Objectives in Tracking Oneself. In: Advances in Usability, User Experience, Wearable and Assistive Technology. AHFE 2021. Lecture Notes in Networks and Systems, vol 275, pp. 34–41. Springer, Cham. https://doi.org/10.1007/978-3-030-80091-8_5

may need to be estimated e.g. by involving an independent observer (Korotitsch and Nelson-Gray, 1999). Due to the ever smaller circuit boards and sensors that could be integrated into mobile devices, the possibility of *IT-supported self-tracking* emerged, on which we focus in this article. Mobile phones have become a particularly popular self-tracking device due to features such as automated tracking and statistics generation. The data that can be collected with different devices is manifold. It ranges from measuring essential body functions, such as the heart rate, to sleep, nutrition, smoking, stress, weight, or mood (Choe et al., 2014). Nowadays, people also track themselves and analyze their data beyond medical applications, e.g. to optimize themselves or increase well-being (Lupton, 2014). The motivations and *purposes why people want to quantify themselves* are as complex as the data that can be collected (Sharon and Zandbergen, 2017). In our context, we regard the term motivation as the underlying psychological mechanisms involved in self-tracking. These can, for example, be self-design or self-healing (Gimpel et al., 2013). With the term purpose, on the other hand, we refer to the objectives of tracking, not in terms of specific parameters tracked, but in terms of the broader target of the tracking practice. We only focus on the purposes in this work. While various different purposes of self-tracking through technology were taken up by existing literature, the knowledge about them is scattered in various works that focus on specific other aspects such as medical use cases, tracking abandonment, or practices of extreme users of tracking. Thus, it is challenging to acquire an overview on the diverse purposes of self-tracking. Having such an overview is highly relevant to develop tailored tools that can better address specific concerns by considering how the individual purposes differ and to identify aspects that require further research. Hence, we aim to *collect and systematize the purposes of self-tracking* and provide with this article a *taxonomy* synthesized from the results of a structured literature review.

5.2. Methodological Approach

For the literature review the approach according to Kitchenham was used (Kitchenham and Charters, 2007). Two data sources were used for the literature analysis: Scopus and AISeL. The search term was developed iteratively according to the relevance of the resulting documents. It consists of two parts, one formed by words for *self-tracking* and one limiting the search space to *purposes*. Figure 5.1 shows which of the words and phrases finally belong to which part of the search term.
Since Scopus has a powerful search interface with additional operators, this literature database served as the basis for the search. One of these additional operators used is the “W” operator, where words in the query must just lie within a certain number of terms (n). Using the “W” operator, it was possible in Scopus to combine the terms related to self-tracking and those related to purposes without requiring them to be part of an exact phrase. For the final search string, we also used wildcards to include the plural form or related words as well as we used loose phrases to include only specific combinations of several words. In addition, we restricted the publication year and the subject area in order to focus on newer and technically supported self-tracking.

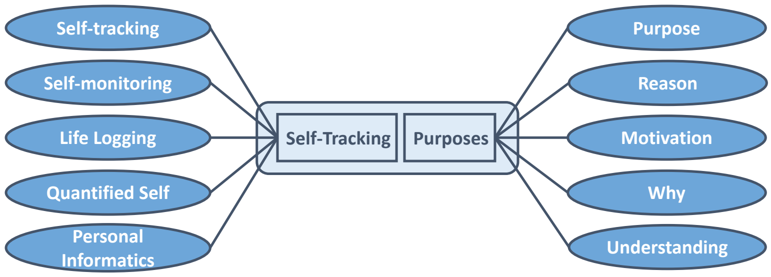

Figure 5.1.: Composition of the search term

The final search term for Scopus looks as follows:
TITLE-ABS-KEY (("self tracking" OR "self monitoring" OR "life logging" OR "quantified self" OR "personal informatics") W/5 (purpose OR reason OR motivation* OR why OR understanding)) AND PUBYEAR > 2009 AND (LIMIT-TO (SUBJAREA, "COMP"))*
A direct transfer of the string for AISeL was not possible, because especially the W-operator is not available there. Since a simple AND conjunction resulted in a large number of irrelevant documents, the search was limited to the title, but publication year and subject area were not restricted.
The final search string for AISeL was as follows:
title:("self tracking" OR "self monitoring" OR "life logging" OR "quantified self" OR "quantified selfers" OR "personal informatics") AND title:(purpose OR reason OR motivation OR why OR understanding)
The search was conducted at the end of 2019. The search string used in Scopus returned 57 documents, the one in AiSeL returned eight documents. Four documents were duplicates, so that 61 documents were obtained for further analysis. The resulting documents were first filtered by title (35 remaining), then by abstract (20 remaining) and finally by the full text (final 8 documents). Only documents were included that investigate for what purposes people track themselves in connection to technology. While we restricted our search to articles related to computer science, it could not be determined if all the articles make a clear distinction between IT-supported tracking and other forms. However, we decided to consider all the statements from the included articles.

5.3. Results

First, we describe the overall objectives of the articles. Afterwards we present the results on systematizing the *purposes of IT-supported self-tracking*. Nearly all of the articles investigate the motivations, practices, or cultures of people who use self-tracking. In one study, the adoption of activity-tracking devices in regard to pre-existing motivation and activity level is researched (Jarrahi et al., 2018). In another study, so-called Extreme Quantified Selfers are studied in the self-tracking process in order to identify the workarounds, which they use for a better self-tracking experience (Choe et al., 2014). One article looks at common practices in a self-tracking cycle in order to describe optimization potentials in the data integration stage (Whooley et al., 2014). Lupton (2014) examines self-tracking in connection with the social, cultural and political practices of the users. Another paper presents a scale to measure a tool user's aesthetic experience (Suh and Cheung, 2017). As the authors of this article do not directly refer to purposes, the article is not additionally referenced when describing the systematization of purposes. However, the items they used in their scale underpin some of the purposes we describe. The remaining articles are connected to self-tracking of health data. Monitoring and maintaining health is not only important to many individuals, but also to health care systems. Thus, one article investigates from the perspective of health insurance companies how users can be extrinsically motivated to use self-tracking devices (Henkel et al., 2018). A further article examines the motivational aspects that drive people to keep tracking their health data and proposes a motivation model based on the results that shall inform the design of healthcare information systems appealing to the different motivational needs of people (Gimpel et al., 2013). Besides the more physical health aspects, one paper focuses on the possibility of improving mental health by means of self-tracking, exploring the experiences of students (Kelley et al., 2017). Our literature analysis shows that the possible *purposes of self-tracking* through IT are manifold. Most of the articles considered use statements from self-tracking users who were surveyed about their tracking habits and motivations or who state their views in existing material, such as videos or documents. We mainly draw on such statements for our systematization, which is presented in Figure 5.2. The elements in the figure are roughly ordered from top to bottom according to the number of articles in which they appear. It is possible that several purposes apply at the same time. The investigation has revealed that self-tracking purposes can be split in first order into those directed towards an *external* target, i.e. communities, conformity, or assets, and those directed towards an *internal* target, i.e. information, diseases, health, experiences, or achievements.

5.3.1. External Purposes

The purposes in the first category *community* are directed to other people. Self-Trackers are interested in comparing and competing with others (Gimpel et al., 2013; Jarrahi et al., 2018; Kelley et al., 2017). A competition can feel fairer when connected to a community of like-minded people (Jarrahi et al., 2018). Another purpose of sharing self-tracking activities or experiences is to help and inspire others (Gimpel et al., 2013; Kelley et al., 2017). For some self-trackers it is important to have social contact (Jarrahi et al., 2018) and achieve better relationships (Lupton, 2014). When starting tracking, some people don't have a specific goal, but want to tag along with others who started tracking (Gimpel et al., 2013). Self-tracking can also spur a person to achieve a desired look and thus fulfilling the purpose to increase attractiveness (Kelley et al., 2017). Furthermore, there are individuals who want to be able to see their friends' activities (Gimpel et al., 2013) or to proudly share their success (Kelley et al., 2017).

The category *conformity* consists of purposes related to yielding to social pressure and avoiding disadvantages of denying tracking. Lupton (2014) describes that agencies and institutions like employers started encouraging people to track themselves,

Figure 5.2.: Purposes for self-tracking

but want to use the data for pursuit of own interests. With this, a participation in wellness programs at work may be necessary to lower health insurance premiums or monitoring workers' productivity is linked to pay and promotion opportunities, and thus gets less voluntary. The more common the ideal of self-optimization gets, the more people could feel the pressure to adhere to this ideal and start tracking to this end. Otherwise financial disadvantages and moral judgment could be expected (Lupton, 2014).

In the category *assets*, purposes targeted at financial or material benefits are represented. Such benefits are usually offered by parties who have an increased interest in the health of an individual, like insurance companies that want to reduce costs for the treatment of illnesses. The material incentives could not only strengthen people's motivation to reach their health goals, but also constitute purposes of self-tracking in their own right. The insurers provide the incentives for customers who track their fitness and fulfill a predefined fitness goal (Henkel et al., 2018). Some of the insurers subsidize tracking devices. Furthermore, they partly give discounts on premium insurances or provide bonus points to shop e.g. with partners from the sports and health sector. Participants in bonus programs can also receive cash bonuses or gift rewards, depending on the insurer (Henkel et al., 2018).

5.3.2. Internal Purposes

An important category in this group is *information.* Often people want to gain awareness and be mindful by self-tracking. They appreciate the possibility to recognize previously invisible aspects of their life and the ease to just look at their device at any time to see the current status (Lupton, 2014). Self-Trackers are e.g. interested in the status of their heart, fitness level (Kelley et al., 2017), or stress level (Lupton, 2014). It also shows them their individual ranges and limits (Kelley et al., 2017). The purpose of awareness is not necessarily connected to behavior change practices. Some people exclusively want to understand aspects of their life, without a need for change (Whooley et al., 2014). Another common theme for self-tracking is the desire to observe developments over time. This can be the personal evolution (Gimpel et al., 2013), but also a constant exercise level (Jarrahi et al., 2018). Other examples are taking a self-portrait every day to see changes (Choe et al., 2014) or observing how the own posture changes during a day identifying when it was good or bad (Choe et al., 2014). Another manifestation of an information purpose is the wish to identify correlations or patterns. Combining data sets enables detailed analysis of patterns (Lupton, 2014). Therefore, some people just track multiple parameters to find any interesting correlations (Choe et al., 2014). Other self-trackers search for factors that mostly affect their state or behavior (Gimpel et al., 2013). Self-tracking can furthermore help to gain evidence. The data-driven approach of tracking via technology is considered neutral and more reliable than instinct or tradition (Lupton, 2014). It can also provide higher levels of detail (Kelley et al., 2017). People found that they misjudged aspects, such calorie intake (Kelley et al., 2017) and that self-tracking can help them test hypotheses (Kelley et al., 2017; Choe et al., 2014). Data-driven evidence gives higher confidence, e.g. when speaking to a doctor in a case where recommendations are followed, but improvements remain absent (Kelley et al., 2017). The last purpose in this category is having control. Self-Trackers hope to better control their own destiny by making informed choices based on the data (Lupton, 2014; Kelley et al., 2017) or specifically manipulating certain factors that have been turned out relevant for them (Gimpel et al., 2013). Furthermore, self-tracking tools can provide control by assisting with further features like a fitness plan, reminders, or showing the amount of steps taken in comparison to a step goal (Jarrahi et al., 2018).

Health monitoring and promotion play a major role in self-tracking (Choe et al., 2014). If people already suffer from a *disease*, their purposes of tracking are often related to it (Gimpel et al., 2013; Kelley et al., 2017). Managing chronic conditions is especially important (Lupton, 2014). In the simplest case of a disease-related purpose, the person just wants to document disease parameters. These can be specific variables that need to be in a target range, like blood glucose (Choe et al., 2014) or caloric intake (Kelley et al., 2017). Some also document their medication intake or occurring symptoms (Gimpel et al., 2013). Data-driven documentation is also helpful for demonstrating anomalies (Kelley et al., 2017). Self-tracking can further have the purpose to tailor treatments. One can use the tracked variables to adjust medication doses at certain points (Kelley et al., 2017) or to find the right dosage (Choe et al., 2014). Tracking can even function as a treatment for panic attacks (Choe et al., 2014). Another disease-related purpose is to examine effects or

relations, e.g. identifying if different symptoms are related to each other (Gimpel et al., 2013), what behavior increases anxiety or mitigate depression (Kelley et al., 2017), or what effect a medication has (Choe et al., 2014). Self-tracking can also be a tool to identify and minimize triggers. As such, it presents a way for allergy patients to find triggers for physical reactions and interactions (Choe et al., 2014). Known triggers can be logged and minimized, e.g. for atrial fibrillation (Choe et al., 2014), or anxiety (Kelley et al., 2017). As a last purpose in this category, people would like to detect, if they have a disorder. For example, they would like to know, if their poor diet is connected to an eating disorder (Kelley et al., 2017). Purposes to maintain or improve general health constitute another category. Controlling weight is a purpose of this category that is mentioned in several articles (Choe et al., 2014; Whooley et al., 2014; Jarrahi et al., 2018; Kelley et al., 2017). Other purposes include increasing the fitness level (Kelley et al., 2017; Whooley et al., 2014), reducing stress (Lupton, 2014; Kelley et al., 2017), improving sleep quality, and control mood swings (Lupton, 2014). In addition, finding a balance is a purpose (Choe et al., 2014).
Some people use self-tracking in order to encounter *experiences*. A common purpose there is having fun (Choe et al., 2014; Gimpel et al., 2013; Whooley et al., 2014; Lupton, 2014). Self-trackers following this purpose enjoy, for example, engaging with data (Whooley et al., 2014; Gimpel et al., 2013) or playing around with a technical device (Gimpel et al., 2013). Learning something is another purpose of the same category. Self-trackers study themselves as an interesting topic (Lupton, 2014). This includes to track variables over time and find out what can be learned from it without a specific goal (Gimpel et al., 2013; Choe et al., 2014). A special example for a learning purpose is exploring a city by tracking every street walked (Choe et al., 2014). A part of the self-trackers just enjoys to quantify themselves and desire measuring everything (Gimpel et al., 2013; Jarrahi et al., 2018). Some like the experience to master challenges related to the tracking (Gimpel et al., 2013). Creative people can furthermore use tracking for the purpose of self-expression, e.g. representing surfing and skateboarding data in an artistic way (Whooley et al., 2014). The last category of purposes is concerned with achievements. There is a desire to optimize efficiency by observing the time use (Whooley et al., 2014; Choe et al., 2014) especially for work productivity (Choe et al., 2014). Improving performance is another purpose of this category that can specifically relate to a better cognitive performance (Choe et al., 2014) or a more general desire to exploit the own full potential (Gimpel et al., 2013).

5.4. Concluding Remarks

The main objective of the presented systematic literature review is to systematize the purposes for which people use and might use technology to track themselves. In particular, it became apparent that self-tracking can relate to many different areas. The documents that remained for the literature analysis at the end of the exclusion phase focus on specific other aspects than purposes, but all contain information about purposes for self-tracking. On the one hand, this underlines the lack of works that specifically deal with self-tracking purposes, but on the other hand, the variety of focal points is reflected positively in the results of our literature overview, since the self-tracking purposes could be portrayed from different perspectives in this way. A limitation of the presented analysis is that the search string via AISel was rather restrictive. The search via Scopus allowed to filter a large number of irrelevant documents sophistically, but it was not possible to transfer this search string to the AISeL database, since the literature databases have search capabilities of different quality. In summary, it should be noted that the purposes of self-tracking are manifold and depend on the type of user. Therefore, the design of self-tracking applications is an essential aspect for future developments, where it should be considered how the individual purposes differ so that the applications could support them as best as possible. We present our overview on the self-tracking purposes as a frame for consideration in future developments and research.

An *important factor* that mobilizes people to use self-tracking tools in the long run is *intrinsic motivation*. The supply of extrinsic motivation can mainly strengthen an intrinsic motivation already present (Jarrahi et al., 2018). Intrinsic motivation factors that play a role in self-tracking are, for example, self-design or self-healing (Gimpel et al., 2013). When appealing to motivation types, the concrete purposes of an individual can still be manifold (see Figure 5.2). For example, following the motivation of self-healing, the features needed from an application might be very different depending on the concrete purpose or target like identifying triggers for sleep problems versus controlling a cardiovascular disease. Thus, it is highly relevant for the design of self-tracking and analysis applications to *consider the individual purposes and provide tailored features*. Tracking too much data or the "wrong" data (e.g. symptoms instead of triggers) can lead to tracking fatigue and stopping data collection or it may limit later knowledge gain (Choe et al., 2014). An application should help users to *focus on the most relevant data and provide valuable insights for their purpose*. If many data sources are used, the tool should provide *integration of these data*, because a lack of automation can be a high burden for unskilled users (Whooley et al., 2014). Depending on the concrete tracking purpose, real-time feedback can be very valuable to adapt behaviors. Thus, a tracking tool should offer the possibility to choose target variables for a simple real-time feedback according to selectable thresholds. Such a simple feedback could be binary like a light turning on or blinking (Choe et al., 2014; Whooley et al., 2014).

6 Stress-Sensitive IT-Systems at Work[1]

Abstract. High workload, complex and knowledge-intense tasks as well as increased expectations in respect to flexibility and timeliness give rise to work intensification. This can lead to permanent stress causing serious health problems. Thus, it is a major concern to take measures against stress in order to maintain workers' health and productivity. While information technology provides great potential to mitigate work-induced stress, preferences of workers regarding IT-based assistance are largely unknown. Against this research gap, we conducted a quantitative study on the acceptance and feasibility of implementation options for stress-sensitive systems. Our results are intended to inform future research in the design and development of such systems.

6.1. Introduction

Work stress is a major challenge especially in developed countries. Globalization and the increasing use of information and communication technologies have a far-reaching impact on developments in the working world (Walter et al., 2013). One of the aspects is the increasing competitive pressure due to globalization. In addition, the working population is more often expected to be highly flexible and mobile (Siegrist, 2013). With the extensive use of information and communication technology, multitasking and interruptions of the workflow are part of everyday life in numerous companies (Freude and Ullsperger, 2010). Due to the fast transfer of tasks via email, users are faced with the difficulty of processing tasks faster and continuously viewing and prioritizing their email inbox. Projects in the enterprise can be carried out faster by the fact that spatial and temporal borders are overcome. Such developments pose new challenges and increase the stress for the responsible individual (Kielholz, 2008). Studies prove a high work intensity. In the EU, for example, 33 % of workers report to work at high speed about three-quarters of their work time and 10 % of workers even report to 'never' or 'rarely' have time to do their job (Eurofound, 2017). Such working situations can cause stress. The term stress describes strain that can affect the organism (Lohmer et al., 2017). Stress is

[1]The content of this chapter has already been published as follows:
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triggered by so-called stressors that activate the organism by means of challenge, threat, or harm. For stressors that are considered dangerous, the available resources to deal with the situation are assessed. If the resources are appraised inadequate, stress occurs (Lazarus and Folkman, 1984). A high exposure to stress can lead to overstrain, which presents a significant hazard for health and may be e.g. resulting in burnout (Scharnhorst, 2012). Therefore, it is becoming increasingly important for companies to take preventive measures against stress at the workplace in order to maintain workers' health, reduce sick leave, and avoid loss of overall productivity of the company. With the ongoing development in sensor technology and the IT-systems in companies there are various potential approaches to augment IT-based systems with stress-sensitive features. However, for stress-sensitive systems to be successful and useful in everyday working life, it is of utmost importance to take into account the preferences of workers regarding stress measuring methods, purposes of data processing, system feedback, and interaction with the system. Empirical research that systematically analyzes user preferences for all the above mentioned questions is still missing. Hence in order to inform the design and development of stress-sensitive systems, we contribute to the existing research with a quantitative study answering the following research questions:

- RQ1: What is the acceptance of different stress-related measuring methods?
- RQ2: For which purposes is the processing of personal data accepted?
- RQ3: What is the preferred system feedback?
- RQ4: What is the preferred interaction mode with a stress-sensitive system?

The remainder of this article is structured as follows. In Section 6.2, we describe related work. Section 6.3 deals with the design space of stress-sensitive IT-systems because this motivates our empirical investigation. In Section 6.4, we then present the design and results of our empirical investigation. The results of the questionnaire used are described in five subsections according to the respective contents. In the last section, the results are discussed and conclusions are drawn.

6.2. Related Work

First of all, the topic of IT-supported personal stress management deals with the concept of stress. Therefore, *established theories about stress* are related. Established theories (e.g. Folkman and Lazarus (1985); Folkman et al. (1986); Selye (1956)) deal with important aspects of the phenomenon and describe the cognitive processes associated to stress as well as the result of stress such as strains. Further, a review of organizational stress theories is conducted by Sonnentag and Frese (Sonnentag and Frese, 2013). While such works form a valuable underpinning, they predominantly focus on the phenomenon stress itself rather than on how to promote stress management or coping.

Managing stress in IT-contexts or IT-induced stress is an active research field. Coping with such stress has been investigated in early works (e.g. (Benamati and Lederer, 2001; Al-Fudail and Mellar, 2008)). More recently, approaches for managing

IT-induced stress have emerged and are broadly referred to as research regarding *technostress* (e.g. (Ayyagari et al., 2011; Maier et al., 2015; Fischer and Riedl, 2015)). Moreover, a blueprint for the technostress-aware design of information systems has been developed (Adam et al., 2017). While the research community around technostress is mainly concerned with the management of stress *caused by IT* and the *design of information systems*, our main objective is to shed light on the *preferences* of users *to manage stress with the help of IT*. Hence, technostress as a research area is complementary to our research goal and our results can inform the technostress research community. Regarding more holistic *assistance systems for IT-supported personal stress management and their acceptance*, only a few works exist so far. Most notably, tools such as a workload monitor and an e-coach for activity recommendation (NiceWork eCoach) have been developed in the context of the SWELL project (Koldijk, 2016). While sophisticated prototypes have been developed and empirically tested for their effectiveness, there is still not much research available in regard to an empirical analysis about the willingness of participants to provide data and to answer questions which is a necessary precondition for IT-supported stress management. In this direction, a first study on the needs for mobile coaching has already been conducted (Harjumaa et al., 2015) as well as a comparison of specific sampling methods for stress (Atz, 2013). However, none of these studies focuses in detail on the willingness of users to utilize the automatic stress measurement techniques proposed in the literature and on the preferences for certain system feedback and interaction types.

6.3. Questions on How to Design Stress-Sensitive IT-Systems from an End-User Perspective

Fundamentally, an information system acquires data (input), processes it and ultimately delivers results (output) to the user or other systems. In regard to stress-sensitive IT-systems, data acquisition means to capture relevant data about the situation, e.g. the stress-level of the user and other context data. Data processing means to analyze and interpret this data. Delivery of results entails to either directly provide information to the user or to leverage the results in order to provide support e.g. in the form of system adaptations (Adam et al., 2017) or process adaptations (Fellmann et al., 2017). An example would be a messaging system that increasingly shields the user from new messages of specified types such as newsletters or advertisements depending on the current stress level of the user. These messages could be delivered later on if the user is in a more relaxed state.
In the context of data acquisition (input), different information channels exist that reveal data useful to infer the current user situation. Among these channels are physiological parameters that can be recorded through methods like eye tracking, skin conductance measurement, or electrocardiogram (Dimoka et al., 2012). Furthermore, communication data such as received and sent email messages, phone calls or other communication data such as instant messaging can be analyzed. In addition, document and calendar data might serve as a proxy to determine the workload and engagement of a user at the workplace. A prominent device for data collection, particularly in a mobile context, is the smartphone. This type of de-

vice can monitor various stress-related data ranging from steps through phone calls to appointments (Gimpel et al., 2015). The widespread use of smartphones makes them a valuable part of data collection. While the aforementioned channels refer to (semi-) automatic data collection, another approach is to ask the user about the level of stress via self-assessment questionnaires, e.g. by the Perceived Stress Scale (Cohen et al., 1983). All the different data collection options have in common that their feasibility depends on the characteristics of the workplace and on the acceptance of the user. We provide empirical insights on both of these aspects in Section 6.4. In the context of data processing and analysis, two modes of inquiry can be distinguished: First, *descriptive* statements about what currently is the case could be derived. Such statements can be used for personal insights as well as to inform colleagues about the current situation (e.g. that planning for a meeting is not feasible due to workload, even if the calendar has free time slots), or even to provide feedback for supervisors. Second, *prescriptive* statements focusing on what should be done can be derived that are grounded in knowledge about the current state. An example for this would be recommendations for improving the individual style of working (e.g. blocking distractions during the personal biological "prime time" in order to preserve this time for important tasks) or for improving the work organization for entire teams (e.g. distributing tasks depending on the employees' workload). Regardless of the statement type, a decision has to be made in regard to privacy. It has to be determined which types of analyses are allowed (also from a legal perspective) for personal use only, implying a private mode of analysis; and which analyses are allowed for groups of employees implying a public mode of analysis requiring effective anonymization mechanisms. In order to learn about user preferences, we deliberately did not consider legal aspects, but asked in our study about the acceptance and valuation of a wide range of purposes of descriptive and prescriptive analytics.

In the context of results delivery (output), a system can provide results either upon request thus being *reactive*, or it can provide results without an explicit request thus being *proactive*. Since results may be used for interventions, proactive delivery of results can be divided further into information only and autonomous execution. In the former case, the user is notified about possible interventions which then have to be executed manually. In the latter case, the system directly adapts itself according to the data processing results. An example for this has already been introduced in the form of a stress-sensitive message filtering and delay mechanism.

6.4. Empirical Investigation

The aim of the study was to gain insight into the field of research using a larger sample under standardized conditions. For this purpose, a quantitative research approach was chosen with an online survey. The online questionnaire consisted largely of closed questions. In addition, semi-open questions with an additional free text field for "Other" was used and the last question in the questionnaire was modeled as an open question for final comments. In order to gain initial experiences systematically, the representativeness, such as the number and composition of the sample, played a subordinate role in the survey (Bortz and Döring, 2016). The questionnaire was distributed in German language through several channels. For the study, the complete case analysis (CC) was used, which means that only complete data sets were used for the evaluation (Göthlich, 2009). In total, 103 complete records were received and analyzed. The following sections describe the results of the survey. For a better overview, the questionnaire was divided into five different parts. At the beginning of the questionnaire, an introductory text motivated the topic of stress-sensitive information systems at work and described that such systems shall recognize and counteract stress in real time during the work time. The first questions were used to collect data on gender, age and current employment. The second part of the survey refers to the general work situation of the respondents. Questions were asked about job status, working hours and technology usage, among other things. Furthermore, participants should indicate their situation related to sources of stress, e.g. on workload and time pressure. The other parts of the survey relate to possible components of a stress-sensitive system. Thus, the third section covers the acceptance and feasibility of several measurement methods in the workplace. In the fourth section of the survey, the respondents should state for whom and for what purpose they would allow the processing of personal data. Additionally, the participants could choose the desired type of system feedback and express concerns about a stress-sensitive system. The last section is meant to determine the desired interaction mode of the system, or rather whether a stress-sensitive system should provide support automatically, semi-automatically, or only manually. At the end of the questionnaire, participants had the opportunity to comment on the survey.

6.4.1. Characteristics of Survey Participants

At the beginning of the questionnaire, data were collected on gender, age and current employment. Among the 103 participants, 44.7 % were female and 55.3 % male. The age varied between 19 and 67 years. Nearly half of the respondents were between 25 and 31 years old. The question "Do you work?" had the options of "yes", "no", and "student with part-time job / internship". 92 persons (89.3 %) answered yes, two persons no, and nine respondents stated they were students with a part-time job or an internship. As the next part of the survey focused the persons' everyday working life, the use of a skip function led participants who did not work to the third part of the survey.

6.4.2. General Work Situation

The first question of this part concerned the professional status of the working respondents (n = 101). Employees accounted for the largest proportion at around 60 %. The proportion of freelancers, officials, managers and students/interns ranges between 10.9 % and 8.9 %, whereas the proportion of apprentices is only 0.99 % (1 person). Furthermore, it was asked for the company's sector. The most commonly represented sectors were "services" (26.7 %), "education" (22.8 %), and "banks/insurance" (15.8 %).

The participants should also indicate their average working hours and the average working hours at a computer workstation. Most participants worked seven hours or more a day (94 %). The mean value is 8.5 working hours a day. It is noticeable

Table 6.1.: Perceived work situation on a five level rating scale

n=101	Strongly agree	Agree	Partly/ partly	Disagree	Strongly disagree	Mean
1. I have enough time to do my work.	10.9 %	25.7 %	46.5 %	14.9 %	2.0 %	2.71
2. My everyday work is stressful.	13.9 %	33.7 %	48.5 %	4.0 %	0 %	2.43
3. My daily workload is high.	20.8 %	41.6 %	31.7 %	5.0 %	1.0 %	2.24
4. I can use my knowledge at work.	40.6 %	49.5 %	8.9 %	0 %	1.0 %	1.71
5. I consider interruptions by emails or phone calls annoying.	15.8 %	28.7 %	33.7 %	18.8 %	3.0 %	2.64
6. The working atmosphere at my work is good.	30.7 %	47.5 %	17.8 %	2.0 %	2.0 %	1.97
7. Supervisors inform employees adequately about developments & decisions.	11.9 %	34.7 %	26.7 %	23.8 %	3.0 %	2.71

that 60.4 % of the participants, who worked on average 7-8 hours a day spent the same amount of time on a computer workstation on average. The median of the average working hours spent at a computer workstation is between 6 and 7 hours and thus, many participants spent a large part of their average working day at a computer workstation. This may be beneficial for the imagination and assessment of IT-based, stress-sensitive systems. Another question concerned the use of a smartphone at the workplace for professional purposes. This is important for various measurement methods that can be carried out via a smartphone, but also in connection to the permanent accessibility of the worker. Occupational smartphone use shows an almost balanced ratio, with 52.5 % of respondents confirming a use. In a next question, 42.6 % of the respondents stated that they are also expected to be available in their free time. At the end of this survey part, a table should be completed with seven questions as rows and answer options as columns (results in Table 6.1). The questions were intended to give an indication of the working atmosphere perceived by the participants. The answer options were subject to a ranking or ordinal scale (Porst, 2014) in a range of five levels.

There is a slight tendency of the workers to agree in having a stressful working day (mean: 2.43), a high daily workload (mean: 2.24), and to be disturbed by emails / phone calls (mean: 2.64). These statements tend to be in line with the basic idea of this research, namely that everyday working life is becoming more stressful and the workload ever higher, so that the participants might relate well to the fictitious scenarios of the survey. In comparison, the result of the statement "I have enough time to do my work" shows a mean value of 2.71, which tends to be slightly opposite to the answers for the second and third statement. A possible explanation could be that the stressor is due to factors outside the employee's work responsibilities. On average, knowledge can be used and the working atmosphere is good. The results of the statement for sufficient information by supervisors show only a slight tendency for approval.

6.4.3. Acceptance of Measuring Methods for Stress Detection

The focus of the third section was on the assessment of measurement methods and thus on answering **RQ1**. An introductory text pointed out that the following methods for stress recognition shall contribute to a targeted stress reduction and the extent of data processing is intended to be self-determined. The non-employees returned to the survey in this part, so that all 103 participants had the opportunity to answer the questions. Several methods of state detection were presented with explanatory examples and grouped according to the produced data in order to increase clarity. The same scheme was used to query for the groups whether the participants consider a certain method feasible at their workplace and whether they would agree with such a measurement. Table 6.2 below shows the assessments by the participants. For better visualization, the votes for each method have been colored in different shades of red and green (yes = green, no = red). The color gradient depends on the strength of the vote which in turn shows at a glance the strength of approval or rejection of the respective methods.
With regard to the question of whether the participants would agree with the measuring methods presented, a slight increase in acceptance from the group of neurophysiological measurement methods (1.-3.) to self-assessment by questionnaire (8.) can be observed. Neurophysiological measurement methods would be the least accepted ones, especially skin conductance measurement is rejected by many participants (66 %). The collection of communication data receives higher support and an even greater acceptance can be seen for monitoring edited documents (63.1 %) and calendar or work schedule entries (74.8 %). The greatest popularity is achieved by the option of self-assessment through questionnaires with 81.6 %. A similar course of consent can be found in answering the question of how to carry out such measurements at the workplace. However, a clear trend can only be seen in the case of neurophysiological measurement methods, where more than 64 % of respondents deny any possibility of measurement. Furthermore, participants could indicate whether they would agree to the collection of certain smartphone data, even if they did not use a smartphone for their work. In total 76 participants answered the smartphone related questions. As can be seen in Figure 6.1, many participants would agree to collect information about the data connection. This allows to determine whether a person is within the company network or works in the field. Relatively few participants agree to the recording of running apps or the GPS position.

Table 6.2.: Acceptance and appraised feasibility of methods for stress detection

n=103		Is this data collection method feasible at your workplace?		Would you agree to the implementation of this method?	
		Yes	No	Yes	No
Neurophysio-logical data	1. Eye tracking	35.9 %	64.1 %	47.6 %	52.4 %
	2. Skin conductance measurement	32.0 %	68.0 %	34.0 %	66.0 %
	3. ECG (electrocardiogram)	31.1 %	68.9 %	41.7 %	58.3 %
Communi-cation data	4. Email / Instant messaging	43.7 %	56.3 %	60.2 %	39.8 %
	5. Phone data	43.7 %	56.3 %	54.4 %	45.6 %
Documents & Calendar	6. Appointment calendar / Work plan	50.5 %	49.5 %	74.8 %	25.2 %
	7. Edited documents	43.7 %	56.3 %	63.1 %	36.9 %
	8. Self-assessment questionnaire	57.3 %	42.7 %	81.6 %	18.4 %

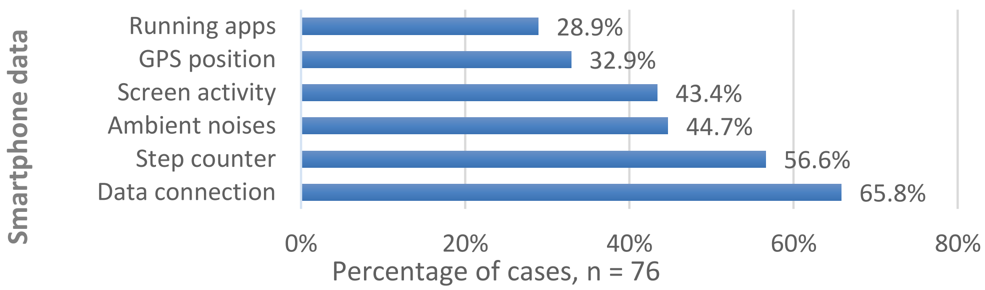

Figure 6.1.: Acceptance of measuring methods utilizing smartphone data

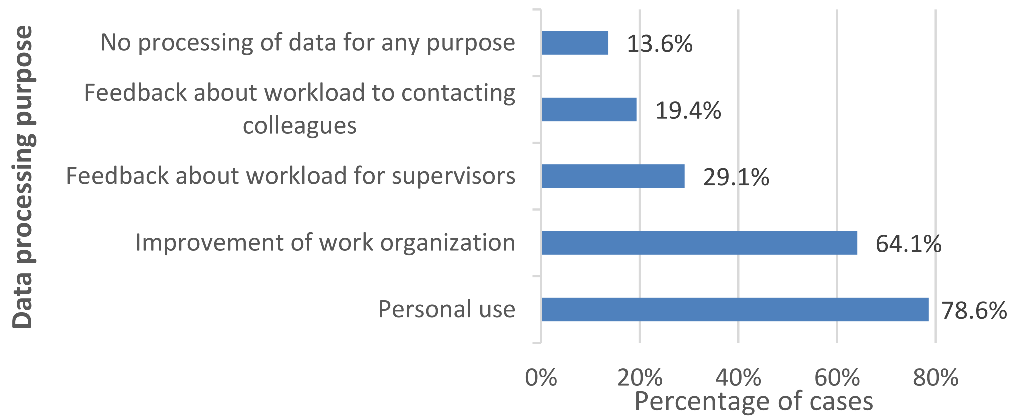

Figure 6.2.: Acceptance of data processing purposes

6.4.4. Data Analysis and System Feedback

The fourth section of the survey was designed to determine the purposes for which a person would consent to the processing of personal data (**RQ2**) and what the feedback from the system should look like (**RQ3**). First, it should be clarified for what purpose the participants would allow the processing of personal data (see Figure 6.2). This determines the extent to which the system should pass on information about a user's situation. All 103 participants answered this question, but since multiple choices were possible, a total of 211 answers were collected.

It can be seen from Figure 6.2 that the information should mainly be used for personal purposes (78.6 %), but there also seem to be a desire for an improvement of the work organization (64.1 %), e.g. with a better distribution of work tasks in stressful situations. Still 29.1 % of the participants would provide their supervisors information on their workload, but only 19.4 % would allow their colleagues to access this data. Overall, the results show that data collection and analysis for a stress-sensitive system would be allowed by most participants, but stress-related information should just be passed to a limited group of people and for selected purposes. However, still 13.6 % of the participants would not agree with any form of data processing. Due to a skip function in the questionnaire, these participants were forwarded to the next part of the questionnaire related to the user interaction. Subsequent questions in this part were answered by a total of 89 participants.

The next question was about the desired type of feedback (cf. Figure 6.3). Multiple answers were allowed for this question. The options to choose were either a warning message on the screen or an audible signal, but it was also possible to write down other ideas in a text box provided. The answers show a clear trend to give a warning on the screen (82 %). Only 16.9 % of respondents want an acoustic signal. Searching for correlations, a connection to the indicated screen working hours of participants could be found. In the group of people whose work time at a computer workstation is up to four hours, the desire for audible feedback from the system stands out in comparison to groups of people spending more time on the screen. The proportion in this category is 36.8 %, while with longer working hours the demand for acoustic

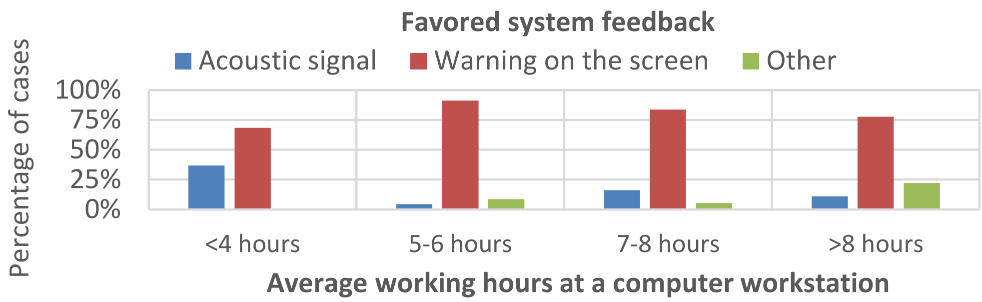

Figure 6.3.: Relation between average working hours at a computer workstation and desired type of feedback

feedback in each case is 16 % and far less. Furthermore, it can be seen that with a daily work time of five or more hours at a computer workstation an increase of the choices for "Other" is recorded. It can be deduced from these responses that, for example, feedback in the form of an email would also be desirable, so that the employee would not be disturbed by direct feedback in the workflow and can decide when to read it. Another suggestion was the use of a smartwatch for feedback. This could also be a good approach to combine measurement (e.g. heart rate data) and feedback in one device.
Next, the participants could state whether the system should refer to the current state or to a predicted future state (e.g. if the system recognizes through task and appointment entries that the workload for the next day is too high). Primarily, feedback on the current status is desired (88.8 %), while just over half of respondents (55.1 %) would also like to receive feedback about a predicted state. Finally, there was a possibility that respondents raised concerns about data collection. Due to possible multiple choices, 106 replies were submitted in total. Privacy concerns are indicated by 40.4 % of the participants and 37.1 % agree with the thought that it could be impracticable. Almost 1/3 of the participants (31.5 %) stated they had no concerns about data collection. Nine persons (10.1 %) used the text box for "Other". The entered free texts also refer to a difficult or complex implementation or to the point of data protection.

6.4.5. Interaction Mode and Final Remarks

The last part of the questionnaire addressed how to interact with a stress-sensitive system (**RQ4**) and the participants had the opportunity to comment on the survey and its topic. Figure 6.4 shows the results regarding the interaction with the system. Full automation, in which the system takes action without being asked, is desired by only 9.7 % of participants (n = 103). Although 68.9 % of participants would like the system to automatically inform them about measured stress data, they want stress-reducing measures to be taken only after approval. 20.4 % of participants would like the system to even become active only on request. A slight trend in the response behavior to the desired interaction can be seen in connection with the responses to the earlier statements of a stressful working day and high workload (see

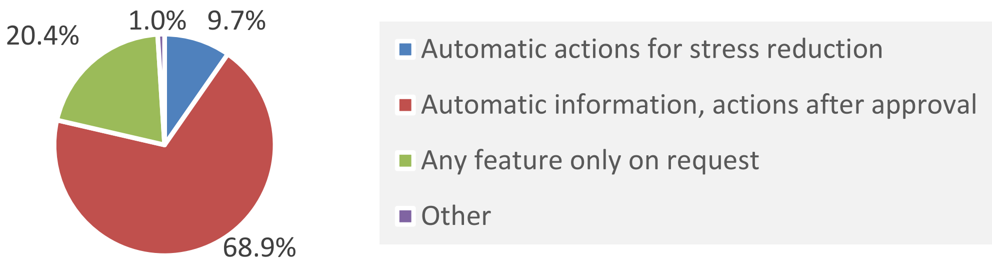

Figure 6.4.: Favored interaction with the system

Figure 6.5). It is noticeable that the desire for a system that autonomously reduces sources of stress in the background is only present in the first three categories for the statements of a stressful working day and a high workload. This means that anyone wishing to have a fully automated stress reduction system has described the daily work as at least partially stressful and the workload also as at least partially high. The strongest form of automation of a stress-sensitive system seems therefore to be related to the level of stress in everyday working life. In addition, the first graph in Figure 6.5 shows a predominantly increasing percentage from "Strongly agree" to "Disagree" in the desire for the system to become active only on request. Of those who strongly agreed to a stressful working day, 14.3 % would want system activity only on request, while of those disagreed, it is even 50 %. In at least half of the cases in each category of agreement, the semi-automatic version of the system is preferred.

Another interesting point is how people from different age groups responded to the question about interaction. This connection is shown in Figure 6.6. While just under 77 % in the under-30 age group favor partial automation and only 16 % want to request the system to become active, the response behavior of older age groups is a bit different. 50 % of participants over 51 years prefer a partial automation and even 40 % a system activity only on request. However, in both age groups the proportion of people who prefer autonomous actions of a system (response 1) is less than 10 %. In contrast to these groups, the proportion of 31-40 year-olds stands out, of which 22.7 % wish that the system tries to reduce sources of stress in the background. At the end of the survey, participants had the opportunity to comment on the questionnaire and its topic. Six participants took this opportunity. In the following, brief remarks will be made on tendencies that can be seen in the comments. There is a clear concern that information on the stress level could be detrimental to colleagues or supervisors. An interpretation of weaknesses that could endanger one's employment is a concern of several people. The privacy aspect also plays a significant role in the comments. It was mentioned that anonymizing the data should help to ensure that any use of data that is not in the user's interest would become unusable and that the data of the individual would thus be protected from misuse. Another aspect mentioned are deadlines. In some situations, where stress is unavoidable, e.g. as a result of a deadline, remarks of a stress-sensitive system could be inappropriate and even obstructive.

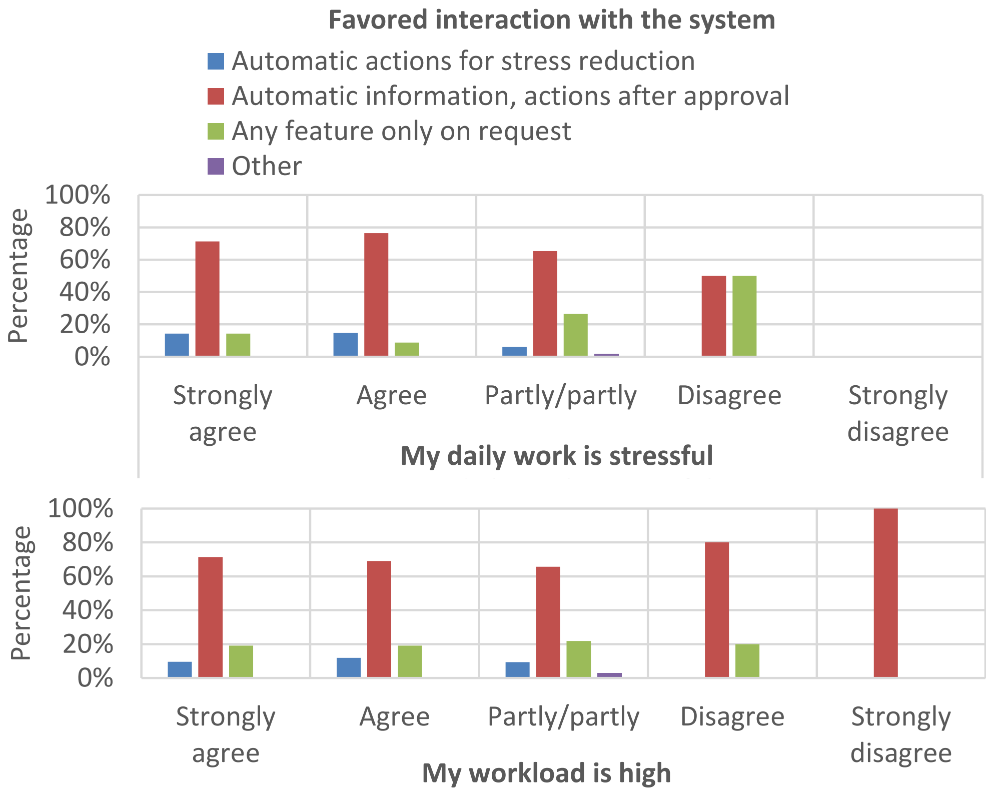

Figure 6.5.: Relation between perceived level of stress / workload and desired user interaction

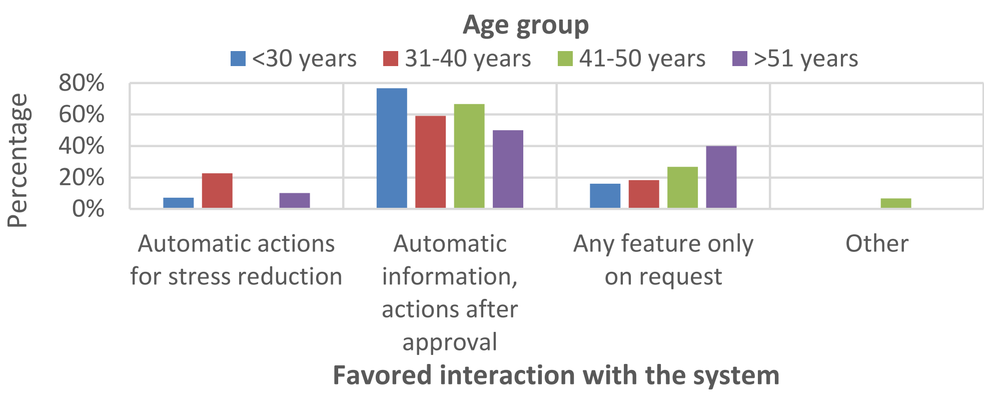

Figure 6.6.: Relation between age groups and user interaction

6.5. Discussion and Conclusions

With advancing developments like an intensification of work, people are often faced with high work pressure and stress. Permanent stress can lead to overstrain, which poses a significant health risk for the individual. Thus, reducing and managing work stress is one of today's major challenges. Advances in sensor technology offer the potential to augment IT-systems with stress-sensitive features, but for these features to be effective it is necessary to take into account the needs and preferences of intended users. This article focuses on the acceptance and feasibility of implementation options for IT-based assistance against individual stress in an organizational context. To this end, a survey was conducted among a convenience sample of 103 people. We have to acknowledge as a limitation of our research that our results cannot be generalized beyond this sample. However, in line with (Bortz and Döring, 2016), in order to gain *initial* experiences on a subject in a systematic way, representativeness in terms of the number and composition of the sample plays a subordinate role. The merit of our investigation is nonetheless that we provide *preliminary insights and tendencies* on the acceptance and feasibility of implementation options for stress-sensitive systems that can be tested through further research. Since the participants answered the questions on a theoretical basis, an interesting point for future research would also be to test the acceptance in practice when providing a prototype to participants. In the following, we summarize and reflect on our most important findings in regard to the defined research questions RQ1-4.

Regarding the **acceptance of measuring methods (RQ1)**, the *most popular variant is the self-assessment by questionnaire* (81.6 %). This could be linked to the fact that people do not like to leave it to measurements to determine their stress levels and instead prefer to validate these measurements by their own assessments. However, a sole assessment by questionnaire is not a reliable method of stress recognition. For example, people with pronounced ambition or perfectionism may be too influenced by their values to be able to set limits. Such attitudes can lead to overstrain, which often may be hardly perceived due to underlying desires and fears (Scharnhorst, 2012). Also, the *utilization of calendar, document, and communication data is quite accepted.* The recording of an employee's calendar and work plan entries (74.8 %) is quite accepted. The acceptance for the analysis of processed documents and email/messaging data with above 60 % is a bit lower, and for an analysis of communication data still 54.4 %. The slight difference in the acceptance could be explained by a possible higher degree of discomfort with the analysis of telephone conversations, especially in qualitative form (e.g. by word recognition), than with the analysis of written text. Perhaps people are also most interested in the analysis of work plan and calendar data, because these methods are more directly targeted to time management and are not perceived that private. *Neurophysiological measuring methods are least accepted.* Possibly this is due to the fact that these methods such as ECG, eye-tracking, or skin conductance measurement put the most noticeable restrictions on the subjects, e.g. in regard to the required use of additional devices (e.g. wearables; camera) and the freedom to move (e.g. through wearing; limited camera area). Also, data from these sources may be perceived as too private and hardly controllable. In summary, our results imply that *integrating a user's own assessment of workload and stress into the measurement methods is*

greatly appreciated and could be complemented in particular by calendar, document, and quantitative communication data.
Regarding the **purposes for which processing of personal data is accepted (RQ2)**, *data processing is accepted predominantly for personal use* (78.6 %), e.g. to provide personal feedback on working habits, but there also seem to be a desire *for an improvement of the work organization* (64.1 %), e.g. with a better distribution of work tasks in stressful situations. The emphasis on personal use might be due to the fear of an abusive use of personal stress data. Also possible competitive behavior between colleagues in the company may be a reason for fewer desire to provide supervisors or colleagues information on the stress level, because identified high loads could be interpreted as weakness. Accordingly, when developing a stress-sensitive IT system, transparency and the option to choose a private mode is important. The privacy of the user must be taken very seriously and legal conditions such as those imposed by the General Data Protection Regulation (GDPR) must be adhered to (e.g. by processing data only locally on behalf of one single user on his or her personal device).
Regarding the **system feedback (RQ3)**, it depends a lot on which working environment an employee is in. Since *information and recommendations are predominantly desired for private purposes*, messages in this direction that are displayed on a screen should be designed in a decent way to reflect the private nature of information. In addition, acoustic signals are also heard by colleagues or other persons and these could in turn draw conclusions about the personal degree of workload and stress, hence they should be optional. The system should therefore recognize the current situation of the user in real time and then silently provide information on the stress status, possibly also in connection with direct countermeasures for stress reduction such as micro-breaks or relaxation. The potential of newer devices like smartwatches to provide users information in a more decent way could be tested in a work context. *Much to our surprise, the survey participants showed only moderate interest in a prediction of future stress states* (recognizable e.g. through closely staggered appointment calendar entries). Further investigations are necessary to determine the reasons. Perhaps people consider such predictions as inaccurate or they worry about getting more stressed by information about stress in advance.
Regarding the **preferred interaction mode (RQ4)**, it turns out that many of the survey participants want a possibility to influence the measures of the system and do not want decisions by the system that they cannot influence. A completely automated system is probably also still unimaginable for many due to its novelty. The strongest form of automation of a stress-sensitive system seems also to be related to the level of stress in everyday working life, as a higher perceived stress level in everyday working life seem to lead to a higher desire for automation of a stress-sensitive system. However, it is apparent that a semi-automated system, in which the user first has to agree to countermeasures, is the most desired version All in all, there is a *clear interest in predominantly semi-automated systems, which inform the user about current workload and stress, but only carry out countermeasures to reduce stress after approval.* This means that there is a general interest in assistance for stress reduction, but that the user should remain responsible for decisions to initiate any measures. An aspect mentioned in the comments are deadlines. In some

situations, where stress is unavoidable, e.g. as a result of a deadline, remarks of a stress-sensitive system could be inappropriate and even obstructive. For these cases, additional settings for such a system should be considered. It would be conceivable to deactivate the interactivity of the system so that a user is not interrupted by warnings or restricted by stress reduction measures adopted by the system.

All in all, high workload and work pressure as well as the negative consequences they provoke such as burnout are among the most urgent problems of today's working world. Therefore, incorporating stress sensitivity into IT-systems is an important aspect that not only has the potential to maintain employee health, but also to promote long-term productivity and well-being. We hope that our empirical insights inspire more research on this important topic and help to delineate the design space for stress-sensitive IT-systems at work.

7 Combining Automation and Self-Assessments for Stress Management[1]

Abstract. With the ongoing acceleration of everyday life, there is an increasing risk of long-term stress together with a lack of opportunities for recovery. While the organism activates resources through stress and thus, allows for handling demanding situations, it is important to recover in order to regain balance. Therefore, permanent stress can harm performance and is often accompanied by health problems like back pain, depression, or burnout. As smart devices like smartphones are widely used and have numerous sensors integrated, they enable IT support for personal stress management in everyday life. We propose a framework demonstrating dimensions relevant to an IT support based on the basic pillars of stress emergence together with measures for coping. By proposing to use a combination of automatic measurements with answers from psychology questionnaires, we intend to strengthen early stress prevention as well as tailored recommendations for stress management with a higher chance of being adopted. We complement the framework with results from an online survey. The results suggest that self-assessments on stress-relevant topics would be quite accepted. In contrast, the participants seemed skeptical about receiving recommendations for stress management.

7.1. Introduction

The possible triggers of stress are manifold. Some developments in modern everyday life that can lead to stress are acceleration, flood of information, and blurring boundaries between life domains. Such developments also influence the opportunities for recovery. Imbalance in life can cause physical and mental discomfort. Permanent stress can even lead to negative health consequences, such as burnout. Studies commissioned by health insurances show a critical increase of mental illnesses in recent

[1] The content of this chapter has already been published as follows:
Fellmann, M.; Lambusch, F.; Pieper, L. (2019): Towards Combining Automatic Measurements with Self-Assessments for Personal Stress Management. In: 2019 IEEE 21st Conference on Business Informatics (CBI), pp. 604–611. https://doi.org/10.1109/CBI.2019.00076

decades. In Germany as an example, the incapacity for work due to mental illness has been increasing over the last 20 years (Storm, 2018). Therefore, it is highly relevant to develop effective measures to counteract stress at an early stage. While technology usage on the one hand can cause stress e.g. through interrupting the user with notifications, on the other hand it provides opportunities for objective measurements and insights on development over time as well as tailored advice for personal stress management. However, it is not yet clear how people can best be supported and what their preferences regarding IT-supported stress management are. We propose to utilize the three pillars of stress emergence, namely stressors, cognitive appraisal, and stress reactions, as a starting point for assistance in stress management. In the following the emergence of stress with an emphasis on the three pillars is briefly described.

The term stress describes strain that can affect the organism (Lohmer et al., 2017). Stress is triggered by so-called stressors, that activate the organism by means of challenge, threat, or harm. Stressors can be classified into physical, mental and social stressors. The physical stressors include, for example, noise, hunger or overstimulation. Mental stressors include e.g. overload, underload, and loss of control, while social stressors include conflict and isolation (Litzcke et al., 2012). The cognitive appraisal of stressors plays a central role in the emergence of stress, as all stressors are filtered and categorized by the human. There are several factors like personality, cultural perspectives and behavioral patterns that influence the filtering. A stressor is then rated as positive, dangerous or irrelevant. For stressors that are considered dangerous, the available resources to deal with the situation are assessed. If the resources are appraised inadequate, stress occurs (Lazarus and Folkman, 1984). Stress hormones such as adrenaline, noradrenaline, or cortisol are secreted by the activation of the so-called sympathetic nervous system and start the stress reaction in the brain and in the body (Mokhayeri et al., 2011). The activation of the parasympathetic nervous system after a stress situation provides relaxation and recovery (Dillon et al., 2016). If the body is under stress in the long term, it will lead to negative health consequences. The resilience of humans depends on the personality and the values of the individuals (Alarcon et al., 2009; Scharnhorst, 2012). For example, people with pronounced ambition or perfectionism may be too influenced by their values to be able to set limits. Such attitudes can lead to overstrain, which often may be hardly perceived due to underlying desires and fears. Overstrain presents a significant hazard for health and may be e.g. resulting in burnout (Scharnhorst, 2012).

This article presents a framework for IT-supported stress management that focuses on the identification and coping of stress based on the basic pillars of the emergence of stress. Although various stressors and stress reactions can already be recognized through technology, cognitive appraisal plays a central role in the emergence of stress as described above. Capturing information on the whole process of stress emergence may add further value to IT-supported stress management. However, it is important to consider the willingness and preferences of people to use certain features of an intended system. Thus, the proposed framework is complemented by results from an online survey. The questions of the survey focus on the aspects shown in the framework. For example, the presence of stressors and the willingness to utilize automatic stress recognition are investigated. Furthermore, the survey sheds light on the willingness of the participants to contribute statements on stress-relevant topics to a system by self-assessment. The remainder of the paper is structured as follows. In Section 7.2, related work is described. Section 7.3 introduces the framework that identifies components of stress identification and coping. Section 7.4 deals with the results of the empirical investigation. Then, a discussion follows in Section 7.5 and in the last Section 7.6 a conclusion is drawn.

7.2. Related Work

First of all, the topic of IT-supported personal stress management deals with the concept of stress. Therefore, *established theories about stress* are related. Established theories (e.g. (Folkman and Lazarus, 1985; Folkman et al., 1986; Selye, 1956)) deal with important aspects of the phenomenon and describe the cognitive processes associated to stress as well as the result of stress such as strains. Further, a review of organizational stress theories is conducted by Sonnentag and Frese (Sonnentag and Frese, 2013). While such works form a valuable underpinning, they predominantly focus on the phenomenon stress itself and not on how to support stress management. *Managing stress in IT-contexts or IT-induced stress* is an active research field. Coping with stress in IT-contexts has been investigated in early works (e.g. (Al-Fudail and Mellar, 2008; Benamati and Lederer, 2001; Galluch et al., 2015)). More recently, approaches for managing IT-induced stress have emerged and are broadly referred to as research regarding *technostress* (e.g. (Ayyagari et al., 2011; Fischer and Riedl, 2015; Maier et al., 2015; Ragu-Nathan et al., 2008; Riedl, 2012; Riedl et al., 2014). Moreover, a blueprint for the technostress-aware design of information systems in enterprises has been developed (Adam et al., 2017). While the research community around technostress is mainly concerned with avoiding the potential side effects of IT, our main objective is to strengthen the perspective on how IT can positively contribute to managing stress that can originate from a lot of other sources than technology. Hence, technostress as a research area is complementary to our research goal of improving personal stress management with IT.

More closely related to our research ambition of IT-supported personal stress management are research works in regard to *stress monitoring* aiming to provide feedback to the user. Fueled by the quantified-self or life-logging movement (Gurrin et al., 2014; Jacquemard et al., 2014), many prototypes aim at stress recognition and the provision of feedback to the user. A tool supporting self-reflection using a dashboard has been suggested by Li et al. (2011). In addition, unobtrusive stress detection approaches have been explored e.g. via computer keyboard usage (Hernandez et al., 2014), mobile devices such as the cStress approach (Hovsepian et al., 2015), the myStress-app (Gimpel et al., 2015) or via wrist-worn devices (Gjoreski et al., 2016). Also, combinations of activity trackers and smartphones have been explored for daily stress recognition (Lawanont et al., 2019). Moreover, not only stress, but also other constructs such as academic performance, sleep quality and mental health are detected using sensors and mobile phones (Sano et al., 2015). Besides, approaches to predict changes e.g. in cognitive performance using the Heart Rate Variability (HRV) have been developed (Tsunoda et al., 2017). Although stress monitoring

is an important building block for IT-supported personal stress management, we do not narrow our focus to stress monitoring since also the personal appraisal of stressors and mitigating stress reactions (e.g. using recovery measures) are relevant for personal stress management.
Regarding more holistic *assistance systems for IT-supported personal stress management*, only a few works exist so far. Most notably, tools such as a workload monitor and an e-coach for activity recommendation (NiceWork eCoach) have been developed in the context of the SWELL project (Koldijk, 2016). While sophisticated prototypes have been developed and empirically tested for their effectiveness, there is still not much research available in regard to an empirical analysis about the willingness of participants to provide data and to answer questions which is a necessary precondition for IT-supported stress management. In this direction, a first study on the needs for mobile coaching has already been conducted (Harjumaa et al., 2015) as well as a comparison of specific sampling methods for stress (Atz, 2013). None of these studies focuses in detail on the willingness of users to utilize automatic stress recognition in combination with the willingness to answer questions on stress-related topics.
In summary, we aim to contribute to the body of knowledge in regard to IT-supported personal stress management with first devising a framework that demonstrates the dimensions of IT-supported personal stress management and second with an empirical analysis concerning the willingness of end-users to answer stress-related questions and to utilize automatic stress recognition.

7.3. Fundamentals for IT Support

In order to maintain the health of an individual in the long term, it is highly relevant to reduce permanent high loads and to promote appropriate recovery. Although stress is a very complex construct and may be hard to recognize to the full extent, utilizing technology could serve as a remedy to raise awareness on personal stress factors and support a person in taking countermeasures. The following subsections introduce the framework for IT-supported stress management that was briefly introduced in Fellmann et al. (2018). Subsequently, the components and its basis in literature are described in more detail. The framework is intended to explore the design space of IT support for personal stress management in everyday life.

7.3.1. Framework for IT-supported Stress Management

As described in Section 7.1, the founding pillars of the emergence of stress are *stressors*, *cognitive appraisal*, and *stress reactions.* Therefore, the framework for IT support shown in Table 7.1 is based on these three components as column headers. Horizontally, the table is divided into two parts: *IT-supported measurement and IT-supported coping strategies.* The contents of these parts are also derived from the literature, which is described in the following subsections. The first of the two parts refers to the collection of data on stress-related factors whether automatically or trough user input. Showing the status of such personal factors and the development over time to the user could raise awareness for imbalances. Furthermore,

Table 7.1.: Framework for IT-supported stress management

	Stressor	***Cognitive Appraisal***	***Stress Reaction***
Subject to IT-supported Measurement	**Environment:** • Noise • Light • Weather **Communication:** • Phone Calls • E-mails **Organization:** • Appointments	**Well-Being:** • Perceived Stress • Emotions **Personality:** • Neuroticism • Conscientious-ness • Extroversion	**Physiology:** • Heart Rate • Skin conductance **Behavior:** • Physical Activity • Sleep • Technology Interaction
IT-supported Coping Strategy	**Problem-oriented:** • Avoiding Stressors • Time-/Resource-/Task- Mgmt. • Setting Priorities and Goals	**Emotion-oriented:** • Mindfulness • Relaxation • Social Contacts • Sports	**Problem-oriented and/or Emotion-oriented:** • Cf. Column 1-2

these measured stress indicators can be analyzed to derive and recommend suitable countermeasures for personal stress management. Thus, the second horizontal part relates the three pillars to corresponding coping strategies that can be used as a basis for recommendations. Each field of the table shows categorized examples of possible measurement subjects or coping strategies.

Regarding the subjects to measurement, the listed examples of *stressors* and *stress reactions* can be recognized without active user input, e.g. through sensors, as described later on in more detail. Stressors as potential triggers of stress have a more indicative character, while stress reactions are symptoms of actual stress. However, we propose to also integrate the measurement of stressors in order to be able to recommend strategies against triggers even before stress arises. For the design of a system for IT-supported stress management, the focus should be on unobtrusive, mobile options of measurement that can easily be integrated into everyday life. Large measurement equipment that disturb everyday actions should be avoided. Thus, the categorized examples shown in the framework are chosen according to stressors and stress reactions that can already be measured unobtrusively. When using automated measurements, sufficient reliability of the data has to be ensured. For this reason, a combination of several stress assessment tools has to be preferred (Dimoka et al., 2012).

In order to capture *cognitive appraisal* like perceived stress, active user input (e.g. via self-assessment) is required. However, this user input may be a valuable complement to an automated measurement and could improve the adaptation of the system features to the user's perception. As the appraisal of stressors plays a key role in the emergence of stress, considering it might also help to recommend accu-

rate strategies for stress management at an early stage. Since contributions from users require time, we investigated in a part of our online survey (see Section 7.4) whether and how much time would be reasonable for responding to questionnaires for self-assessment.
The framework also relates stress factors to *coping strategies*. These are important for the derivation of suitable counteractions to be recommended by a stress management system. For example, a person could receive a recommendation to reappraise a stressful situation by doing mindfulness exercises. The system could then guide the user through certain exercises. In order to even prevent stress, it would also be possible that the system suggests adjustments in a time schedule based on information collected. This would be a step towards reducing permanent high loads and maintaining health of the individual in the long term. In the following subsections, the components of the framework are discussed in more detail.

7.3.2. Measurement of Stress-related Factors

In accordance with the three pillars of the emergence of stress regarded in the framework, this section is divided into the measurement of stressors, cognitive appraisal and stress reactions. As the measurement of the cognitive appraisal is a special case due to the required contribution of the user, it is described after the measurement of stressors and stress reactions.

Measurement of Stressors. Potential stressors for humans are, for example, environmental influences such as weather, light and noise. With regard to the *weather*, factors that have an influence on the mood are temperature, humidity, air pressure and hours of sunshine (Sanders and Brizzolara, 1982). Weather data can be determined e.g. by any popular smartphone with sufficient accuracy by retrieving GPS, time information, and generally accessible data from the Internet (Bogomolov et al., 2014). Shortwave *light*, which is often emitted by energy-saving lamps, is another potential stressor. It can be measured by light sensors even indoors (Ciman and Wac, 2018), including among others the brightness of screens (Stütz et al., 2015). *Noise* is another potential stressor and can be measured by using microphones (Kardous and Shaw, 2014). It has already been shown in experiments that the noise level can be measured with a smartphone and linked significantly to the daily stress level (Stütz et al., 2015). In addition to environmental impacts, e-mails and phone calls can also be stress indicators. For *phone calls*, stress indicators can be derived from several factors together, including the number and duration of calls (Sano and Picard, 2013). The medium *e-mail* seems to be particularly relevant, because much of the communication in companies is still handled via e-mail (Riedl, 2013). For analyzing this, the number of incoming and outgoing emails can be considered. Having a lot of *appointments* can also be a stressor. The number, length, and type of appointments can be determined by accessing a digital calendar.

Measurement of Stress Reactions. An example of a stress reaction is an increase in a person's *heart rate* (Riedl, 2012). One way to measure the heart rate is to use a wristband, e.g. in the form of a fitness tracker or a smartwatch (Muaremi et al., 2013). Increased perspiration is another indication of stress and can be measured by means of an increased *skin conductance* (Dimoka et al., 2012). Stress has a negative effect on fine motor skills, which is why e.g. a changed *interaction with technology* is an indicator of stress. In order to measure this kind of stress reaction, one can consider, for example, the input gestures to control a smartphone, the pressure on a touchscreen and the number of spelling mistakes in text input. Furthermore, a smartphone's accelerometer and GPS also allow the measurement of the user's *physical activity* (Ciman and Wac, 2018). A lack of *sleep* can be considered a stressor and a stress reaction at the same time (Chen et al., 2013). For measuring sleep, a combination of different sensor data is typically used, e.g. accelerometer data and heart rate monitored by a smartwatch (Pombo and Garcia, 2016).

Measurement of Individual Appraisal. In order to obtain information about the cognitive appraisal of stress-relevant factors, the use of self-assessment questionnaires is common practice. Although information provided by the user cannot replace sensor measurements in terms of time and data, they can be a valuable complement. The possibilities of self-assessment range from regular surveys on the well-being to the derivation of the stress perception from personality traits based on standard questionnaires of psychology. By using technology, such as a smartphone or computer application that shows such questionnaires to a user, the answers could quickly be chosen and feed into the logic of a stress management system. To inquire, for example, *perceived stress* there are psychological instruments like the perceived stress scale (PSS). PSS is a quantitative query tool for measuring how stressful situations are appraised (Cohen et al., 1983). The questionnaire exists in two versions. While the 14-question version has proven to be more reliable, the 4-question version allows the user to fill it out faster and thus, lends itself to repeated stress measurement. A questionnaire to query ten positive and ten negative *emotions* that occurred during a predefined time interval is the Positive and Negative Affect Schedule (PANAS) (Watson et al., 1988). This instrument can also be used to determine the stress level of test persons (Muaremi et al., 2013). Furthermore, questionnaires for the determination of personality traits can provide clues about the individual stress perception of a person. For example, the Big Five personality model divides each personality into five controls, each of which can lie between two poles. The Big Five shows a correlation between pronounced *neuroticism* and more perceived stress (Duggan et al., 1995). In addition, people with pronounced *extroversion* and *conscientiousness* show a more positive mood and less perceived stress (Vollrath and Torgersen, 2000). Questionnaires such as the Big Five personality test would only have to be answered once or very rarely, while the well-being should be inquired more frequently.

7.3.3. Coping Strategies and IT-based Interventions

Stress coping refers to regaining balance by adapting to stressors. According to Lazarus and Folkman (1984), coping strategies can be problem-oriented or emotion-oriented. *Problem-oriented coping* means avoiding potential stressors as much as possible. For an IT-supported stress management, it makes sense to show users which stressors they are most exposed to and how they could improve this situation. With sensor measurements, environmental factors could be pointed out directly so that countermeasures can be recommended before stress arises. Regarding phone calls, e-mails, or appointments, the system could e.g. provide recommendations for effective self-management and an adaptive scheduling assistance to prevent overflow. In *emotion-oriented coping* approaches, the focus is on the cognitive appraisal of stress and on how to alter the appraisal. For this purpose, mindfulness exercises and relaxation techniques are suitable, and also sports or social contacts. These can relativize the influence of stressors. Emotion-oriented coping can be carried out preventively as well as in specific stress situations, whereby an assistance system could provide recommendations for exercises, meditation practices, autogenic training, or progressive muscle relaxation.

7.4. Survey Results

A stress management system could raise a user's awareness on personal stress factors and support proactive behavior against negative health consequences resulting from high stress levels. We complement the proposed framework with results from a survey. The aim of the study was to gain an insight into opinions on aspects of the framework by means of a larger sample. This section is divided into five parts according to different topics of the survey: (1) characteristics of the survey participants, (2) the presence of stressors among respondents, (3) the willingness and acceptable frequency to manually contribute information on stress-related topics, (4) the willingness to utilize automatic stress recognition, and (5) used coping strategies and the desire for IT-supported stress management. The online questionnaire with mainly closed questions was conducted with a total of 111 participants. Beforehand, the questionnaire was pre-tested with five persons to verify applicability, completeness, comprehensibility and quality. The link to the survey was distributed via e-mail, social networks, and messengers. Regarding participant selection, we used convenience sampling which is especially suited for preliminary studies in which new concepts or applications are to be explored (Boxill et al., 1997).

7.4.1. Characteristics of the Survey Participants

Of the 111 respondents, 62 (55.9 %) were male and 49 (44.1 %) were female. The age of the respondents was between 14 and 63 years. More than half (57.6 %) of the survey participants were between 22 and 25 years old. In addition, a large proportion (64.9 %) of those surveyed were studying. 21.6 % of the participants were employed and 2.7 % stated that they do an apprenticeship. The remaining 10.8 % of respondents were not employed at the time of the survey.
Furthermore, the participants were asked for their perceived stress over the past two weeks in order to learn more about the relevance and currency of stress among the respondents. For this reason, it was inquired if stress occurred during the last 14 days, 7 days or even the day of the survey. More than eight out of ten respondents (82 %) were stressed in the last 14 days and still 78.4 % in the last 7 days. With regard to the day on which the survey was completed by the participants, nearly 4 in 10 people were stressed (39.6 %).

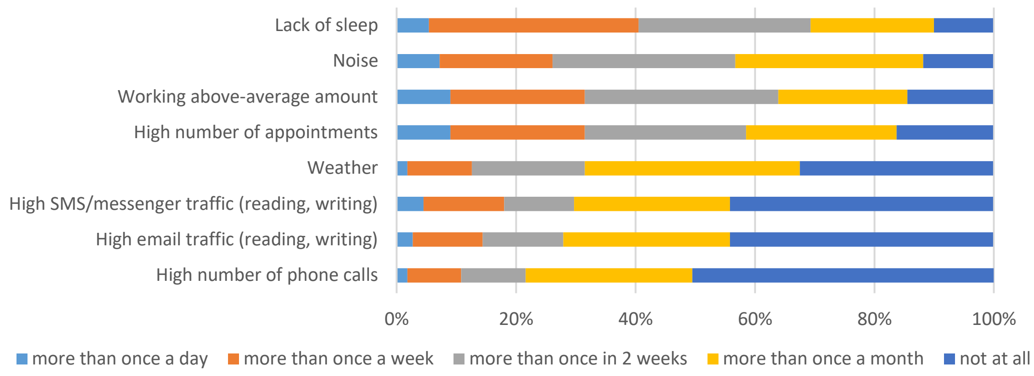

Figure 7.1.: Frequency with which participants are affected by certain stressors

7.4.2. Presence of Stressors

Stressors as the possible triggers of stress were subject to the first questions related to the framework. At the beginning, the word "stressor" was defined to provide a consistent understanding among the participants. Subsequently, it was asked for different stressors whether they are perceived as stressful and how often the participants are affected by them. The stressors listed included noise, weather, lack of sleep, email traffic (reading, writing), SMS/messenger usage (reading, writing), a high number of phone calls, high workload, and a high number of appointments. An exemplary scenario was described for each of the stressors, so that the participants could mark the situation as a possible stress trigger with "yes" or "no". The exemplary situations chosen by the most participants as stressful were: trying to focus while there is a lot of noise (78.4 %), too many appointments (67.6 %), above average work without time for private things (65.8 %), and getting up early with a lack of sleep (64 %). In contrast, reading and writing emails was stated to be stressful only by 29.7 % of the participants. Furthermore, the participants could state how often the corresponding stressors affect them in their daily life (cf. Figure 7.1). 50.5 % of the participants declare that a high number of phone calls does not affect them at all, while lack of sleep occurs for 40.5 % of participants more than once a week or even more than once a day and furthermore, is only irrelevant to 9.9 % of participants.

7.4.3. Willingness to answer Questions on Stress-related Topics

Since considering the cognitive appraisal of the individual is important for tailored assistance in stress management, part of the survey was about the willingness to answer personal questions related to stress (cf. Figure 7.2).
In particular, it should be determined, which types of questions are accepted and how often they could be asked by a system. In order to determine which types of questions the respondents would answer in principle, a distinction was made in questions about personality, sleep behavior, mood and stress level. The willingness to answer such types of questions could be indicated by "yes", "no", and "don't know".

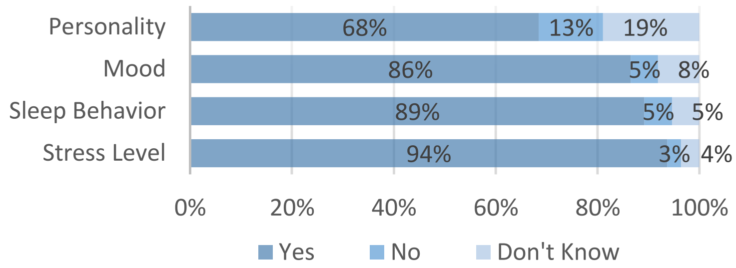

Figure 7.2.: Willingness to answer personal questions related to a certain stress topic

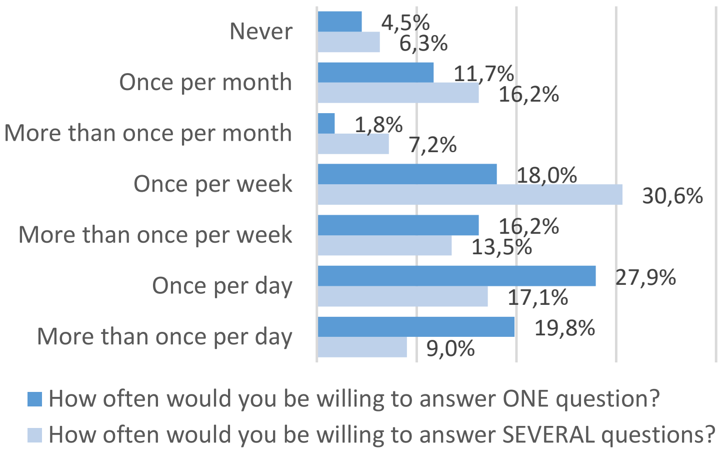

Figure 7.3.: Accepted frequency to answer questions on stress-related topics

Many respondents were willing to answer questions regarding sleep behavior, mood, and stress levels. The acceptance for these three types was each over 85 % while less than 5.5 % of the participants would not answer such questions. Most participants would answer questions about the level of stress (93.7 %). Questions about one's own personality come across some more resistance. However, still 68.5 % of respondents would answer personality questions, 12.6 % would reject them and 18.9 % of respondents were undecided. It should also be clarified if and how frequently a person would be willing to answer one or more questions. Figure 7.3 shows the results.
Almost half (47.7 %) of respondents would be willing to answer one question at least once a day and still 34 % of respondents would answer one question at least once a week, but not on a daily basis. The willingness to answer several questions per day is lower, but many participants would answer several questions at longer intervals. Only about 26 % of the respondents would be willing to answer several questions at least once a day, while 44 % of respondents would be willing to answer several questions at least once a week, but not on a daily basis. About 14 % of the participants would still be willing to answer one question not weekly, but at least once a month. For answering several questions, it is 13 % of participants. Only 4.5 % of respondents would not be willing to answer one question at all, and 6.3 % several questions.

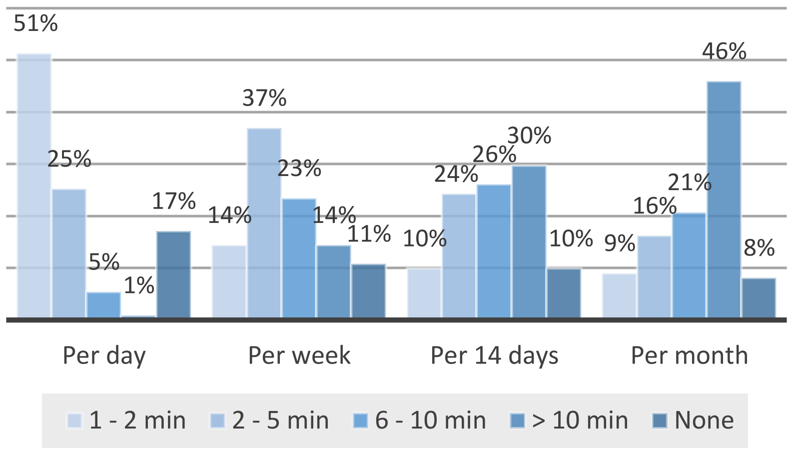

Figure 7.4.: Accepted expenditure of time to answer stress-related questions

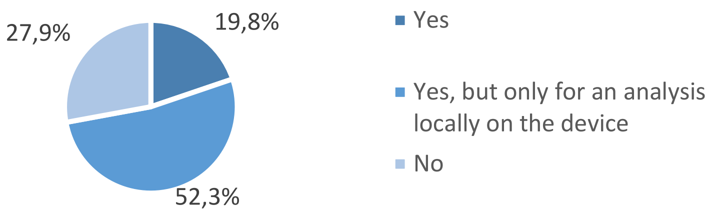

Figure 7.5.: Willingness to provide smartphone data for analysis

In order to get some clues about the ideal length of a questionnaire, the participants were asked how much time they would be willing to spend on answering stress-related questions in total. Figure 7.4 presents the results, which show that most people would spent at least a few minutes to answer questions. About half of participants would spend between one and two minutes on a daily basis and 31 % would even spent more time. For the weekly and biweekly expenditure of time there is no real trend recognizable. 37 % of respondents would be willing to spend between two and five minutes per week and also 37 % would even spent more time. On a biweekly basis, 80 % of respondents would be willing to spend at least two minutes, whereof 30 % would spent more than ten minutes. 46 % of respondents would be willing to spend more than ten minutes per month.

7.4.4. Willingness to utilize automatic Stress Recognition

As described in Section 7.3.2, many stressors and stress reactions can be recognized by using a smartphone. The survey participants were asked whether a personal stress management system would be allowed to analyze stress-related data from their smartphone (see Figure 7.5). 52.3 % of the participants would agree, but only if the analysis would be executed locally on the respective device. Almost a quarter of the respondents answered this question in the negative. The remaining 22 respondents agreed with a data analysis, even if it is not carried out locally.

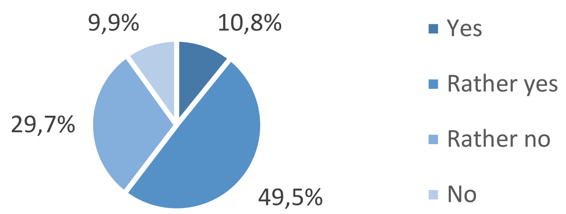

Figure 7.6.: Willingness to use an app that recognizes the stress level

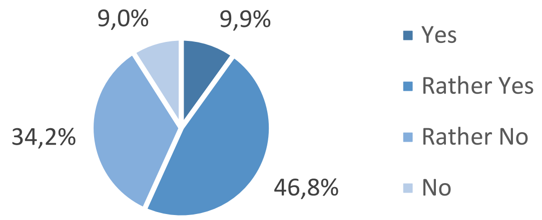

Figure 7.7.: Willingness to adopt recommendations for personal stress management

The last question addressed the willingness to use a stress-sensitive application. The results are shown in Figure 7.6. The proportion of those participants willing to use an app that recognizes stress is approximately the same to those who would not use such an app. However, there is a difference in the people who express a tendency. That is, 55 people would tend to use an application and only 33 people tend not to use it.

7.4.5. Coping and desired IT-Support

The survey also addressed coping strategies. The emotion-oriented and problem-oriented coping strategy were described to the participants with some examples for clarification. The first question asked which type of coping would be used. 47.7 % of respondents indicated to use both strategies, while 32.4 % stated to use only the problem-oriented and 19.8 % the emotion-oriented coping strategy.
Another question considered whether recommendations from a stress-sensitive application would be accepted and realized. The question referred to an example of a (fictional) smartphone app. Respondents could clearly respond with yes or no or indicate a tendency. Figure 7.7 shows the result of the question. The majority of respondents indicated a tendency. Overall, more than a half of the participants (56.7 %) would at least tend to adopt recommendations.
When asked about the interaction with the system (cf. Figure 7.8), 51.4 % of the participants stated that it should inform the user automatically, but should wait for the user's consent to take action. 37.8 % of the participants want the system to become active only upon request. Only 9 %, of respondents want the system to automatically take measures to reduce stress. It is therefore becoming apparent that the system should not become active directly, but should wait for the person's consent.

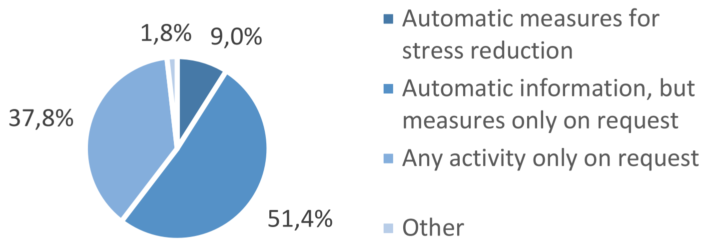

Figure 7.8.: Desired interaction with the system

The participants could finally add comments on the survey in a free text field. Some indicated that in a stressful situation they wish for practical tips for reducing stress or encouraging messages. There is also the desire that the collected data are provided for their own self-reflection. Furthermore, it was noted that a constant reminder of having stress could increase the perception of stress, so that a support should be subtle. Respondents also give the data protection aspect an important role and partly see it as a barrier to using IT-supported stress management.

7.5. Discussion

In the previous sections we described a framework for personal stress management and results from an online survey. The framework relates the aspects of stress emergence to coping strategies. We describe exemplary subjects to measurement for each category that could be measured in everyday life. For a future stress management system to be effective the persons' acceptance and willingness to use certain features is highly relevant. Therefore, we complement the framework with results from an online survey, which provide a first glance on opinions regarding the aspects of the framework. We have to acknowledge as a limitation of our research that our results cannot be generalized beyond our sample. While our participants were mostly young students, the sources of stress and the attitudes towards IT-supported stress management could vary widely. However, we hope that our results can inform the creation and conduct of further surveys by pointing out first tendencies and raising further questions.
Regarding the stressors, the once that are mostly perceived as stressful as well as frequently occurring are lack of sleep, noise, above average work, and too many appointments. Email traffic and phone calls seem to be less relevant to many of the participants. This could be a hint at a necessary prioritization for integrating measurement features of certain stressors, like noise, into a system.
As user inputs for stress assessment are considered very important for a tailored adaption of an assistance system to an individual's perception and needs, the survey included questions about the willingness to answer personal questions related to stress and its individual appraisal. The results indicate that all queried types of questions could be integrated into a stress-sensitive assistance system, but that users should have the option of selecting which topics are allowed, because e.g. the willingness to answer questions about the personality is proportionally lower. Fur-

thermore, the willingness to answer questions depends on the number of questions asked and time that has to be spent. An implementation option would be to carry out short questionnaires daily or weekly, but extensive questionnaires only at long intervals.
The answers to the willingness to provide smartphone data for analysis show that nearly three quarters of the respondents would provide their data. At the same time about half of the respondents would presuppose an analysis locally on their device, which is in line with additional comments from some participants at the end of the questionnaire. These comments confirmed that data protection and privacy is an essential aspect for every system handling personal data. Therefore, it should be transparent for a future system, which data is used and for which purpose. If possible, the data should even be stored and processed only locally. Regarding the willingness to use an app that recognizes the stress level, no clear trend is apparent. The number of participants who would use such an app is similar to those who would not. A major difference can only be seen for chosen tendencies, where the number of participants who stated "rather yes" is twenty percent higher than for the answers "rather no". The willingness to adopt recommendations for personal stress management shows a similar picture. For both questions to be answered appropriately it could be necessary to demonstrate a prototype to the participants, so that the answers are less dependent on the person's imagination of a possible system. The answers regarding the desired interaction with the system clearly shows that the majority of our participants wants a stress management system to wait for the person's consent before it becomes active for countermeasures.

7.6. Conclusion

All in all, high stress levels can lead to serious health problems and loss of productivity. Therefore, it is particularly important to take early steps to prevent and manage stress. Technology can support this process by recognizing stress-related factors and providing the user advice in preventing and managing stress based on these data. To this end, we present a framework for IT-supported stress management that relates aspects of stress measurement with aspects of stress coping. It is based on the basic pillars of stress emergence. Therefore, we propose not only to consider stressors and stress reactions that can be measured automatically, but also cognitive appraisal as an important part of the emergence of stress that additionally may require a person's contribution by self-assessment. Capturing information on the whole process of stress emergence may add further value to IT support for personal stress management in everyday life. It could, for example, be helpful in order to suggest personal stress countermeasures at an early stage as well as to provide tailored recommendations for stress management with a higher chance of being adopted. We hope that our framework will inspire and inform future developments of IT-supported personal stress management systems.
Regarding the realization of real-world systems, we complement our framework with an empirical investigation to shed light on the users' willingness to answer stress-related questions and to utilize automatic stress management. The main result of this investigation is that potential users like the idea of IT-supported stress man-

agement: Nearly three quarters of the respondents would provide their smartphone data for such a system, whereby half of the respondents prefer local data analysis on the device. Regarding feedback for the system to improve, participants are in general willing to answer questions in relation to their stress, but it strongly depends on the number of questions asked and time required. We interpret both results as encouraging for future research as well as development activities on the important topic of IT-based personal stress management.

8 Measures and Tools for Personal Productivity Management[1]

Abstract. In view of the ongoing alarming numbers of incapacity to work due to mental illness, it is important to pay attention to the factors that maintain long-term productivity of the individual. Recent research is concerned with examining relevant parameters that are measurable through technology and play a role for recognizing productivity factors such as cognitive performance or stress. However, in practice there are constraints regarding the available data sources and motives of people to use tools for self-tracking and management. In this article, we first present results from a literature review on productivity measures from research and then, complement it with initial results from an online questionnaire, which asked for the use of conventional tools by individuals. Besides frequencies of usage, we highlight major drivers for people to use applications for collecting data and managing oneself.

8.1. Introduction and Motivation

An alarming development that can be observed in today's working world is the blurring of boundaries between life domains while intensification of work further proceeds. A broad European study points out that 45 % of workers carried out work in their free time in order to meet high demands and 33 % of workers report to work at high speed about three-quarters of their work time (Parent-Thirion et al., 2017). Such conditions can lead to stress and a long-term exposure to stress can lead to serious health problems (Béjean and Sultan-Taïeb, 2005). Especially in the context of work that is characterized by a high degree of freedom, the worker often has to decide on his/her own responsibility what to do next, what methods of work are used, or what could be accomplished on a daily basis (Drucker, 1999). In order to support individuals in a healthy as well as productive self-management, it is particularly important to identify and observe the factors that maintain long-term productivity. Modern technologies such as wearables offer great potential to

[1] The content of this chapter has already been published as follows:
Lambusch, F.; Fellmann, M.; Poppe, M.; Weigelt, O.; Hein, S. (2020): Personal Productivity Management in the Digital Age: Measures from Research and Use of Conventional Tools. In: Wirtschaftsinformatik (WI2020) Zentrale Tracks: GITO Verlag, S. 632–647. https://doi.org/10.30844/wi_2020_f5-lambusch

collect information and support the user, see e.g. Gurrin et al. (2014) and Sarker et al. (2017). One advantage of these devices is that they are equipped with a large spectrum of sensors that work *unobtrusively* and hence provide a seamless integration into everyday life. Using such devices enables the continuous collection of data about individuals or their environment. This makes it possible to measure and observe *factors that influence individual productivity* and help people to better cope with challenges at work. Unfortunately, up to now there is no systematic overview on literature regarding productivity factors that can be measured unobtrusively.
Furthermore, when it comes to realizing the potential of IT-based productivity management via the creation of new productivity tools that are intended for everyday use, there are constraints that have to be considered. These comprise e.g. the available data sources and motives of people to use tools for self-tracking and management that cannot be ignored. In order to support individuals instead of burdening them with the introduction of new processes, a setup is necessary that does not noticeably impact or rather complicate their existing routines. Thus, it is important to know how frequently conventional tools (e.g. activity tracker, digital calendar) are already used for self-tracking and self-management since they constitute a valuable *source of data*. Moreover, although some studies are available concerning the reasons why users engage with and abandon smart devices in general (Lazar et al., 2015; Harrison et al., 2015), it is not yet much known about the various factors influencing the usage behavior regarding conventional tools for productivity-related self-tracking and management. However, for an effective IT support in productivity management, people's perception of such tools and their motives have to be studied. In addition, also the attitudes towards technology and personality traits can be *obstacles or drivers for using self-tracking and management tools* and hence have to be considered. Such analyses are largely missing in the current literature concerned with IT-based productivity management. Against this background and the stated current knowledge deficiencies, we aim to answer the following research questions:

- **RQ1**: *Which productivity factors that are unobtrusively measurable through IT are described in research articles over the last years?*
- **RQ2**: *What prerequisites in the form of data sources are already given in practice through the usage of conventional tools?*
- **RQ3**: *What are major obstacles and drivers for the use of conventional applications for self-tracking and management?*

As a first part of this article we present results from a systematic literature review in Section 8.2 referring to RQ1. In order to answer RQ2 and RQ3, we conducted a cross-sectional survey study applying a convenience sample of $N = 564$ individuals. In Section 8.3, the procedure and results of the survey study are described. Finally, we discuss our results and draw conclusions in Section 8.4.

8.2. Systematic Literature Review

The literature review that is presented in an initial German version in Poppe et al. (2019) serves to present the state of research on productivity factors that are unobtrusively measurable through IT (**RQ1**), which means that employees shall not be influenced or disturbed by measurement procedures. As part of the systematic literature review, 32 relevant publications were examined. The literature review shows that individual productivity at work can be influenced by various factors such as well-being, mood, cognitive workload, and communication richness of a person, which can be subject to measurement by utilizing technology.

8.2.1. Method

The literature research was carried out according to the structured approach of Kitchenham and Charters (2007). The literature database Scopus[2] was chosen, as it has a large index across a large number of sources. Only the results from 2010 onwards were taken into account. The search process started by listing possible context-relevant keywords and searching for synonyms. In order to identify initial keywords, a pre-review of relevant articles such as Tsunoda et al. (2017) and Yano et al. (2015a) was conducted. Subsequently, search terms were formed by combining keywords. It became clear that terms from the areas of productivity, employees, and sensor-based recording of productivity must be included in a search term for this topic, because otherwise the proportion of relevant work in the result set is too small. Thus, four different search terms were created in an iterative process, which delivered relevant results. These were finally combined with a logical OR operation. This resulted in the following final search string:

```
TITLE-ABS-KEY( (productivity AND measur* AND people
    AND (worker* OR workload OR activit* OR job OR office)
    AND (wearable OR sensor*))
  OR ("stress recognition" AND (job OR office OR worker* OR employe*)
    AND (wearable OR sensor*))
  OR ("cognitive performance"
    AND (job OR office OR worker* OR employe*)
    AND ("heart rate variability" OR "heartrate variability" OR hrv))
  OR (((measur* AND happiness)
      OR (productivity AND "knowledge work"))
    AND wearable) )
AND PUBYEAR > 2009
```

Scopus offers the possibility to perform searches with a large nesting depth, which was necessary here. A transformation of the search term for use in other search engines that allow little or no nesting depth was not fully possible, which is why they were not used in this literature search.
At the time of the search (February 2019), 48 documents were found at Scopus using the search term developed. The exclusion process is illustrated in Figure 8.1. Articles were excluded in which no concrete sensor-based data were used or in which a sensory recording disturbed the workflow of the participating persons. Likewise, studies were not considered, in which no direct connection between recorded data

[2] https://www.scopus.com

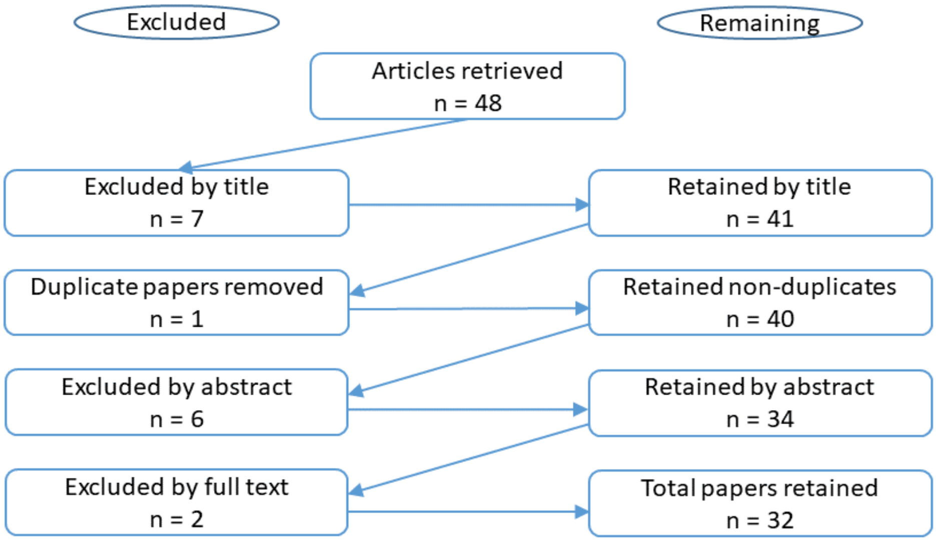

Figure 8.1.: Article exclusion process

and productivity factors of workers was described. There remained 32 publications relevant to this work.

8.2.2. Results

The concept-oriented approach according to Webster & Watson was chosen for the investigation of the research topics (Webster and Watson, 2002). With this approach, the literature sources examined were mapped to concepts that are shown in Table 8.1. While the first column shows references to the literature sorted by year of publication, the table header contains the concepts found in the literature. The lines below contain crosses, if the concept was considered in the corresponding literature source. The concepts identified in the context of this work can be divided into the three categories: *objectives*, *subjects of consideration*, and *parameters*. These three categories are explained in more detail below.

Objectives. Three concepts were identified in relation to the objectives. In 75 % of the cases (24 publications) this is a *data analysis* of either already existing data (10 publications) or data collected by the user (14 publications). A total of 16 papers deal with the *collection of data*. In 9 cases the goal of the work is a *prediction of productivity factors*, whereby e.g. algorithms are developed on the basis of data analysis, which serve among other things to early recognize a decreasing cognitive performance and to make the person or a superior aware of it (Tsunoda et al., 2017). Some authors also describe the development of a method for predicting stress or cognitive performance.

Table 8.1.: Concept matrix

Article		Concept																	
		Objective			Subject of Consideration					Parameter of State Detection									
		Measurement	Data Analysis	Prediction	Cognitive Performance	Stress	Well-Being	Work Setting	Happiness	HRV	Blood Pressure	Skin Conductance	Brain Activity	Phys. Activity	E-Mail	Pers. Interaction	PC Interaction	Aur Quality	Light
2018	Anusha et al. (2018)	x	x			x						x							
	Berelson et al. (2018)	x	x					x										x	x
	Di Lascio (2018)	x	x		x		x					x							
	Gloor et al. (2018)	x	x	x			x	x		x									x
	Jebelli et al. (2018a)	x	x			x							x						
	Jebelli et al. (2018b)	x	x			x							x						
	Jebelli et al. (2018c)	x	x			x							x						
	Özsever and Tavacıoğlu (2018)	x	x		x	x				x		x							
	Rodrigues et al. (2018)	x	x		x	x				x									
	Sanchez et al. (2018)	x	x	x		x						x							
	Yoo and Chung (2018)		x	x	x					x				x					
2017	Canazei et al. (2017)		x		x		x	x		x									x
	Sanchez et al. (2017)			x		x								x			x		
	Tsunoda et al. (2017)			x	x					x									
2016	Chang et al. (2016)		x				x			x				x					
	Mark et al. (2016a)		x	x	x	x									x		x		
	Nakashima et al. (2016)		x			x								x					
	Schwartz et al. (2016)	x	x		x			x		x				x					
	Tsuji et al. (2016)		x		x			x						x		x			
	Tsunoda et al. (2016)			x	x					x									
2015	Tsunoda et al. (2015)			x	x					x									
	Yano et al. (2015a)	x	x						x					x					
	Yano et al. (2015b)	x							x					x					
2014	Thielmann et al. (2014)	x	x		x	x				x	x								
2013	Jiang et al. (2013)		x		x		x											x	
	Muaremi et al. (2013)	x	x			x				x									
	Teso et al. (2013)			x	x	x	x		x							x			
2011	DiDomenico and Nussbaum (2011)		x		x					x				x					
	Hernandez et al. (2011)		x			x						x							
	Prinsloo et al. (2011)				x					x									
	Seigneur (2011)	x							x										
2010	Setz et al. (2010)		x		x	x						x							
	Total	16	24	9	17	15	6	5	4	14	1	6	3	9	1	2	2	2	3

Subjects of Consideration. The concept matrix presented above illustrates that most of the research identified deals with the analysis of recorded data, e.g. for testing for correlations or creating classifiers as well as predicting changes in a person's state. The most common areas of research are *cognitive performance* and *stress*. Other areas investigated were the determination or prediction of people's *well-being* and the optimization of the *workplace design*. In these studies, the motivation of the authors was to achieve a lasting improvement of the conditions so that the productivity of the working persons could be maintained or increased in the long term.

Parameters of State Detection. As the concept matrix shows, many researchers capture people's states using *heart rate variability (HRV)* to algorithmically predict cognitive performance and stress. In order to determine the HRV, most of the articles describe the use of a portable device to record an electrocardiogram (ECG). However, *physical activity* during the day or at night is also frequently examined in order to gain insights into the influence on personal productivity factors. In this context, data collection is often carried out with different portable systems, so-called wearables, which contain a large number of built-in sensors.
Another area deals with the evaluation and prediction of stress and high workload, especially in the work environment. Measurements were carried out mainly by using sensors on the wrist and observations of activities at a computer workstation (also by means of multimodal sensor measurements). For stress recognition, a correlation between working method and stress is formed in some experiments. For example, keyloggers and monitoring programs were installed on the work computers of the test persons to analyze the *PC interaction*. These programs could, for example, record the keystrokes or the number of deletions of letters per minute. The number of open program windows or the movements and clicks of the mouse were also evaluated (Sanchez et al., 2017). In another work, monitoring programs were used to record the frequency of checking incoming *e-mails*, the time spent on daily e-mail work, and the duration and number of *personal interactions* in the form of telephone calls or direct conversations with colleagues (Mark et al., 2016b). While HRV was recorded as a parameter in many studies, few studies deal with the electrical *skin conductance* that changes under current or impending stress. Such publications can be found at the beginning of the defined search period (Hernandez et al., 2011; Setz et al., 2010). While this parameter no longer appeared in the analyzed articles in the following years, it was increasingly used again in 2018. The *skin temperature* was also examined as a possible parameter in these publications for the first time that year (Anusha et al., 2018; Yoo and Chung, 2018).
Further research is being carried out to improve human performance. Several authors describe the use of portable devices for electroencephalography (EEG) in their publications in 2018, in which they want to measure *brain activity* in order to determine cognitive performance (Jebelli et al., 2018a,b,c). For example, sensors were built directly into the helmets of construction workers, so that the workers did not have to wear any additional equipment that would hinder or interfere with their work (Jebelli et al., 2018b). However, some work also deals with issues that do not examine the way people work, but rather the effects of changes in the working en-

vironment. For example, it was investigated to what extent a reduction of illnesses (e.g. caused by sitting for long periods) is possible by standing workplaces (Schwartz et al., 2016). The results included opinions and suggestions for discussions on computer workstations. In another article the effects of the current standard short-wave white *light* on well-being and cognitive performance were investigated (Canazei et al., 2017).

8.3. Empirical Study on the Use of Self-Tracking and Self-Management Applications

Information and communication technology (ICT) devices provide users with a very comprehensive set of opportunities for self-tracking and self-management. The literature reviewed above reflects a considerable portion of the parameters and features one could think of. Interestingly however, typical users of smartphones or wearables may not actually scoop the potential inherent in their devices and applications. Therefore, we set out to examine, how frequently individuals use the most common features or applications inherent in their devices (see **RQ2**). Gaining insights into the patterns of use of typical users are invaluable to tailor applications to the needs of users. It is worth noting that our approach goes beyond describing patterns of use. More specifically, we aim to identify the structure underlying users' self-tracking and self-management activity. Finally, referring to **RQ3** we aim to identify predictors of frequency of use. More specifically, we focus on two aspects, namely attitudes towards technology and personality traits. For instance, while members of the quantified self-movement may track themselves extensively, other users may not be aware of the opportunities of self-tracking, may be reluctant to share their data due to privacy concerns, or may not care about becoming better at all in any of the parameters tracked. With regard to attitudes towards technology, we examined whether acceptance of ICT and ICT privacy concerns are related to the frequency of self-tracking and self-management applications. With regard to personality, we focused on proactive personality (Bateman and Crant, 1993), and two facets of functional perfectionism (Frost et al., 1990), as these dispositions tap into the motivation to perform well and to constantly improve one's performance.

8.3.1. Methods

We conducted a cross-sectional survey study using an electronic survey and applying a convenience sample. Of the initial 737 persons who accessed our survey, 181 individuals did not provide information on ICT-use. We therefore had to exclude them from the focal analyses. A sample of $N = 556$ individuals completed all parts of the questionnaire for a response rate of 75 percent. We posted the link to our study on several forums for researchers seeking participants (e.g., survey circle) and sent out invitations to participate through listservs of a university in Germany. The survey was not closed, i.e. usable without a user-specific token, although the used tool tracked progress and did not allow to restart after completion. On average participants of the focal sample were 29.59 (SD = 10.40) years old. Age ranged from 18 to 74. 68 % of our participants were female and 32 % were male. Our sample

– although not representative of the population – covered a broad range of industries, occupations, and social backgrounds. One sixth of our participants came from research and development, education, and health care each. The remaining participants came from other industries. 21 % had a leadership position. 45 % worked full-time, 36 % worked part-time, and 19 % were students, currently not employed. The majority of our participants frequently used ICT devices for professional and private purposes on a regular basis. In detail, we asked for the usage of laptops or similar devices (subsequently summed up as PCs), smartphones, tablets, and smartwatches. The use of PCs and smartphones is particularly frequent in both areas of life. For occupational purposes laptops are used at least once a day by about 63 % of the participants and smartphones by about 45 % of participants. About 7 % of the participants never use PCs and about 17 % never use smartphones for professional purposes. In contrast, 68 % of the participants never use a tablet and about 95 % never use a smartwatch for their work. For private purposes there are less people who never use a tablet (about 49 %) or smartwatch (about 85 %) than there are for professional purposes. Smartphones are used most frequently for private purposes. About 94 % of the participants use a smartphone several times a day, while still about 54 % of participants stated to use PCs at least once a day.
In regard to our research questions, we measured frequency of self-tracking activities, frequency of self-management activities, acceptance of technology, ICT privacy concerns, and personality traits such as proactive personality. The frequency of self-tracking was measured by providing a list of 13 features (e.g., heart rate) and self-management activity by a list of 12 features (e.g., monitoring progress towards goals). We applied 9-point rating scales ranging from 1 (never) to 9 (several times a day). In Figure 8.2 and Figure 8.3, we present the specific self-tracking and self-management activities with their associated frequencies of use, respectively, which are described in Section 8.3.3. To measure the acceptance of technology we used 9 items from Marchewka and Kostiwa (2007) tapping into perceived ease of use and perceived usability of ICT devices. We gauged ICT privacy concerns with 4 items from Marchewka and Kostiwa (2007). We applied 5 Items to capture proactive personality (Seibert et al., 1999) and 4 items each to capture the personal standards facet and the organization facet of functional perfectionism as a personality trait (Altstötter-Gleich and Bergemann, 2006). Response format for the measures of attitudes towards ICT and personality ranged from 1 (totally disagree) to 5 (totally agree). We estimated reliability of the validated scales leveraging Cronbach's Alpha. Reliabilities for the focal scales are presented in Table 8.2 on the diagonal. All scales reached acceptable to excellent internal consistencies. Hence, we formed composite scores for each variable by combing all items (mean across all items).

8.3.2. Analyses

Given that the list of self-tracking and self-management applications is very long, we aimed to explore the underlying structure of usage patterns. We leveraged exploratory factor analysis to identify a limited set of factors that describes the patterns of use more parsimoniously. The general rationale behind our factor analysis was that similar applications or features which are typically used jointly will form a common factor. By contrast, applications or features used by different people and typically not used together will load on distinct factors. We checked assumptions for conducting exploratory factor analysis. We applied promax rotation to allow factors to be correlated (which produces oblique, non-orthogonal factors). Factors were extracted if eigenvalues exceeded values of 1 (Kaiser criterion). After interpreting factor solutions, we combined all items loading highly on a common factor (and yielding no cross-loadings) to an index reflecting the specific facet of self-tracking or self-management. We calculated correlations among all variables to link attitudes towards ICT and personality with patterns of application use.

8.3.3. Results

Factor analyzing the 13 items of self-tracking resulted in a 3-factor solution. We labeled the three resulting factors: *health-related* (e.g., track heart rate), *habits* (e.g., track location), and *affect* (e.g., track moods or physical pain). Figure 8.2 displays which activities formed the respective factors for self-tracking (indicated as bold headlines on the left side). Factor analyzing the 12 items of self-management yielded a 3-factor solution, too. We labeled the three resulting factors: *organization* (e.g., calendar), *goals* (e.g., setting priorities), and *avoid distractions* (e.g., apps helping to stay focused). Figure 8.3 displays which activities formed the respective factors for self-management. We combined items loading on a common factor to a composite score of for instance health-related tracking, self-management – avoiding distraction etc. We also calculated an overall score combing all items to a global score of self-tracking and self-management app use frequency, respectively. Descriptive statistics are presented in Table 8.2. This table also presents the correlations among the following focal variables:
1_SEX, 2_AGE, 3_ITAC (ICT acceptance), 4_ITPC (ICT privacy concerns), 5_PROA (proactive personality), 6_PPER (perfectionism – personal standards), 7_PORG (perfectionism – organizing), 8_STRO (self-tracking – overall), 9_STHE (self-tracking – health related), 10_STHA (self-tracking – habits), 11_STAF (self-tracking – affect), 12_STTT (self-tracking – time tracking), 13_STFT (self-tracking – food tracking), 14_STCI (self-tracking – chronic illnesses), 15_SMOV (self-management – overall), 16_SMOG (self-management – organizing), 17_SMGP (self-management – goals and progress), 18_SMAD (self-management – avoid distraction), 19_SMTI (self-management – timer), and 20_SMPS (self-management – practicing serenity). Given that the self-tracking and self-management tools in the "Oher Apps"-category (e.g., timer and practicing serenity) did not load on a common factor, we display correlations at the item level for these applications in Table 8.2 for descriptive purposes only and focus on the extracted self-tracking and self-management factors in our focal analyses.
We found that acceptance towards ICT yielded the strongest links to all aspects of self-tracking and self-management as evidenced in significant correlations ranging from .13 to .43. Concerns regarding privacy were negatively related to almost any form of self-tracking and self-management (except for affect and avoiding distraction), albeit concerns were less predictive than acceptance. In sum, negative attitudes towards ICT as reflected in low acceptance and high privacy concerns are factors that explain why at least some users may refrain from using the opportunities of ICT.

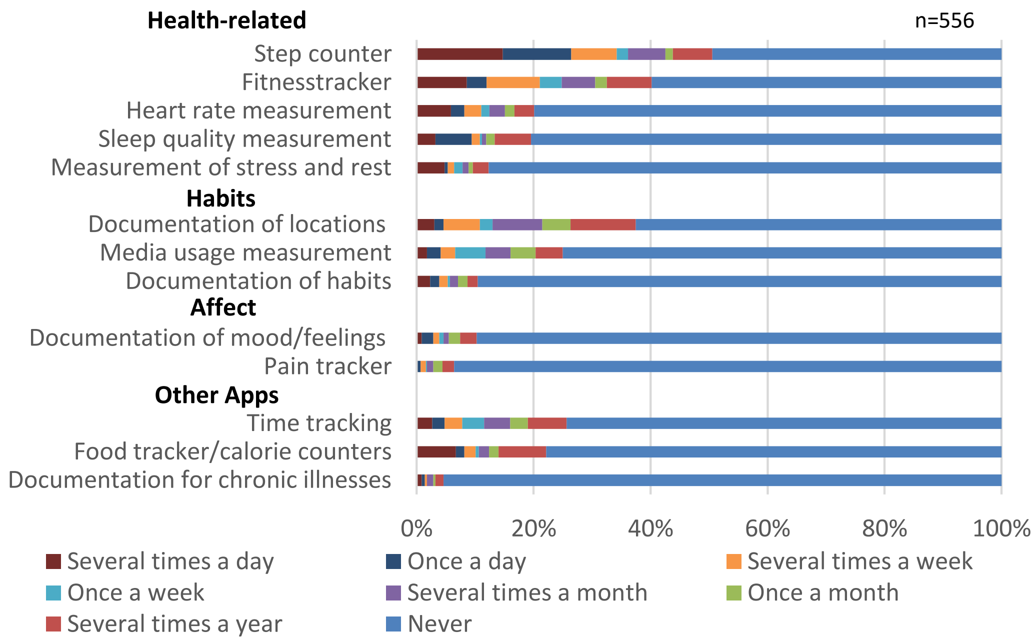

Figure 8.2.: Factors and frequency of use of self-tracking activities

With regard to dispositions, proactive personality correlates positively with self-tracking and self-management (except for tracking affect). Significant correlations ranged from .17 to .33. Personal standards and organization – the two focal aspects of perfectionism – related positively to self-tracking and self-management, as well. Correlations ranged from .10 to .24. In sum, personality traits contribute to explain why individuals use self-tracking and self-management applications more or less frequently. With regard to demographics, age yielded a negative association with self-tracking and self-management. We found no sex differences.

8.4. Discussion and Conclusions

In view of the ongoing work intensification, it is important to pay attention to the factors that maintain individual long-term productivity. In this article, we look at the two facets of productivity management in the digital age: 1) measures from research and 2) the use of conventional self-tracking and self-management tools. Below, we reflect on our most important findings in regard to the defined research questions RQ1–3.

While there is a plethora of tools that could be used to measure productivity-related factors, it is challenging to get an overview on the relevant parameters for long-term productivity. Thus, we systematically analyzed research articles of the last years. *Regarding unobtrusively measurable productivity factors described in research which answers* ***RQ1***, an increase in research activities to record different productivity parameters can be observed. The subjects of considerations range from cognitive

Table 8.2.: Correlations regarding attitudes, personality traits, and application usage

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1_SEX	1,32	0,47																			
2_AGE	29,59	10,40	,17																		
3_ITAC	5,30	1,06	-,12	-,20	(.91)																
4_ITPC	5,40	1,21	,00	,19	-,25	(.85)															
5_PROA	3,25	0,69	-,05	-,05	,19	,00	(.77)														
6_PPER	3,27	0,89	-,09	-,11	,13	,07	,51	(.85)													
7_PORG	3,95	0,79	-,17	-,01	,15	,06	,39	,31	(.87)												
8_STRO	1,95	1,10	-,02	-,10	,34	-,21	,23	,15	,11												
9_STHE	2,30	1,78	-,03	-,03	,27	-,18	,21	,15	,11	,94											
10_STHA	1,82	1,16	,05	-,16	,31	-,19	,17	,09	,09	,63	,36										
11_STAF	1,27	0,85	-,10	-,11	,14	-,06	,07	,00	-,03	,30	,11	,16									
12_STTT	1,87	1,79	,05	-,11	,25	-,15	,16	,14	,07	,36	,27	,41	,05								
13_STFT	1,84	1,99	-,12	-,10	,22	-,13	,09	,07	,15	,34	,33	,19	,07	,18							
14_STCI	1,17	0,91	,04	,01	,07	,04	,06	,02	,00	,21	,17	,17	,12	,13	,10						
15_SMOV	2,78	0,98	,03	-,19	,43	-,14	,33	,23	,20	,48	,35	,51	,22	,41	,27	,17					
16_SMOG	5,05	1,82	,08	-,14	,42	-,13	,27	,17	,17	,34	,26	,34	,14	,26	,17	,08	,85				
17_SMGP	1,69	1,37	,00	-,07	,24	-,11	,26	,24	,19	,44	,35	,41	,15	,32	,31	,17	,72	,37			
18_SMAD	1,29	0,89	-,04	-,12	,13	-,02	,15	,09	,05	,30	,17	,41	,19	,28	,11	,16	,52	,20	,34		
19_SMTI	3,06	2,21	-,02	-,28	,24	-,06	,17	,09	,09	,17	,10	,22	,13	,33	,11	,05	,44	,22	,21	,16	
20_SMPS	1,22	0,90	-,05	-,01	,15	-,09	,16	,07	,06	,25	,15	,27	,29	,14	,20	,17	,38	,18	,31	,31	,11

Note: N = 556 (for all correlations). M = Mean, SD = standard deviation.
Correlations coefficients of r > |.08 | are significant at p < .05. Correlation coefficients of r > |.10 | are significant at p < .01. Alpha reliabilities are presented on the diagonal in parentheses.

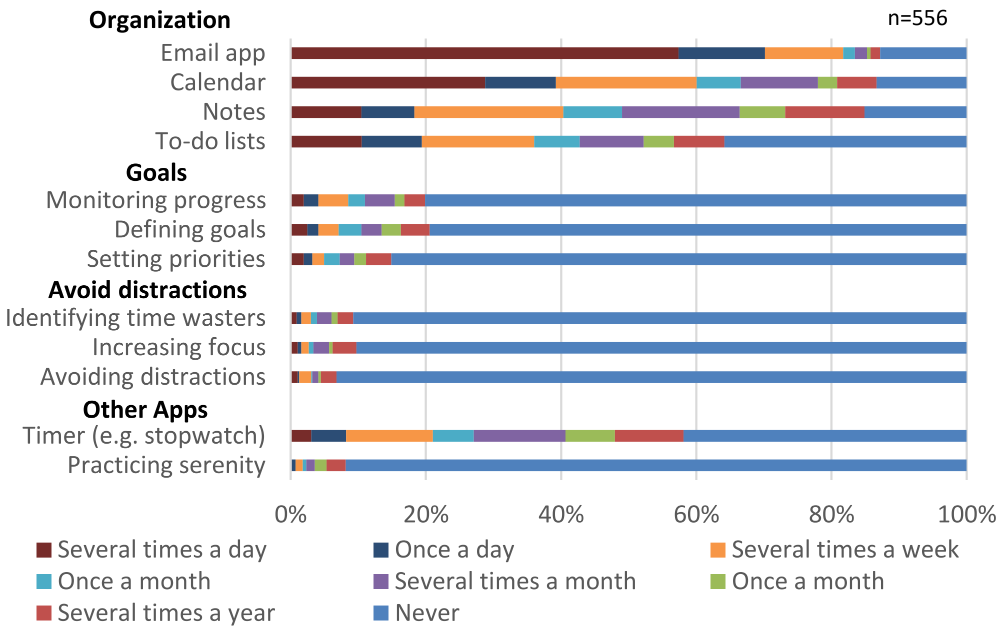

Figure 8.3.: Factors and frequency of use of self-management activities

performance to the work setting. Although there is a wide spectrum of parameters that are considered for state detection, heart rate variability is a surprisingly often proposed parameter that can be used in several contexts. Despite increasing attention to the issue of maintaining and increasing employee productivity in the workplace, challenges remain in terms of data collection and analysis, as well as actual relevance to individual productivity. In addition, parameter measurements have to be interpreted with caution since they might not always strictly correspond to the change of one specific productivity factor (e.g. measuring an increased skin conductance could be caused by physical activity as well as by mental stress).

In order to build productivity management tools that are helpful in everyday life, it is important to consider which conventional tools are used so far since they constitute a valuable source of data. This could inform the design of new applications or even be considered as a constraint. In this direction, we have investigated *how frequently conventional tools for self-tracking and management are used so far, answering **RQ2***. Our self-report survey study reveals that the most commonly used applications can be clustered to three factors of self-tracking, namely *health-related*, *habits*, and *affect* as well as three factors of self-management, namely *organization*, *goals*, and *avoid distraction*. It might be worthwhile to discuss in which of these categories new productivity-related measurements and support features could be integrated and displayed in existing systems. Looking at the frequencies of usage, in self-tracking the *health-related applications to track physical activity showed the highest frequencies of use* in our sample. This could be due to the trend in quantified self to improve especially physical performance, but also to the availability of various commercial fitness trackers. Regarding self-management, the use of applications for a better organization is very common and frequent in our sample. It is not surprising that email and calendar applications are used frequently, but *we did not expect such a high percentage of people regularly using notes and to-do lists. This could build a good basis to integrate new features of productivity management, such as a feature of to-do lists to prioritize items according to the current cognitive performance of the user.* Applications regarding goals or avoiding distractions are not that frequently used. It remains a question for future research, what the reasons may be. It could be the case that existing tools do not comprise enough functionality or are not that well-known, but also that support in these areas is not seen that important by many people.

Furthermore, it is also highly important to consider individual factors for using conventional tools. Hence, in our study we also analyzed the *influence of personal characteristics, attitudes towards technology and personality traits on the use of self-tracking and self-management, answering **RQ3***. With regard to correlates we found that attitudes regarding ICT may explain why some persons are more inclined (or reluctant) to apply technology-assisted self-tracking and self-management. Furthermore, we found that specific personality traits may predict the use of technology-assisted self-management, namely proactivity and perfectionism. At the heart of proactive personality is an urge to constantly become a better performer or to improve procedures one is involved in. Consistent with this view, individuals, who consider themselves as constantly striving for improvement, tend to leverage self-tracking and self-management applications more frequently than persons who do not value proactivity as much. *It remains an open question for future research, what features would make IT-supported self-management more interesting and helpful for people with less pronounced proactivity or perfectionism.* In this direction, new hypotheses could be generated. Finally, older persons tend to use self-tracking and self-management applications less frequently than younger persons, albeit age effects were very small.

The results of our survey study should be interpreted in the light of its limitations. These limitations have implications for future research. First, cross-sectional data do not allow for drawing conclusions regarding cause and effect. For this reason, we confined our analysis to describing correlational patterns among the focal variables, albeit regression analyses not reported here yielded similar patterns of results. Second, our sample may not be representative of the general population and dropout may bias results. Although, we have obtained a rather large and heterogeneous sample in terms of demographics and ICT-use, generalizability of our findings will remain an issue for future research. Finally, we have focused our analysis at the individual level and have neglected the role of organizational context in shaping ICT-use habits (e.g. norms to frequently use specific self-management tools for teamwork). Despite these and additional limitations however, our survey study may be considered an important first step towards better understanding the use of ICT for self-management.

9 Requirements and Opportunities for Smart To-do Lists[1]

Abstract. Today's working world can be characterized by an increase in flexibility, complexity, and speed. For employees, it is challenging to keep pace to dynamic professional requirements and to constantly collect and prioritize necessary tasks in order to stay well-organized. While there is a plethora of IT-supported to-do lists that help to remember important or necessary tasks, these lists are predominantly rather simple and provide only little support for managing work and life. Hence in our paper, we focus on advanced approaches for personal task and time management via improved IT-supported to-do lists. Such lists could proactively support the user by (i) collecting and prioritizing tasks, (ii) providing context-sensitive reminders, and (iii) tracking activities in order to provide insights regarding progress, productivity, and health-related aspects that in sum could be considered as "intelligent". Towards the IT-supported realization of such lists, we collect initial requirements by analyzing existing and upcoming tools as well interviews we conducted about work organization with professionals in the IT-domain. Based on this, we provide an integrated requirements catalog and comment on opportunities for further research.

9.1. Motivation

The digital transformation has rapidly changed and continues to change the world of work tremendously. On the bright side, improved work flexibility (Shore et al., 2012) in terms of content, time, and location provides employees with additional autonomy with regard to how they do their jobs. On the dark side, work can be characterized by high complexity, time-pressure, constant interruptions, and multitasking as well as work-intensification that is ongoing over decades (Green and McIntosh, 2001). In sum, employees face growing challenges upon managing their work and keeping track

[1] The content of this chapter has already been published as follows:
Fellmann, M.; Lambusch, F.; Dehne, M. (2020): Towards Intelligent Personal Task and Time Management: Requirements and Opportunities for Advanced To-do Lists. In: 10th International Workshop on Enterprise Modeling and Information Systems Architectures (EMISA2020), CEUR Workshop Proceedings, vol 2628, pp. 25–31. https://ceur-ws.org/Vol-2628/paper4.pdf

of relevant tasks as well as managing progress, productivity, and health. Therefore, it is of vital importance to equip employees with powerful tools in order to tackle these challenges and be successful. In this regard, it can be observed that in daily work, many activities or projects typically involve a series of tasks, people, deadlines, and locations. No matter how big or small these projects are, success is always largely dependent on the organizing skills of the people involved. This is still a big challenge that often is mastered with the help of simple means such as paper-based to-do lists, or notepads, despite the many technical possibilities. However, these methods are time-consuming and also not always effective, since e.g. reminders are missing. In spite of a plethora of applications on the market that are designed to provide better time and task management, most of them are rather a digitalized version of paper-based to-do lists or notebooks and lack intelligent features such as context-sensitive reminders. Context-sensitive means that, for example, reminders of important tasks such as project planning do not appear when the user is attending a meeting or that reminders appear only on pre-determined locations or situations. While some to-do lists already provide such features, a more sophisticated approach should consider the task context as well. With this, using an email or calendar application could trigger another task context and thus different reminders than e.g. working with an Integrated Programming Environment (IDE). State-of-the-art tools are largely unable to learn or draw logical conclusions that would be needed for such behaviors. A further example illustrating this deficiency is booking a conference trip that takes place for several days abroad. This usually includes booking a hotel and means of transport. However, state-of-the-art to-do list tools usually cannot infer this even if such a behavior occurred frequently in the past sequences of user actions.

In sum, intelligent to-do lists would relieve the user by automatically collecting and resubmitting tasks, while recognizing priorities, scopes of tasks, and deadlines. Beyond that, they could additionally assist the user in tracking activities in order to provide insights regarding progress, productivity, and health-related aspects. In this regard, they could e.g. suggest tasks implying concentrated and complex work when the user is at her/his daily performance peak or could remind the user to take a break. Finally, an intelligent to-do list should provide integration with established software like Outlook and fitness trackers. To sum up, support for personal task and time management with intelligent to-do lists is highly relevant still today. Despite this relevance, requirements for intelligent to-do lists are still an under-researched topic which we address with our preliminary contribution. To do so, we elicit requirements from literature, existing tools, and interviews and compile them into a preliminary requirements catalog.

9.2. Background

Increasing the degree of automation for to-do lists is a great challenge. Although they are a popular tool for managing personal information, unfortunately they do not yet act according to user behavior. Furthermore, entries are currently only written in free text, from which the system cannot derive any useful information (Gil and Ratnakar, 2008). In this way, Gil and Ratnakar (2008) emphasize the capability of to-do list systems to extract details from the user's free text and create a task.

An early approach in this direction is the concept of RhaiCAL (Faulring and Myers, 2005). Moreover, once a task (e.g. visiting a conference) has been recognized, advanced approaches try to create action plans for tasks (e.g. book hotel, book transportation) (Kokkalis et al., 2013). One important problem here is that systems would need to have "common sense" or domain knowledge. An example for the former would be that the systems knows how long a project status meeting usually lasts. An example for the latter would be that it should know when people usually have dinner or how long a dinner usually lasts. It could even imply to draw logical conclusions, such as not inviting a vegetarian to a dinner in a steakhouse. The need of learning "common sense" knowledge and acting accordingly to save the user time when inputting data has already been put forth by Mueller (2000). However, in order to provide an effective support in personal task and time management, also user preferences are important and could complement "common sense" knowledge. This has already been acknowledged by Berry et al. (2006) and is explored more recently by Geetha et al. (2018). In this context, it is stated that the biggest time management problem is purely personal. Every person, especially very busy workers, have different background preferences regarding the calendar. This includes e.g. priorities and times of tasks, but also to what extent these tasks are shared with others.

In this direction, PTIME was developed as one of the first applications that memorized and learned the preferences of the user (Berry et al., 2006). More recently, the Intelligent Daily Scheduler was developed which automatically generates free time slots for upcoming tasks from the free time of the personal calendar and learns by repetitions (Geetha et al., 2018). While it is important to recognize to-dos and make plans, it is equally important to remind the user if he or she is unaware of upcoming tasks or appointments. However, already two decades ago, studies have shown that many users have a problem with their reminders because they appear at inappropriate times. This led to the observation that context-information is needed for the generation of adequate reminders (Dey and Abowd, 2000). Regarding timing for reminders, much can be learned from the stream of research concerned with timing for work interruptions, see e.g. Rissler et al. (2017b) for a literature review. Regarding location-aware reminders, current approaches try to additionally infer the correct location for task reminders (Suzumura et al., 2018). To summarize, there are ongoing developments in regard to to-do list item creation, task planning, and context-sensitive reminders. In spite of this, statements about requirements are scattered among these works and also do not consider two important aspects. First, they do not investigate what current tools developed outside scientific research offer the user in response to (presumed) market demands. Second, they do not contain empirical statements about what employees consider as important features. Our contribution hence lies in addressing this gap by summarizing requirements found in literature and derived from state-of-the-art tools and interviews with employees. Our requirements are then compiled into a preliminary requirements catalog.

9.3. Requirement Elicitation

9.3.1. Sources for Requirement Derivation and Procedures

Requirements were collected using two different methods. First, *literature and tools* were studied. Since some tools have not yet been described in scientific papers, we opted against separating requirements from scientific papers and those identified by inspecting tool descriptions. Searching for literature and tools was accomplished using various web search engines with combinations of keywords such as "artificial intelligence", "time management", "task management", "calendar tool", and "time tracking". For the identification of state-of-the-art tools, we used one major product weblog where innovative products are announced, namely on ProductHunt[2]. Second, we conducted *semi-structured in-depth interviews*. An interview guideline was prepared in advance and followed during the interview. In the first part of the interview, partners were asked questions about their current methods for time and task management. They were then asked whether they could imagine using applications that solve such tasks in an intelligent way and what functions these applications should have (the term "intelligent" was clarified beforehand). Since the interviewees should also consider visionary future technologies and not only focus on the state-of-the-art, the next part asked for functions of such systems that could be developed in the next 20 to 30 years. At the end of the interview, the interviewed persons prioritized the functions collected in part 2. A total of four people with a background in IT-industry took part. A fifth participant served as a pretest. However, since the results of this pre-test were also helpful for the evaluation, it was also included in the overall evaluation of the interviews. The evaluation of the interviews was based on Mayring (Mayring and Fenzl, 2014) using the software MaxQDA to support the interpretation and coding process. Finally, a consolidated requirements model was created (see Section 9.3.2).

9.3.2. Consolidated Preliminary Requirements Model

The consolidated requirements catalog has been developed based on all requirements identified using the sources and procedures described in the section before. This involved a process of consolidation, clustering, and ordering of the requirements. The final catalog is presented in the form of a mind map (cf. Figure 9.1). It moreover indicates the source as well as the frequency range of elicited requirements per category.

Requirements fall into five broad categories: *Task Management*, *Tracking*, *Reminder*, *Preference Management*, and *Cross-cutting Requirements*. In more detail, *Task Management* contains requirements regarding the creation of tasks and work support. The former mainly comprises "intelligent" assistance for the creation of tasks based on textual descriptions, e-mails, or from voice messages as well as classification of tasks according to pre-defined categories and prioritization. The latter comprises requirements for working with the to-do list such as recommendations for the next best action, sharing to-dos with colleagues, and receiving predictions for the time needed to physically change the location that e.g. depends on the transportation

[2] `https://www.producthunt.com/`

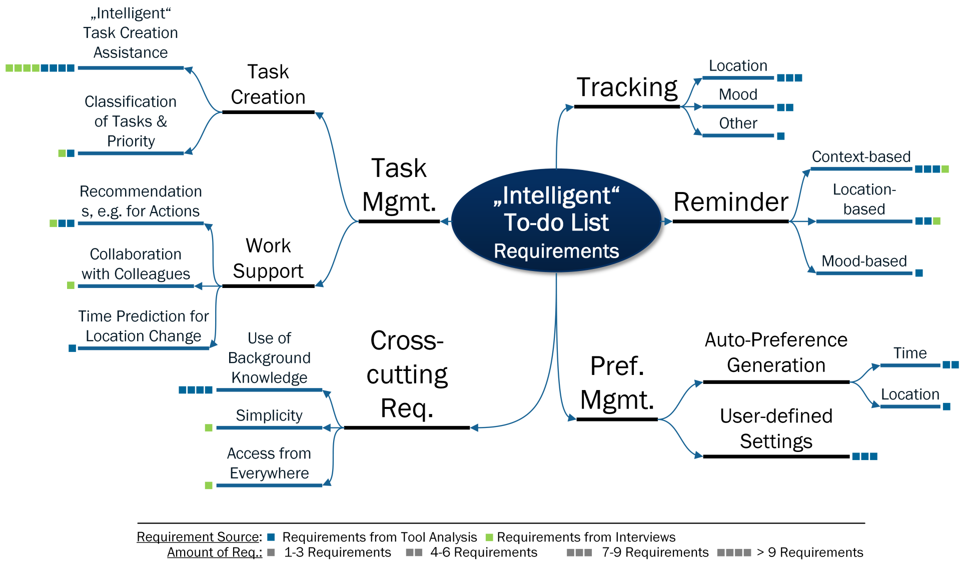

Figure 9.1.: Requirements catalog for IT-supported "intelligent" to-do lists

means and traffic, which some of the advanced tools already provide. Since the to-do list should adapt to the context, *Tracking* is required. Here, location, mood, and other tracking data (e.g. time-use or physiological data) have been elicited. Tracking such data can be used for more adequate *Reminders* that could be context-based, location-based, or mood-based. While location- and mood-based reminders simply take the users' GPS position and emotional state into account, context-based reminders could be adaptive to the current situation in complex ways, e.g. considering what the user has done before, what the user could do now and what the goals of the user are. In regard to *Preference Management*, the system should be able to learn preferred timeslots or locations for engaging in to-dos based on previous data (e.g. no appointments on early Monday morning) as well as provide the possibility for various user-defined settings. Finally, in regard to *Cross-cutting Requirements*, the system should be capable to leverage background knowledge such as preferences of co-workers (e.g. working times, diet preferences for meetings) or common-sense knowledge (e.g. public holidays, average speed of transportation means) and should be simple to use and accessible from everywhere, which could be accomplished via cloud-based access.

9.3.3. Discussion

Regarding requirements elicitation from literature, despite the large amount of popular guidebook literature, surprisingly little works are available on the precise topic of IT-supported personal task and time management, and even more so in regard to to-do lists. In addition, found literature mainly offered descriptions of developed tools from which requirements had to be derived since they were not explicitly mentioned. As a further limitation of our research, we focused on functional requirements and some cross-cutting aspects, leaving non-functional requirements largely open for future research. Regarding tool analysis, ProductHunt was useful to get an overview of current tools on the market. Most of the functions however had to be derived from user comments or by downloading and testing the tools, since often no in-depth documentation was available. Finally, regarding requirements elicitation with interviews, it was helpful that participants were invited to actively think about requirements of advanced future tools. A major limitation of the research in this direction is the number of five interviewees with IT-background which creates potentials for future research.

9.4. Conclusion and Research Opportunities

Despite the fact that personal time and task management is one of the most important topics in work life, surprisingly little research is available so far regarding the requirements for intelligent task and time management tools that could be embodied in "intelligent" to-do lists. Therefore, our work makes a contribution in this field, although our results are very preliminary. However, we provide a preliminary overview of key requirements of intelligent task and time management systems that support the user in the creation of to-dos and provide context-sensitive reminders or suggestions for relevant tasks. Future research opportunities lie in the interrelation of these requirements, e.g. context-sensitive reminders require in some form tracking the user. Further research opportunities lie in the selection, adjustment or adaptation, application and finally evaluation of research results of various sub-fields of Computer Science, Business Information Systems and Organizational Psychology.
In regard to task management, the question is *how natural language processing for extraction of information from texts could be combined with other data* (e.g. previous tasks performed on the day) to increase the accuracy of to-do item generation. Moreover, psychological models could be used to explore the question *how the ordering of daily tasks may impact the individual*, e.g. in terms of perceived progress or fatigue at the end of the work day. This could be relevant to optimize the ordering of to-dos. Likewise, the utility of physiological models of cognitive performance in relation to the time of day for task ordering could be studied. Regarding tracking, further questions would be *to analyze the prospects and limitations of integrating work-related time tracking data with more physiological tracking data into a combined approach*. For example, heart rate variability (HRV) allows to detect stress, but the question is whether such data could be applied in task scheduling to avoid stressful working conditions. Regarding reminders, the challenge is *how to predict the acceptability and utility of a reminder that might interrupt the user*. Extensive prior research on work interruptions can be leveraged on this aspect as well as machine learning techniques. Finally, regarding the user model, the question is *how to combine different approaches for knowledge representation* such as rules, ontologies, or general common sense knowledge catalogs like Kokkalis et al. (2013) with machine learning techniques. All in all, intelligent personal task and time management offers a plethora of interesting research questions. They are worthwhile to explore not only for the sake of improved "mechanization" of planning and scheduling activities, but also for ensuring long-term productivity, well-being, and health.

10 Smart Self-Management Concept[1]

Abstract. The development of the knowledge-based society and ubiquitous information technology offer individuals a variety of personal and professional possibilities. At the same time, increasing flexibility in modern everyday life can lead to high working pressure and blurring boundaries between life domains. Thus, self-management skills steadily grow in importance. These skills are not only important for productivity, but also for health and well-being. The availability of various small sensors and their easy integration into everyday life enables new kinds of data collection. Data ranging from heart rate to location can be analyzed and combined with data about tasks and time schedule to provide guidance in self-management. However, up to now it is unclear how such a guidance based on sensor information could be designed and how it can positively contribute to self-management. In our research, we hence provide a first contribution towards context-aware assistance for self-management of knowledge workers. To do so, we first devise a scenario to show how such a system could positively contribute to self-management via a set of interventions based on sensor data. We then present an architecture that conceptualizes a context-aware system integrating several data sources along with descriptions of implementation options of such a system. With this, we intend to provide an overview on the design space relevant for the construction of such systems. This overview is meant to inform and inspire the future design of concrete systems that assist knowledge workers in the enhancement of their self-management skills.

10.1. Introduction

Work intensification and blurring boundaries between personal and work life pose major challenges in today's society. Many workers are often pressed for time. Frequent interruptions and multitasking constitute additional difficulties for the planning and completion of tasks. According to results of the Sixth European Working

[1] The content of this chapter has already been published as follows:
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Conditions Survey, 45 % of workers carried out work in their free time in order to meet work demands (Eurofound, 2017). More than every fifth worker did this several times a month or even on a daily basis. The overall findings of the survey indicate that many of today's workers face very high work demands. Stress resulting from high work intensity can have negative effects on work performance and is furthermore a risk factor for personal health and well-being (Leka et al., 2003). Long-term exposure to stress can lead to serious health problems like back pain, depression, and burnout (Béjean and Sultan-Taïeb, 2005). Possibly causing poor productivity and absenteeism, consequences of work-related stress not only pose a major problem for workers, but also for the organization they work for (Leka et al., 2003).

While the organization is responsible to support workers by paying attention to good working conditions, it is often not feasible for supervisors to adjust the amount of work on a daily basis to meet the current capacity of each employee. This is even more true in the context of work that is characterized by a high degree of freedom, i.e. the worker often can decide on what to do next, what methods of work are used, or what could be accomplished on a daily basis (Drucker, 1999). However, the improvement of self-management competencies can help the individual to cope with high demands in everyday life. We follow here the definition that self-management competence comprises the willingness and ability to manage the own life responsibly and to shape it in such a way that productivity (e.g. in terms of knowledge, skills, health), motivation, well-being, and balance in life are promoted and maintained over the long term (Graf, 2012). This means that self-management is also about becoming more efficient and effective, but should always be linked to handling the own resources carefully. Graf (2018) points out two key abilities for effective self-management: *self-reflection* and *self-development*. Self-reflection corresponds to determining necessary changes and development steps whereas self-development denotes the operationalization of these steps. The author figured out that many people, even if they know what they should change, find it particularly challenging to take action in order to accomplish the latter, i.e. reach self-development. As a lack of success in achieving goals weakens self-esteem and well-being, it is important to promote taking action.

Therefore, we propose to assist workers in self-management at both stages, self-reflection and self-development, by utilizing the opportunities provided by modern information technology. Existing tools, such as to-do lists or digital calendars, offer only rudimentary support for self-management. The latter, for example, support creating appointments and may warn when these temporally overlap, but they do not plan for the workload accompanying certain appointments. Furthermore, most of the existing tools are static and require continuous manual adjustment. In regard to this problem, sensor technology that has become ubiquitous in recent years might serve as a remedy. Mobile and wearable devices, such as smartphones and smartwatches, have various built-in sensors, for example, an accelerometer or gyroscope (Kilintzis et al., 2017; Shoaib et al., 2015). Thus, a wide range of contextual information can be made accessible to assist users. The devices not only offer the chance to collect data, but are also capable to unobtrusively provide guidance at any place (Maier and Wörndl, 2015) and remind the user of taking necessary actions.

Up to now, no integrated architecture has been proposed that incorporates vari-

ous sensor data to provide users analysis and recommendations specifically for supporting their self-management. In this research in progress article, we present an architecture of a personalized and situation-aware assistance system for smart self-management. Regarding self-management at work, we focus on knowledge work. According to Davenport (2005), "knowledge workers have high degrees of expertise, education, or experience, and the primary purpose of their jobs involves the creation, distribution, or application of knowledge". Therefore, working conditions for knowledge work differ from that of other work. For example, knowledge workers are often not bound to fixed working hours and locations (Laihonen et al., 2012). An assistance system for smart self-management may be of particular relevance for the group of these workers as managing themselves is a substantial factor determining their productivity (Drucker, 1999).
In the next section, our vision of smart self-management is explained in more detail. Section 10.3 presents the proposed architecture for the assistance system. Finally, we conclude with a discussion and outlook.

10.2. Smart Self-Management – The Vision

Before we introduce the constituents and architecture of our smart self-management system, we describe a vision towards smart self-management in this section. The purpose of presenting such a vision is to illustrate the envisioned integration of a smart self-management system in personal life and the possible effects of system usage independent from technology choices and constraints. In addition, the demand for assistance in self-management may be very individual. Besides the aforementioned changes in the working world, there can be a variety of other reasons motivating interest in support for enhancing self-management skills. Hence, we describe our vision in the following by adapting the notion of personas (Cooper, 2015) in order to provide concrete descriptions. The notion of personas stems from user-centered design and is intended to explore potential preferences and expectations regarding a product by creating vivid fictional characters representing user groups. In general, multiple personas are at first described independently from interacting with the system and the focus is on making up their personal details and exploring their goals. However, in this article we use a persona mainly as an instrument to illustrate how the assistance system for self-management is envisioned to be integrated in one's daily routine and which interventions may be important. In this sense, a single fictional character directly in action with the system is described below:

Karl (48) is an independent business consultant and father. Karl has built up a satisfied customer base and has accompanied some of the customers for many years. Unfortunately, his workload is difficult to predict, because his customers spontaneously contact him with smaller jobs. Hence, it is particularly important for Karl to make the most of his time.
This Friday, his smartwatch running the smart self-management assistance system wakes him at 6 am, an hour earlier than normal. This is because the assistance system of his watch, which he uses consistently since the first signs of burnout and a sick leave last year, has recognized that Karl has enjoyed an excellent sleep quality over

the last few nights, so getting up early is no problem. At the same time, the system knows that there will be a lot of traffic on the streets on Friday afternoon, so Karl should start working at 8 am to be able to return in time before the traffic jams start. He has scheduled several interviews with clients on this day. During this working day, the system rarely interrupts with notifications because it learned that disturbances are undesirable for entries of the type *customer contact* in the appointment calendar. Against a warning from the system, Karl has scheduled four interview appointments seamlessly and even over the lunch break. As the system recognizes an increased stress level and a decreased cognitive performance, it announces itself after the last appointment unremarkably with a vibration and suggests taking a break. Because the system has learned from the answers of the short weekly questionnaires that Karl can relax well during movement, it furthermore recommends going for a walk. Thereupon, Karl takes a walk through the nearby city park and eats a snack in his favorite café near the lake in the park.
After this break, Karl decides to do some desk work. So he drives home, relaxed and as planned by the system without traffic jams. Subsequently, the system recognizes that Karl enters his home office and reminds him to perform an outstanding evaluation of a client's files. While Karl is still fully absorbed in his work, after 1.5 hours his assistance system makes him aware that his planned time budget for this client will soon be exhausted. He decides to write an e-mail to the client and ask him to send some missing data. On the basis of these data he will finish his already sophisticated evaluation in a short time on Monday.
Now, the system suggests Karl to play with the children or to cook for his family. Alternatively, he could now get a birthday present for his mother, who has her birthday next Wednesday, because Monday and Tuesday are already scheduled with appointments all day, as the system points out. Karl decides to prepare dinner together with his children and set the table. He plans to get the gift during Saturday shopping. Karl's wife does not return from work until 6 pm today. With great pleasure she sees that dinner has already been prepared. Moreover, she surprises Karl with a theater visit that evening. The grandparents will take care of the children. For the way to the theater, the assistance system suggests going a station by tram and the rest on foot. Both enjoy the warm summer evening and Karl can now relax very well, because he has achieved his professional and private goals, also thanks to the coaching provided by his assistance system.

10.3. Architecture for Smart Self-Management

In order to realize the vision of a context-aware assistance system for smart self-management, the system has to be composed of various hardware components (computing devices, sensors) and software components (e.g. for data analytics and user feedback). Designing such a system is a complex and complicated task since numerous components have to be selected and composed to an integrated system. We intend to ease this design task by presenting a conceptual architecture that contains a set of elements and their relations relevant for the creation of smart self-management systems. This architecture is shown in Figure 10.1. Fundamentally, the architecture has been developed by following the core idea that information systems essentially

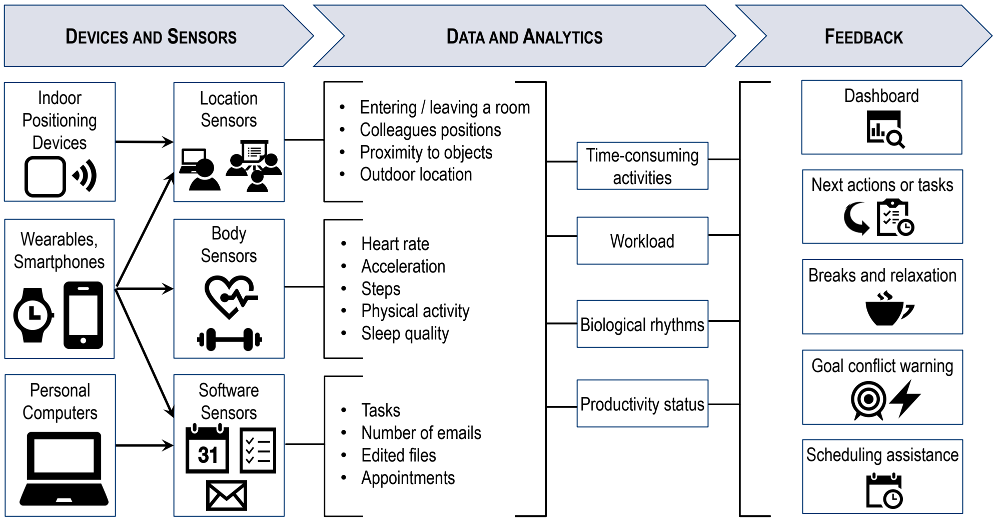

Figure 10.1.: Architecture for smart self-management

acquire or receive information, process it, and deliver relevant results to the user. Therefore, the architecture consists of three main parts: *Devices and Sensors*, *Data and Analytics* and *Feedback*. Instruments and mechanisms to collect data are shown on the left side of the architecture, while the center shows relevant data that can be retrieved and information resulting from further analyzing these data. The right part of the architecture contains the different components of system feedback generated to inform and assist the user. In the following sections, we describe the parts and components of our architecture in more detail.

10.3.1. Devices and Sensors

To create an assistance system that can automatically adapt its interventions to individual circumstances, contextual information is required (Alegre et al., 2016). An established definition of context is provided by Dey (2001), who states that "context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves." As the assistance system is envisioned for everyday usage, context data needs to be collected mainly without user intervention and in an unobtrusive way, i.e. via sensors. The term "sensors" here not only means physical sensors, but any kind of technology capable to automatically sense the context of the user. We distinguish roughly between three types of sensors according to the data they record. These are *Location Sensors*, *Body Sensors* and *Software Sensors* (cf. Figure 10.1, the right column of rectangles subordinated to *Devices and Sensors*). Location sensors identify the user's current position indoors (e.g. being in a specific room) or outdoors (e.g. longitude and latitude). This information is relevant since it can help to detect the current context of the user, e.g. working in the office or relaxing in a public park. Body sensors monitor a user's activity (e.g. walking) and physiological data (e.g.

heart rate), which are especially important for considering well-being and health aspects of self-management. Software sensors are used to identify software-based work and to monitor contents related to the used application. By using these kind of information, it becomes possible to retrieve the working context, e.g. if the user currently is in a meeting, works on a document, browses for information on the web or is engaged in organizing and communication.

Regardless of the sensor type, data can be collected by utilizing modern off-the-shelf technology that can fulfill the sensing tasks thus helping to implement an unobtrusive as well as cost-effective sensor. In this regard, devices for collecting data are shown on the leftmost part of Figure 10.1. They are grouped in *Indoor Positioning Devices*, mobile devices such as *Smartphones or Wearables* and *Personal Computers*. These devices can be used to implement various sensor types, i.e. there is an 1:n relation between devices and sensor types.

Research regarding *Indoor Positioning Devices* is still ongoing and diverse. These systems utilize, for example, Wi-Fi, Bluetooth, or ultrasonic (Lymberopoulos et al., 2015). Most technology in the field of location-awareness is focused on more or less exact position data. For assisting knowledge workers in self-management indoors we consider a user's proximity to rooms, persons, or objects as main issue rather than exact positioning. Therefore, Bluetooth Low Energy (BLE) beacons may be valuable. These hardware transmitters periodically send a signal that can be received by Bluetooth compatible devices, such as smartphones or smartwatches. The transmitted data then lead to proximity or position information. Although, extra hardware in terms of transmitters is necessary, it is possible to attach beacons to every entity relevant for self-management and to easily deploy them by using an app that recognizes proximity to certain beacons. It is, for example, possible to attach one beacon to an office desk and one to a wall in a meeting room to make smart devices aware of the difference between being in one of these rooms. Thus, beacons may suit well for retrieving indoor location context for smart self-management.

Smartphones and *Wearables* such as smartwatches are devices that in particular can be integrated easily in daily life. While smartphones are already widespread, smartwatches are an emerging wearable technology with numerous features and embedded sensors (Kilintzis et al., 2017; Maier and Wörndl, 2015). Furthermore, as these watches are wristband-type devices, they are unobtrusive, light-weight, and do not interfere the user in daily processes. In contrast to smartphones, smartwatches deliver regular and more accurate data in respect of body sensors, because they are worn directly on the skin (Shoaib et al., 2015). Since both, smartphones and smartwatches, can give feedback even in a mobile context, we propose to use them as core devices of the context-sensitive assistance system. As smartwatches typically can be coupled with a smartphone, function and load can be distributed between both devices (Houben and Marquardt, 2015). For example, due to limited battery capacity, some of the tasks such as outdoor positioning using GPS may be delegated preferably to another mobile device such as a smartphone.

Personal Computers finally can be used to identify software-based work and to monitor contents related to used applications via an additional software running in the background that records all types of events. By using these kind of sensors it becomes possible to retrieve, for example, information from digital calendars, mailing

programs, writing tools, or web browsers. At a desk-based office workplace, data can be collected from personal computers (PCs), which can be stationary or portable. In more mobile settings, information about used applications can also be recorded via a background app on the smartphone.
All the aforementioned devices are envisioned to be connected and to share information to form a large data basis. A database can be implemented using dedicated database technology, most notably time series databases (e.g. influx as on open source database). Time series data then can be analyzed in an efficient way in order to provide the user feedback and assistance.

10.3.2. Data Analytics

In order to process the collected sensor values, data analytics capabilities are required. These capabilities are necessary to aggregate data, detect patterns, and analyze developments over time. For example, to detect the work-related stress level which is relevant for activity suggestions or even breaks, a variety of sensor data originating from different devices has to be aggregated and combined. Among these data could be heart rate, the amount of processed mails, the number of meetings per day etc. Another example would be to detect the amount of time a user dedicates to one topic. Here, various data concerning the processing of documents, related e-mails as well as visited websites have to be aggregated. Such data aggregation, combination and interpretation can be executed on different levels of abstraction. Fundamentally, we differentiate between *lower-level data analytics* and *higher-level data analytics* according to the self-management context.
In the lower-level analytics, basic pieces of information are retrieved via an Application Programming Interface (API) from raw sensor values. It should be noted here that retrieving values via APIs already implies some sort of pre-processing of the raw sensor values. This is implemented in the device as the lowest level of data processing that for our purposes of improved self-management is out of scope (in addition, it is also vendor-specific and the industry competes on how well this is implemented, making the lowest level of data processing rather non-transparent). In the process of lower-level analytics, various data spanning all sensors is retrieved, stored in a database and some simple calculations are performed such as e.g. calculating average values or min/max values for a given time span. Regarding location sensors, information on outdoor or indoor location is processed, such as the user's proximity to places, buildings, rooms, objects, or colleagues. Also, information from body sensors can be processed such as the user's heart rate, physical activity, or sleep quality. Moreover, data from software sensors can comprise contents from various used software tools ranging from writing tools through digital calendars and mailing programs to web browsers. The analysis of these contents can lead to information about, for example, assigned tasks, created appointments, number of e-mails (received or sent), or time spent on editing specific files.
In the higher-level analytics, several results of the lower-level analytics are aggregated to even more complex information associated with the self-management factors productivity, motivation, well-being, and health. We identified four important components of higher-level analytics. The first component is called *time-consuming activities*. It is used in order to analyze time spent on certain activities and sub-

sequently, to identify exhausted time budgets or activities on which time may be wasted. Existing time tracking software, even leading tools like RescueTime[2], analyze time spent on used tools and websites only. They largely lack to automatically associate time-consumption to more than basic activity categories such as "creating" or "organizing" without an extensive manual configuration. Using additional sensor data such as location and time may help to improve this situation. Second and even more important, they lack to automatically monitor activities where no operations on a device are performed. By utilizing the proposed lower-level information, it will become possible to even capture such activities. For example, entering a rest area or meeting room can be recognized by location sensors. Similarly, appointments in a digital calendar or physical activity can be used to identify the user's situation.

The second higher-level component is called *workload*. As a high workload in the long-term can lead to decrements in performance, motivation, well-being and health (Hockey, 1997), it is important for smart self-management to observe the workload over time. A generalized workload measure could be inferred from the amount of tasks, appointments, emails, opened files, and physical activity. Furthermore, a user's cognitive workload can be estimated to regard individual reactions to demands. Current research considers, for example, how heart rate variability can be used to recognize or even predict changes in cognitive performance that are caused by mental workload (Kraft et al., 2017; Tsunoda et al., 2017).

Biological rhythms as the third analytics component considers the human's circadian rhythms that drive the patterns of cognitive, behavioral, and physiological processes. As the biological clocks influence, among others, activity, sleep, and mood, rhythm disruption can lead to consequences like reduced motivation, performance, and health (Foster and Kreitzman, 2014). In order to determine biological rhythms or their disruption, especially body sensor information like sleep and activity timings and also heart rate variability may be relevant. Furthermore, as biological rhythms could already be associated with patterns of smartphone app use (Murnane et al., 2016), software sensor information from several devices on a timeline could be analyzed in combination with physiological information.

The fourth higher-level component will analyze the *productivity status*. The time tracking software RescueTime presents a productivity value according to time spent on certain tools or websites. As the quality of outcome is at least as important for knowledge work as the quantity (Drucker, 1999), considering only time spent on activities may not be sufficient to characterize knowledge workers' productivity. For example, if decreased cognitive performance is recognized, taking a break for recovery may be productive, but randomly surfing the internet when near an alertness peak may be not. Therefore, we propose to combine information from time-consuming activities, workload, and biological rhythms, to create more comprehensive measures regarding also aspects related to motivation, well-being, and health.

[2] `https://www.rescuetime.com/`

10.3.3. Feedback

In order to assist the user in self-management, the system has to provide transparent feedback. Different mechanisms can be used in order to support self-reflection or self-development (for an introduction to these two concepts, cf. Section 10.1). For the first, we propose to present the user information delivered from data analytics in a so called *dashboard*. The information should be visualized in a way that also shows changes over time. The system is envisioned to further provide the user the opportunity to define goals related to the information presented, e.g. to work on high-leverage tasks at alertness peaks.
In order to support self-development, we propose encouraging the user to take action by providing recommendations on carrying out or omitting activities. These recommendations are intended to have preventive effects on work-related stress. To ensure transparency, the system could show an additional hint of why the certain recommendation occurs. For example, for the component called *next actions or tasks*, a next task could be chosen according to an urgent deadline or alertness peaks. Similarly, the system could intervene distracting actions. Recommendations of *breaks and relaxation* are likely to depend on workload and biological rhythms. On the one hand, the system could recommend a break, e.g. if decreased cognitive performance is predicted. On the other hand, it could intervene, e.g. if the user only forgot about time seemingly. A *goal conflict warning* would occur, if carrying out or omitting certain activities contradicts a specified goal, e.g. the user carries out a certain work longer than the self-defined goal is. The *scheduling assistance* component could extend the existing mechanisms of digital calendars that warn the user when appointments overlap to also regard workload and biological rhythms. The system could then recommend a suitable date and time according to these factors, when the user is about to plan an appointment.
Finally, feedback could be delivered by personal computers in a stationary context and by smartphones or smartwatches in a mobile context.

10.4. Discussion and Future Work

In this article, we first motivate why self-management is increasingly important, given the continuously growing flexibility of knowledge workers made possible by modern IT systems. We also introduce the two concepts of self-reflection and self-development, whereby the former is required for the latter and self-development in turn is required for an effective self-management. Unfortunately, self-development is hard to achieve even if the individual is successful in self-reflection. This calls for an improved IT-support. To address this issue, our research effort aims at providing an improved IT support for knowledge-workers' self-development. In more detail, we propose a conceptual architecture for a context-aware assistance of self-management for knowledge workers. With this, we intend to provide an overview on the design space as a first step towards the construction of systems that assist self-management. Therefore, it is meant to inform and inspire the future design of concrete assistance systems. We describe how such a system could positively contribute to self-management via a set of interventions made possible by lower-level and higher-level processing of sensor data. In addition to this, theoretical imple-

mentation options of such a system are described.
It is planned to extend the proposed components for data collection in the future by integrating questionnaires that could periodically or situationally be presented to the user on a smartphone or PC. Answers from psychology questionnaires can, for example, reflect a person's experiences of positive or negative moods (Quirin et al., 2009; Watson et al., 1988). Considering not only measured data, but also subjective appraisal will have an impact on the quality of system interventions to enhance individual self-management skills.
A prototypical implementation and subsequent evaluation of the system components is a main issue for our future work. On this basis, the implementation options could then be adjusted or extended. As a next step, the accuracy of sensor data from different sources will be observed. Physiological data from current smartwatches, for example, may be more accurate in workload monitoring for user activities with little movement than in motion (Binsch et al., 2016). If higher accuracy will be required, e.g. approaches to filter misleading data could be used (Ra et al., 2017). Furthermore, the interplay between different devices has to be arranged and tested. In this regard, also technological questions have to be solved such as dealing with data transmission between devices and buffering data if connectivity is lost.
It may be important for users that the system can be configured according to personal preferences in order to influence system feedback. There could then be options to choose between recommendation modes ranging from reactive feedback, i.e. the system presents recommendations only on request, to proactive feedback, i.e. the system intervenes automatically. It is conceivable that the user could also specify times, where proactive recommendations are undesired, or that a vacation mode can be chosen. Furthermore, machine learning algorithms could be utilized to let the system learn from user reactions to certain recommendations. As a result, the system could adjust, for example, the frequency of recommendations. User preferences and opinions are, however, subject to separate further research efforts that we are actively pursuing.
From the above future research options and plans, it should become evident that developing such as system is not a one-shot short-term research activity. It is rather a process of research spanning multiple years that we want to share and discuss with the research community. With the proposed architecture, we provide the first contribution on this new avenue of research. It is envisioned to lead to self-management assistance systems that encourage people to work smarter and to excel in self-development. Among the most important merits that we envision with such a system is that time shall be gained by systematically organizing and shaping life in order to maintain and promote balance in life.

11 The Data Perspective for Smart Self-Management[1]

Abstract. In today's working world, work intensification and blurring boundaries between life domains pose major challenges. Stress resulting from high working pressure combined with a lack of opportunities for recreation can cause serious physical and mental health problems. As sensor technology has become ubiquitous and enables new kinds of data collection, it can serve as a foundation for sensor-enabled personal work support systems (SPWSS) assisting users in coping with high work demands while considering individual resources. Such systems could interpret collected data and generate recommendations geared towards maintaining the user's health, productiveness and well-being. However, building systems of this type is a complex task due to the large number of sensors, devices, and software components that have to be integrated. Moreover, this kind of work support relies on processing personal and intimate data from users and thus, require the willingness to share these data. As a first step towards building SPWSS, we investigate the data perspective of such systems. In doing so, we present an architecture of connected devices. Since the willingness of users to share their personal data is a crucial prerequisite for such systems, we furthermore present results from an empirical investigation concerning the willingness of users to share selected data for specific purposes.

11.1. Introduction and Motivation

Mobile devices such as smartphones or tablets are widely used. They help us to work, learn, and manage our social relationships. All this can be done independently of location and time. While there are many benefits, the boundaries between life domains can become vague with a high flexibility. Furthermore, the increasing usage of information and communication technology can cause a high intensity of work. Resulting stress threatens motivation, performance, well-being, and health (Leka et al., 2003; Béjean and Sultan-Taïeb, 2005). Also, the complexity and information

[1]The content of this chapter has already been published as follows:
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intensity of work constantly increases. Especially for the increasing proportion of knowledge-intense work (Eilers et al., 2017), these challenges are amplified greatly since this kind of work goes along with a high self-responsibility. Therefore, it is a major challenge to carefully deal with individual freedoms and resources to avoid overload. In order to improve the management of personal resources, advanced work support systems are required. Such systems should not only consider formal aspects of the work such as routines that have to be followed (e.g. process models) or organizational structures, but also individual data (e.g. heart rate, activity level, tasks, appointments) to support the user in promoting productivity, motivation, well-being, and balance in life over the long term. As sensor technology and smart devices are increasingly integrated in everyday life, these technologies can serve as a valuable instrument to collect data that can be leveraged by sensor-enabled personal work support systems (SPWSS). Such systems may include the monitoring of one's everyday behavior and the identification of necessary development steps. Thus, they can consequently drive the development through recommendations and perform progress checks. Implementing such systems is a highly complex and challenging task. Therefore, as a first step, we investigate how various sensors and smart devices can work together to collect data that can be used to support individuals in their working environment.

The remainder of this article is structured as follows. In Section 11.2, we present an architecture of connected devices for SPWSS and in Section 11.3, we show results of an empirical analysis focusing on the willingness of users to share their data for such systems. In Section 11.4, we discuss our results and provide a conclusion.

11.2. Architecture of Connected Devices

To elicit potential components of SPWSS, literature was analyzed to find features that are relevant for personal work support. As a result, potential components for the steps data collection, data analysis, and feedback generation have been identified. These components are described in more detail in (Lambusch, 2018). In the following, we present a complementary IT-architecture of the data collection for SPWSS that contains relevant devices and illustrates their connections (cf. Figure 11.1). The architecture follows the key notion that data needs to be collected mainly without user intervention and in an unobtrusive way in order to assist users effectively in everyday work.

The central hub of the architecture is a smartphone that collects data from various sensors that can in turn be retrieved from various devices. Among these devices is the smartwatch. Current smartwatches such as Samsung Gear, Apple Watch or watches from Huawei have numerous built-in sensors (Kilintzis et al., 2017) and deliver more accurate physiological data (e.g. heart rate, steps) than smartphones (Shoaib et al., 2015). The data can be retrieved from a smartwatch via an Application Programming Interface (API), which can already include some sort of pre-processing of raw sensor values (e.g. deriving heart rate from PPG signals) implemented in the device. In addition, other devices such as stationary beacons can be used to retrieve proximity data that is valuable for indoor location and navigation. From this, it can be detected e.g. if the user works in the office or is in a meeting room. The smart-

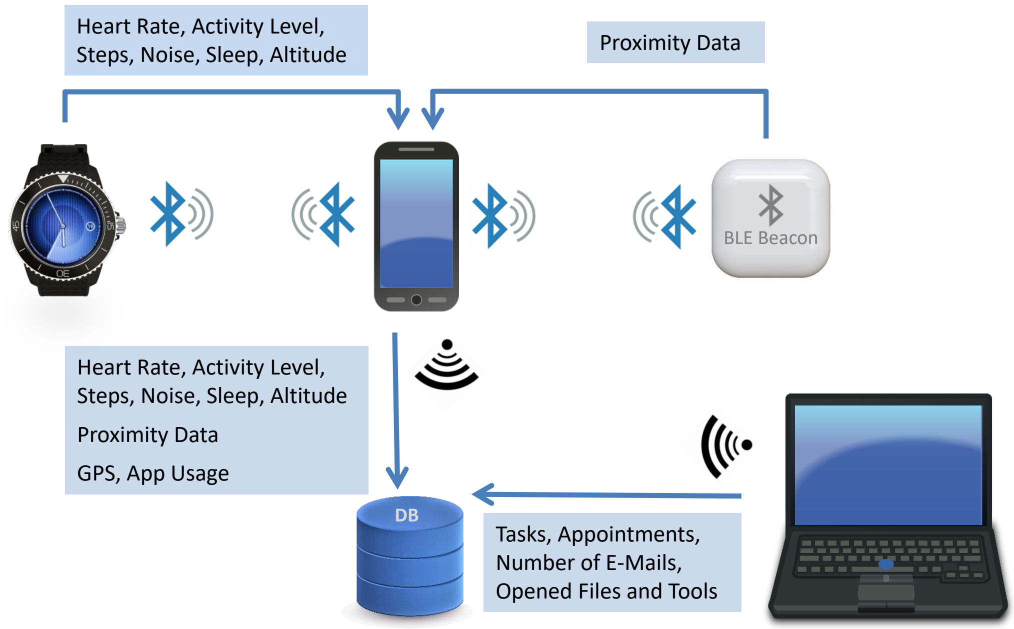


Figure 11.1.: Architecture of connected devices for sensor-enabled personal work support systems (SPWSS)

phone retrieves the data from the smartwatch and beacons via Bluetooth and can collect further information on its own, e.g. from GPS or app usage. Furthermore, it is possible to capture software-based work and to monitor contents related to used applications (e.g. appointments, incoming mails) via additional software running on the computing devices such as laptops or tablets. Data from the smartphone and a personal computer are sent via internet to a database. There are dedicated databases for such purposes, called time series databases. As the focus of the figure is on the data collection components of SPWSS, data is only sent to the database, while data analysis and feedback that would be sent back to the devices are not shown here.

11.3. Willingness to Provide Data

For the implementation and usefulness of SPWSS, it is important, which data may be collected and analyzed. Since some data needs to be aggregated and combined in order to provide users comprehensive feedback, the lack of single components of data collection may lead to a lack of single or even multiple components of the analysis and related feedback. As the presented architecture contains several connected devices that have the potential to collect a wide spectrum of data, considering the willingness of users to share their personal data is a crucial step to check the feasibility of the system. In this section we present results from conducting a survey, where we focus on the willingness of users to share selected data for the purpose of personal assistance.

Table 11.1.: Data collection categories

Category	Data
Body	Heart Rate, Activity Level, Steps, Noise, Sleep, Altitude
Software	Tasks, Appointments, Number of E-Mails, Opened Files and Tools
Location	GPS Position, Position in Building

The survey was conducted over one week. The request for participation was sent via a mailing list referring to the information systems research community and thus, in particular, to researchers and practitioners with an IT-focus. The survey resulted in 39 complete data sets. The participants were on average 32 years old. 19 of the 39 participants were between 20 and 29 years old, 17 were between 30 and 39, and 3 participants were between 40 and 49 years old. 41 % of the participants were female and 59 % male. All participants had a job, which is a prerequisite for answering questions in the context of personal work support. Among others, the participants were asked to choose in a table whether statements on their daily work and the structure of their tasks are absolutely, rather, partly, rather not, or not at all true or cannot be assessed. For example, one row of the table contained the statement “My tasks are subject to strict guidelines” together with the options to choose. There are mainly little deviations from the moderate value “partly” in the results. However, the arithmetic mean of the responses indicates that most participants have a large share of knowledge-intensive work. Many participants stated that there are rather no strict guidelines and rare instructions for carrying out tasks. For new tasks, it is only partly clear how to proceed. For many participants, their tasks are rather not similar and often only partly related. The largest deviation from the moderate value can be found in the answers to the statement concerning the time management of everyday working life. The majority of respondents have no or little specifications of what to do when. Also the working hours are fixed only for about 21 % of the participants. The rest either has flexible working hours or even no fixed working hours at all.

The questions about the data that participants would give to an assistance system were classified into data collected on the body, software, and location. An overview of the categories is presented in Table 11.1. For each data collection category, a brief introductory text in the survey exemplified the application and contribution to assistance features.

The results on the willingness to share data collected directly on the body are shown in Figure 11.2. Only 13.2 % of the participants would not share any of the listed data. Most participants would be fine with the collection of data on their number of steps (71.1 %), their heart rate (68.4 %), or physical activity (65.8 %). More than a half of participants would share data on the noise level (60.5 %) or their sleep quality (52.6 %). The altitude might be collected for 42.1 % of participants.

The results on the willingness to share data collected on used applications and content retrieved from them is shown in Figure 11.3. Data on appointments might be collected for the most participants (76.3 %). Data on tasks would be shared by 63.2 % of participants and the number of emails by 60.5 %. Only data about opened files and programs would be provided by proportionally few participants (34.2 %).

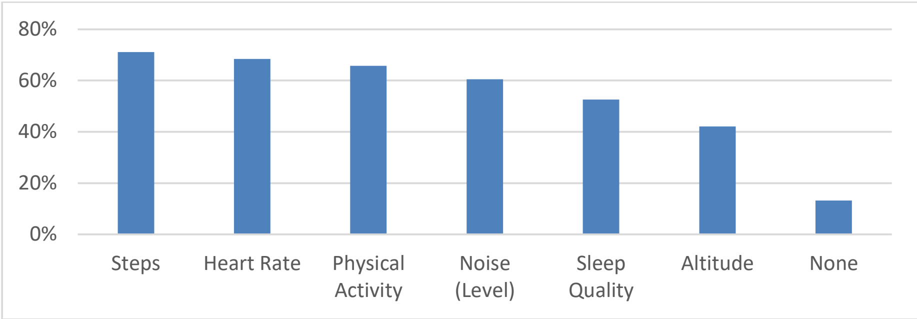


Figure 11.2.: Willingness to share data collected on the body

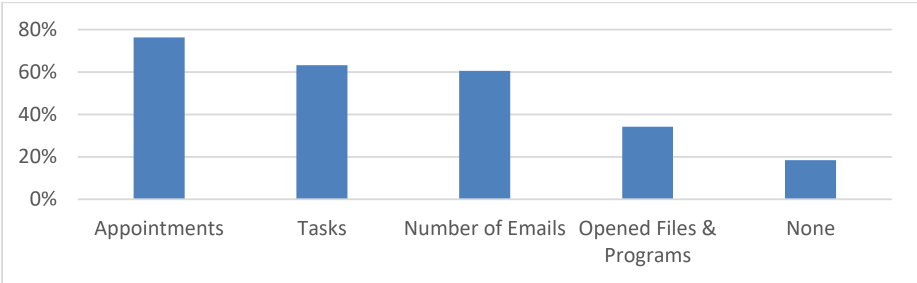


Figure 11.3.: Willingness to share data collected on software

The number of participants who would in principle not share the listed data is with 18.4 % slightly higher than at data on the body.
The results on the willingness to share data collected on the location is shown in Figure 11.4. Almost half (47.4 %) of the participants would not provide any positioning data. While 42.1 % of participants would share their GPS position, 31.6 % would share their position in a building.
In a free-text field, participants could indicate why they would not agree to collect the various described data. It is clear from the entries made by ten of the 39 participants that there are in particular privacy and data protection concerns. It is feared a possible misuse of data and attack on privacy. The protection of data that is being processed by a person using a support system is also mentioned. This comment is

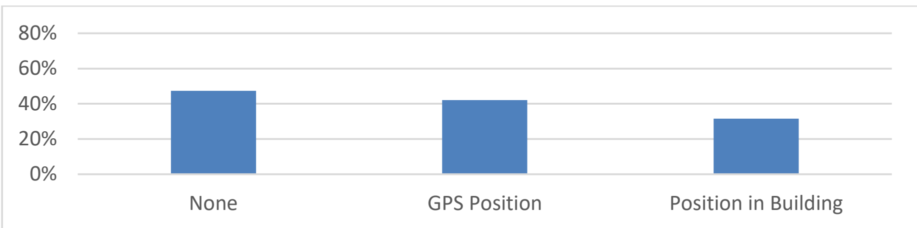


Figure 11.4.: Willingness to share data collected on the location

presumably based on the information that would be collected on the content of used applications. In one entry it is stated that an assistance would be used, if data were collected only locally and there could be no access by others.

11.4. Discussion

In this article, we investigate the data perspective of sensor-enabled personal work support systems. Therefore, we presented a technical architecture of data collection components as well as results from an empirical investigation concerning the willingness of users to share data covered by the architecture. The survey results show that the majority of the participants would be willing to provide data collected on the body or on software, while there are much more concerns sharing the location. Maybe there are particularly big security concerns if the collected data is not only personal, but one is even physically traceable by them. These concerns may be amplified for the indoor location that may specify the position in terms of a concrete room in a building. Besides the position in the building, the willingness to provide data about opened files and programs is the lowest. This may be due to the fact that processing external data in files is subject to additional regulations of data protection. Furthermore, information from files may be more detailed than appointment entries or listed tasks. Surprisingly, the willingness to share physiological data such as the heart rate is relatively high. Maybe assistance with respect to well-being, where such data are necessary, is particularly desirable. The highest willingness to share data is in appointments, which may indicate a desire for scheduling support, but it is also possible that this data is only perceived as less sensitive.
The study has certain limitations that offer potential for future research. One limitation is due to the number of participants. For future investigations we aim to conduct a survey over a longer period of time and to spread the participation request more widely. Furthermore, the participants may have had a research background as well as an IT-background. This could influence the willingness to collect and share data, so that further investigations with people of a broader spectrum of contexts are required. While the present work is more tailored towards knowledge-intense work, the approach could be extended to other work domains such as industrial production where different types of sensors (e.g. in smart clothes) are available and different questions have to be answered (e.g. number of specific body movements performed).
Responsible handling of confidential information is a crucial factor for establishing SPWSS. Protection against access from outside should be implemented through appropriate security mechanisms. When using a database, privacy could be considered e.g. by aggregating data directly on the device and sending only high-level information to the database that are less sensitive. A completely local solution would be another option that could become more feasible in the future with the rapid development of high-performance mobile devices and the integration of more and more technologies into one device. Currently, however, there are limitations in the features and performance of existing devices. By choosing a modular design for the implementation of SPWSS, the user could choose the desired assistance features according to the data collection components that would be accepted.

12 Architectural Concept for a Wearable Recommendation System[1]

Abstract. Modern information technology has a high potential to assist people in their daily life via assistance systems. However, such systems surprisingly still lack appropriate solutions tackling the challenges of modern work-life. By now, work aspects such as productivity have been considered mainly separately from other aspects such as one's health and fitness level. Regarding the latter, wearable technologies (like smartwatches or fitness trackers) are commonly used to gather sensor data (such as GPS, heart rate, etc.) and provide supportive recommendations. To support employees in promoting balance between different aspects of their work-life such as productivity and well-being, these features should be more integrated than this is the case in existing systems. To this end, we present an architectural concept for a wearable recommendation system designed to provide personal recommendations with the ultimate goal of supporting workplace productivity and well-being. In addition, our architectural concept also covers the aspect of user feedback to allow for improvements regarding the relevance of recommendations. We derived our conceptual architecture from related work, by considering the characteristics of the technology to be integrated and motivational scenarios describing the intended use of the system. With our architecture, we hope to inspire future efforts towards wearable recommender systems that integrate productivity and well-being.

12.1. Introduction and Motivation

In the past decades, working conditions and requirements have changed for many employees. Overall, more knowledge-intense and complex tasks emerged accompanied

[1] The content of this chapter has already been published as follows:
Richter, H.; Fellmann, M.; Lambusch, F.; Kranzusch, M. (2022): Towards an Architectural Concept for a Wearable Recommendation System to Support Workplace Productivity and Well-Being. In: Human-Computer Interaction. User Experience and Behavior. HCII 2022. Lecture Notes in Computer Science, vol 13304, pp. 416–429. Springer, Cham. https://doi.org/10.1007/978-3-031-05412-9_29

by higher workloads. Many employees have to deal with a higher degree of flexibility in their daily work (Eurofound, 2021; Green, 2001). In turn, those employees are required to provide advanced skills in self-management, i.e., in managing their resources such as time, attention, focus, motivation, health, and other aspects. This also challenges employees to balance their work and private life, as those boundaries increasingly tend to vanish (Green, 2001; Barber and Jenkins, 2014), especially when working from home. Hence, employees may even suffer from health issues caused by those circumstances, which, in turn, results in a possible loss of human capital for organizations (James et al., 2018).

Furthermore, the COVID-19 pandemic has intensified those existing issues and even caused new ones. For instance, Froböse and Wallmann-Sperlich (2021) reported that young Germans have become "world champions" in daily sitting with an average of 10.5 hours per day, mostly due to their work. The average for the overall German population was estimated at 8.5 hours of sitting per day, which is also significantly high and dangerous for maintaining a healthy lifestyle. Additionally, Nesher Shoshan and Wehrt (2021) believe that virtual meetings (whose number and relevance has drastically increased due to the COVID-19 pandemic) are significantly more exhausting to people than conventional meetings (which were usually common before).

These issues indicate an urgent demand for interventions, measures, and compensations to sustain long-term productivity, health, and well-being. However, providing interventions is challenging. *First*, due to the lack of awareness that interventions in the form of recommendations are necessary at all. In this regard, Froböse and Wallmann-Sperlich (2021) discovered a remarkable gap between the people who are actually living in a healthy way (which are just approximately 1 out of 9) and those who are just perceiving themselves this way (which are approximately 61 % out of all). This indicates that many people would require and benefit from a healthier and more balanced way of life while not even being aware of that. *Second*, many effects and interrelations must be considered to provide relevant recommendations. For example, according to Abdel Hadi et al. (2021), doing sport can mediate negative effects from work, such as exhaustion. Unfortunately, they also discovered that work-related rumination actually inhibits such recovery activities by decreasing the motivation to become physically active. This effect is even amplified for highly intrinsically motivated employees who experience less job-detachment than extrinsically or unmotivated employees. Thus, simply providing recommendations for increased motivation or productivity and at the same time providing suggestions for increased physical activity might not lead to the desired effect. *Third*, even if it is possible to generate relevant recommendations, there is still a gap between knowing and acting. Just being aware of problematic circumstances and relevant solutions regarding productivity and health does not necessarily lead to actual better behavior in response. This is even amplified by habits that could interfere with or inhibit behavior change.

In the light of these challenges, advanced systems are required that (i) can raise people's awareness for potential productivity and/or health and well-being issues, (ii) provide relevant recommendations, and (iii) nudge the user to follow the recommendations or to provide feedback to the system usable for tailoring the recommen-

dations to the user's needs. These requirements inevitably lead to complex systems that track the user's context via sensors, generate relevant recommendations, and adapt to user feedback. Since only a few systems up to now exist and building such systems is challenging due to the high complexity of the components and their relations, we have developed a generic architecture for such systems. It could serve as a blueprint for building such systems.
The remainder of the chapter is structured as follows. Section 12.2 provides a brief overview of background literature and related work. This is followed by motivational scenarios in Section 12.3 that demonstrate how a visionary wearable recommendation system optimizing workplace productivity and well-being could be applied. Afterwards, we derive our conceptual architecture in Section 12.4. Finally, we conclude our work and provide an outlook on our ongoing developments in Section 12.5.

12.2. Background and Related Work

In this section, we briefly introduce the fields of the quantified self, smart wearables, and smartwatches. We look at those fields as our anticipated system has to observe its users and their behavior through sensors. This is usually discussed in the field of the quantified self, where wearables are used to sense important physiological data of an individual, making them worthwhile to explore. Furthermore, this section introduces some related work containing architectures or frameworks with a scope similar to our vision of a wearable recommendation system.

12.2.1. Quantified Self

The term *quantified self* does not originate from the scientific community. According to a team of authors around Gary Wolf (Quantified Self, 2023), its core idea is all about "self-knowledge through numbers". That is, gaining more comprehension and understanding about oneself by measuring and interpreting some values in numbers (e.g., steps per day, heartbeats, etc.). Swan [9] provides a more precise and well-defined definition to extend this approach. It states that *quantified self* is an umbrella term for the practice of tracking any kind of biological, physical, behavioral, or environmental data about itself. Moreover, individuals may be highly intrinsically motivated in gathering such data and changing their behavior accordingly. In contrast to this definition, we believe that individuals do not have to track their data manually to satisfy the core idea by Gary Wolf et al. (Quantified Self, 2023). Instead, we assume that it is just enough that an individual's data is tracked (e.g., by a technical device) with that individual's consent. By the data and information gathered this way, individuals should be supported in achieving their personal objectives. To understand what such tracked data can be, Swan (2013) provides an overview based on a blog post by Konstantin Augemberg. The data is categorized and summarized with examples in Table 12.1.
However, from our perspective, this overview lacks considering physiological data, as it is not covered by any other category yet. Further, physiological data is already measured by many devices (Reeder and David, 2016) and is key to compute derivative factors like happiness, energy, or stress. Hence, we added it to Table 12.1.

Table 12.1.: Overview for categories of quantified self data and examples (Swan, 2013) with the extension of physiological data

Data type	**Examples**
Physical activities	Miles, steps, calories, repetitions, sets, metabolic equivalents
Diet	Calories consumed, carbs, fat, protein, specific ingredients, glycemic index, satiety, portions, supplement doses, tastiness, cost, location
Psychological states and traits	Mood, happiness, irritation, emotions, anxiety, self-esteem, depression, confidence
Mental and cognitive states and traits	IQ, alertness, focus, selective/sustained/divided attention, reaction, memory, verbal fluency, patience, creativity, reasoning, psychomotor vigilance
Environmental variables	Location, architecture, weather, noise, (environmental) pollution, clutter, light, season
Situational variables	Context, situation, gratification of the situation, time of day, day of the week
Social variables	Influence, trust, charisma, karma, current role/status in the group or the social network
Physiological data	*Heart rate (variability), blood pressure, skin temperature, skin conductance, respiratory rate*

For this work, we mainly focus on such quantified self data that can be captured with wearable devices.

12.2.2. Smart Wearables and Smartwatches as Building Blocks for Wearable Recommender Systems

Smart wearables are portable, computationally sufficient, and compact devices that are body-worn and useful for everyday tasks (Yoon et al., 2016). The most commonly used smart wearable is the smartwatch, as it combines many features that are desired by customers (e.g., paying via NFC, making calls). Further, it can be equipped with several sensors like accelerometers, gyroscopes, microphones, optical sensors, contact sensors, ambient light sensors, or GPS (Reeder and David, 2016). For instance, this enables them to track physiological data, physical activities, environmental and situational variables. Additionally, a smartwatch can receive further information by connecting to the internet via eSIM, WIFI, or a smartphone via Bluetooth. In the light of wearable recommendation systems, these capabilities enable smartwatches to be part of a larger system. Such a system may have the following characteristics:

1. It integrates with various data sources, such as smartwatch data and other sensors.
2. It has a modular and decentralized structure where all components can be developed and adapted independently.
3. It is based on the idea of sourcing out computational expensive tasks to components with larger computational capacities to save energy on devices with small batteries.

Regarding the first point (integration of various data), smartwatches are highly limited in terms of user dialog/input capabilities due to their relatively small screen sizes (Reeder and David, 2016; Lutze and Waldhör, 2016; Niknejad et al., 2020). So it seems inevitable to complement data from smartwatches with data from other devices or even self-assessments that are filled in on, e.g., personal computers. Furthermore, many findings indicate that smartwatches suffer from hard signal noises and data quality regarding their sensors, especially when active movement by the user is involved (Reeder and David, 2016; Niknejad et al., 2020). Thus, having the possibility to consider sensor data by a variety of additional (and more reliable) sources would be a considerable advantage of a wearable recommendation system.
Regarding the second point (decentralized, modular architecture), Lutze and Waldhör (2016) point out that decentralized software architectures are most appropriate for smartwatch apps. In this way, companion apps installed on a paired smartphone can be used for more complex user interactions like changing settings or exploring comprehensive data sets via data visualizations.
Regarding the third aspect (outsourcing of computationally expensive tasks), the smartphone can perform computational-intense tasks required for the smartwatch app, which, in turn, reduces power consumption on the smartwatch. This is highly relevant since battery capacity usually is scarce on smartwatches. According to El-Gayar et al. (2021), the device's battery capacity is key to the continued use of smartwatches alongside appeal (e.g., via styling) and dialog support.

12.2.3. Related Work: Architectures of Existing Research-oriented Systems

The architecture of wearable and mobile recommendation systems that support workplace productivity and foster well-being is still an underresearched topic. However, we could identify some contributions that lead in a similar direction.
Kamdar and Wu (2015) introduce *PRISM* (passive real-time information for sensing mental health) and its architecture. The system gathers data from different sources (e.g., a smartwatch and a PC). Moreover, data acquisition is separated from data storage and processing. In addition, access to the system is enabled via a web application front end where the results can be shown to users.
Roy et al. (2018) introduce a framework for health monitoring and recommendation services. They distinguish between five separate blocks: hardware, software, information unit, recommendation unit, and analytics unit. They also aim for a server/cloud (inside the information unit) that communicates (independently from the wearable devices) with the recommendation and analytics unit to create recommendations.
Next, D'Aloia et al. (2016) introduce *Cicero*, a middleware that can be used to develop persuasive mobile applications. Its key idea is detecting and considering different situations, contexts, and scenarios. Therefore, it considers different factors such as location, motion, environment, time, and social activities.
Soares Teles et al. (2017), propose a computational architecture for context-sensitive mobile applications that requests the users to give information/feedback on their mental states. In addition, web services are used to transfer data from the system to consultative professionals (e.g., medical doctors). Those professionals can also

provide remote interventions to their patients/users through this connection.
Further, Banos et al. (2015) introduce *Mining Minds*, a framework for personalized health and wellness support. They distinguish between four layers: the data curation layer (DCL), information curation layer (ICL), service curation layer (SCL), and a supporting layer (SL). The DCL aims at processing and persisting data from variously different sources. That data is furtherly used by the ICL, which detects contexts and information for the users. Next, that information is used by the SCL to generate intelligent recommendations. For all of those three layers, the SL provides the possibility to link third-party applications which, in turn, can access the data, information, and recommendation services.
Lastly, Li and Guo (2016) introduce *Wiki-Health*, a big data service platform for collecting, storing, tagging, retrieving, searching, and analyzing personal health sensor data from various sources and data types (e.g., structured, unstructured, etc.). Its architecture consists of three layers: the application layer, query & analysis layer, and a data storage layer. For the data storage layer, they consider using different types of storage and databases, depending on the actual data one is dealing with. Further, Wiki-Health has a mobile app that can track several activities, provide alerts or detections, consider the feedback given by the users, and present data visualizations.
To conclude, these contributions exhibit valuable features that can inform our architecture. However, they all are still lacking in presenting a compact and generic conceptual architecture that can be used to develop a wearable recommendation system. Out of all the inspirations we could gather from those sources, we mainly adopt the need for a decentralized system architecture (i.e., sourcing out some functionalities such as the generation of recommendations to a server). Furthermore, we also cover the aspect of considering various sensor data from various sources for computing relevant context and situation-sensitive recommendations.

12.3. Motivational Scenarios for Wearable Recommender Systems

As a first step towards developing a wearable recommendation system, some motivational scenarios are described below. Requirements for a system can be derived from the assumed usage behavior of the fictitious persons involved in the scenarios. This should provide orientation as to which requirements are relevant and in which contexts a recommendation system could be used.

12.3.1. Scenario 1: Self-Management Assistance System for Managers, Freelancers, and Knowledge Workers

Karl (48) is a self-employed management consultant and family man. Karl has built up a base of satisfied regular clients, some of whom he has been assisting for many years. Unfortunately, his workload is difficult to predict because clients can spontaneously come forward with smaller assignments. Of course, he does not want to turn down these clients – especially since he knows many of them well personally. In this respect, Karl needs to manage his limited time well. On this Friday, his

smartwatch wakes him up at 6:00 am, an hour earlier than normal. This is because the wearable recommender has recognized that there will be a lot of traffic on the roads on Friday evening. He now uses the system consistently after the first signs of burnout and a sick leave last year. So he had better start interviewing clients at 8 o'clock to return in time before the traffic jams start. At the same time, the system knows that Karl has enjoyed an excellent quality of sleep the nights before and has abstained from coffee late in the evening (which he did after receiving a brief, system-generated feedback), so getting up early is not a problem. The system seldom gives recommendations during the working day, as it is aware of the "customer contact" type diary entries and knows that disruptions are undesirable here. However, since Karl has scheduled four interview appointments seamlessly and, contrary to a warning from the system, one after the other, even over the lunch break, the system unobtrusively intervenes with vibration. It suggests that the next appointment be made while standing or during a walk. This is because the system wants to prevent Karl's back complaints, which he had ticked off in the list of common complaints when filling out the system's last weekly questionnaire on his state of health. Karl then suggests to his client that the conversation take place during a short walk through the nearby city park. The client happily agrees and immediately suggests inviting Karl to his favorite café near the lake in the park.
After a fulfilling working day, Karl drives home early without traffic jams. He arrived home at 3:30 pm and immediately started to evaluate the interviews and the documents he had been given from his clients. Unfortunately, it turns out that some important data was not mentioned in the interview, and he has to do some more research. Still completely absorbed in his work, the assistance system calls again at 5 pm. It informs him that Karl's planned time budget for this client has been exhausted. At the same time, it suggests that he should now play with the children or cook for his family. Alternatively, he could now get a birthday present for his mother, as her birthday is next Wednesday, but Monday and Tuesday are already planned with appointments all day. Karl decides to prepare dinner and set the table together with his children. He will write an email to the client and ask him to send the missing data instead of doing further research himself. He plans to get the gift on Saturday when he goes shopping.
Karl's wife returns from work at 6 pm. She is delighted to see that dinner has already been prepared and surprises Karl with a planned visit to the theater that evening - after all, the children are now old enough to look after each other. Since Karl has not burned enough calories and exercised enough today, the assistance system suggests taking the tram for one stop and then walking the rest of the way to the theater. They enjoy the warm summer evening, and Karl can now really switch off because he has achieved all his professional and private goals thanks to the coaching provided by his wearable recommender system.

Fundamental Requirements for the Wearable Recommender System:

Provision of information

- Display of messages

- Triggering of vibration
- Triggering of an alarm clock

Data collection

- Recording of sleep quality
- Activity level recording
- Recording of steps taken (pedometer)
- Recording of calories burned

12.3.2. Scenario 2: Assistance System to Support Person-Centered Services

Anna (26) completed her studies in social education two years ago and now works at a family counseling center. In addition, she has been doing a part-time doctorate as an external doctoral candidate at the University of Rostock in service management for social institutions since she graduated. As part of her professional work, she looks after several clients in the same town.

It is Tuesday morning, at 8 o'clock. Anna has an appointment in the city center at 9 am today. Still, her wearable recommender system notifies her of road closure and the associated traffic jam, so Anna chooses the indicated tram connection as an alternative just in time. Anna has a meeting with her most difficult client today, notorious for his choleric temper. After Anna has already had several heated discussions with the client, she is now, on the advice of her colleagues, using a new conversation technique that has a de-escalating effect. She has downloaded the instructions for this into her recommender system. Shortly before the appointment, she is shown the essential rules of conduct again, as she has noted in her calendar that she wants to use this conversation technique for the appointment. Surprisingly, the appointment was very pleasant and constructive, so Anna succeeded. Her wearable recommender system confirms the subjectively good feeling. Her pulse was only elevated at the beginning and then just above the resting pulse during the entire conversation.

Anna wants to go back right now, as there are no more appointments planned for today. However, one of her colleagues seems to have noticed that a client's signature is still missing. As Anna passes the client with the missing signature on her way to the tram, the wearable recommender suggests she visits the client for the signature. Anna succeeds and sends a scan of the document to her colleague. Her colleague is delighted and promises to take over the next on-call duty for her at the weekend.

When Anna arrives home, she immediately sets about completing the minutes of her appointment today. While she is briefly researching a spelling on the web - after all, she wants to edit everything correctly - she accidentally becomes aware of an old school friend's birthday via a social network site. She just wants to write him a few lines, but it turns out that he is also online now, so a conversation develops in which memories of the old school days are revoked. When Anna has already forgotten time and space, the wearable recommender system intervenes with the

message that Anna's time budget for social media has been exhausted this month. At the same time, the system offers to open the document of her dissertation, as the time target she had set herself for this month has not yet been reached. When her school friend wants to start a new topic of conversation, Anna suggests continuing the conversation another time.
After dinner, Anna sits down at her desk and begins to analyze the data material she has collected during work for her doctorate. That evening she wants to transcribe two longer interviews. After 11 pm, the wearable recommender system calls with praise late in the evening. Anna is very hard-working - she has done enough work for today. Would she like to take a short walk around the block and then go to sleep? The background of this message is that the system has noticed a deterioration in her sleep quality in recent weeks. Anna has always worked on her doctorate in a disciplined manner in the evenings. Also, the ambient light sensor has determined that there is too little light in the room, which leads to increased absorption of the bluish light from the computer monitor, which, according to recent scientific findings, also has an unfavorable effect on sleep. In addition, the pulse has already dropped to the level of absolute relaxation, which suggests a rather less concentrated and thus ineffective work. Anna likes the idea of her wearable recommender system suggesting a walk. Since there is a full moon today and the beautifully landscaped gardens of the neighbors with their rose beds also look nice at night, she decides to leave the flat once more and take a short walk around her housing estate. As the last message of the day, she sees praise from the wearable recommender system for climbing the stairs to her attic flat several times today.

Fundamental Requirements for the Wearable Recommender System:

Provision of information

- Display of messages
- Triggering of vibration

Data acquisition

- Recording of the pulse
- Reading GPS data
- Sleep quality recording
- Activity level recording
- Recording of calorie consumption
- Recording of stairs climbed

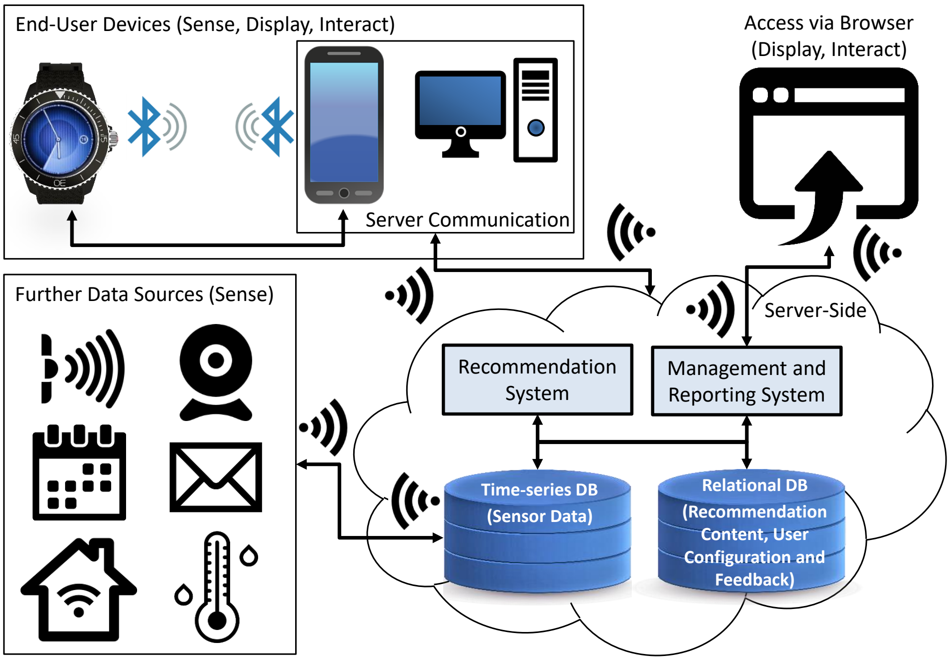


Figure 12.1.: The architectural concept

12.4. Architectural Concept

Based on (i) the background literature with different types of data to sense and the features and limitations of wearable devices (especially smartwatches), (ii) the related work with architectures or frameworks of systems aiming for a similar scope, and (iii) the exemplary motivational scenarios, we derived our conceptual architecture (cf. Figure 12.1).

It consists of three main areas with an additional fourth comprising a single component. **Area 1** (cf. upper left in Figure 12.1) comprises the devices belonging to the end-user. **Area 2** (cf. bottom left in Figure 12.1) comprises all potentially additional sources for sensor data. **Area 3** (cf. bottom right in Figure 12.1) comprises all components placed on a cloud-like server-side. **Area 4** (cf. upper right in Figure 12.1) comprises the general capability of accessing information and manipulating important settings via HTTP using a common browser. We assigned descriptive labels in the form of verbs ("sense", "display", and "interact") to those areas, except for the server-side. Whereas the server-side serves for storing data and processing it (e.g., creating recommendations and reports), the components of the remaining three areas fulfill the tasks of either sensing data, displaying it, or interacting with it. They are the interface to the recommendation system itself. In the following, we describe further details of our architecture.

12.4.1. Area 1: End-User Devices for Sensing, Displaying, and Interacting

In this area, our architecture contains multiple end-user devices. Regarding end-user devices, we distinguish between their capability of communicating with the server on their own or not. As a usual smartwatch does not have this capability, it requires a connection via Bluetooth to a smartphone which can contact the server via WIFI or LTE/5G (especially for Apple devices, as their smartwatch apps cannot run without a companion app installed on the paired iPhone). Moreover, smartwatches can be used to capture tracking data via their sensors. Once this data has been sent to the server, it can be analyzed and considered to create recommendations. Additionally, smartphones or PCs could also be used to sense relevant data (e.g., by logging the activities – such as running software, detecting keystroke or mouse clicks when in use). As the end-users are working with these devices, tools for displaying the recommendations created for them and manipulating their individual user preferences or settings could be deployed on those devices.

12.4.2. Area 2: Further Data Sources for Sensing

This area of our architecture contains several exemplary data sources communicating with the time-series database located on the server-side. Thereby, we intend to emphasize the flexible adaptability of our architecture. The key idea is that any reasonably further sensor besides the actual end-user devices can add data. Hence, the recommendation system does not have to rely only on the sensors of end-user devices (which may be limited in covering contextual situations). Instead, it can take those further sensors of any kind also into consideration. For instance, a sensor for the oxygen content in a room could provide insights on whether the worker should open a window. Further, a calendar integration could ensure that no recommendations are provided in unsuitable situations like important business meetings.

12.4.3. Area 3: The Server-Side

On the server-side, our architecture contains two different databases and systems. The time-series database is key for storing sensor data. It provides special features that are more beneficial for such data than those from a relational database, as it is built around timestamps, which are crucial to detect contextual and situational information. Any sensor data that the recommendation system should consider (i.e., the data sensed by the end-user devices and any further sensors) has to be added to that time-series database. In contrast, the relational database covers all the data that is required besides the sensor data (e.g., the pool or content of recommendations, user feedback to the recommendations given, user preferences, and other settings). The recommendation system generates recommendations based on both sensor data from the time-series database and relevant additional data from the relational database. Furthermore, the management and reporting system provides additional features. Firstly, it analyzes and processes the data stored in both databases. For instance, it could provide the end-users with visually appealing graphs or diagrams on their data over time. Secondly, it manages all the settings that the end-users want to tune. For instance, the user could select special recommendations that are either highly desired or completely undesired. In turn, such tuning could be considered by the separate recommendation system.

12.4.4. Area 4: Access via Web Browser for Displaying and Interacting

To provide an easy presentation and manipulation of information, the system should be accessible via web browser. In this way, dashboards that visualize important data generated by the reporting system can be displayed to the user. Due to advanced possibilities for data visualization on large screens of personal computers, users can leverage this component of the architecture, e.g., for reflecting on and "playing" with their data that could support self-reflection. In addition, web-based access could also be used for an easy system configuration of the recommendation system showing all parameters on a single screen.

12.4.5. Overall Characteristics of the Architecture

Overall, the loose coupling of all components is the key advantage of our presented architecture (cf. Figure 12.1). By that, each component can focus on its key competencies and be developed and maintained independently without risking losing any functionalities of the other components. For instance, developers could easily add further sensors to the system without being forced to update the software on the end-user devices.

In addition, the functionalities of tracking data and displaying/interacting with it could be divided into two separate applications on end-user devices. For example, a smartwatch could run two separate apps: one for capturing sensor data and another for displaying recommendations received from the server. If one of the apps stops working or crashes, the other could still be running. In this way, the principle of loose coupling and modularity could also be applied to end-user devices since their sensors are added to the system as if they were further, additional data sources.

Moreover, separating the recommendation system from the end-user devices, sensors, and databases allows tuning or replacing recommendation techniques or algorithms without the system losing its other functionalities (e.g., sensing data and displaying recommendations).

Finally, sourcing out the main computational activities like generating recommendations or storing and maintaining data to a server-side saves valuable energy consumption and battery life for all end-user devices, especially smartwatches.

12.5. Conclusion and Outlook

In this paper, we have introduced our conceptual architecture for wearable recommendation systems that may assist individuals in their workplace productivity and well-being. Firstly, we have motivated this topic by summarizing recent major challenges many employees face. Afterwards, we briefly introduced the relevant background knowledge for such systems in the field of the quantified self, wearables, and related works with a similar focus. Next, we have sharpened the demand for a wearable recommendation system by introducing illustrative motivational scenarios. In those scenarios, a visionary wearable recommendation system guides its users and

helps navigate the complexities and tackle ordinary working days' challenges. Finally, we have introduced our conceptual architecture, which addresses many issues we derived from the background literature, related work, and motivational scenarios. In our ongoing work, we are currently developing an instantiation of our architectural concept. In this way, we will be able to validate our presented architecture empirically as part of our future work. For our prototype, we currently use Android Studio to develop the smartwatch app running on WearOS and the companion app installed on the smartphone running on Android. Furthermore, we use an InfluxDB as our time-series database that runs on a server that also hosts the simple script implementing the rule-based recommender system written in PHP. This PHP system gathers the data from the InfluxDB, generates a corresponding recommendation and sends it to the user's smartphone, which, in turn, sends it to the smartwatch displaying the recommendation to the user. Further, the user can give simple feedback on the recommendation received. Additionally, the feedback could be enriched on the server-side with the stored data in the databases. Thereby, the feedback quality could be increased in future approaches involving, e.g., automated learning of decision trees. Also, the smartwatch can track physiological data and transmit it to the InfluxDB via the paired smartphone.
Moreover, we can already consider data from multiple sources. We recently explored the possibilities of using additional data, e.g., in the form of data provided by a webcam that extracts user characteristics such as pulse or pose, or data provided by a desktop activity tracking tool. Using these data sources is possible using InfluxDB and simple communication over HTTP. Setting up a separate relational database still remains an open task.
All in all, we are quite satisfied with our architectural concept. It gives us the flexibility and modularity needed to design and implement complex systems that generate context-sensitive recommendations for mobile and wearable devices.

Part III

Assisting in Energy Self-Management

13 A Pictorial Scale of Human Energy and Application Opportunities[1]

Abstract. Individual resource status plays a major role in the literature on employee strain and recovery. Many theoretical accounts draw on the analogy between humans and batteries to describe the ups and downs in individual resource status over time. Taking the battery-metaphor literally, we have developed a pictorial scale to capture momentary resource status in terms of levels of human energy (i.e., high level of subjective vitality and low levels of fatigue). A brief and face-valid single-item measure is particularly useful in ecological momentary assessment research, e.g. surveying employees multiple times over the course of a day. We present empirical results from a diary study across twelve days among 57 employees. The pictorial scale is highly correlated with momentary ratings of subjective vitality and fatigue at the intraindividual and the interindividual level (i.e., has convergent validity). Drawing on these results, we demonstrate how the pictorial scale can be applied in ecological momentary assessment research to track trajectories of energetic well-being over the course of the day. We discuss, how providing personalized feedback to end-users regarding their energetic peaks and troughs over the course of the day or over the course of the week, may be leveraged in technology-assisted management of human energy on the individual and organizational level.

13.1. Introduction

13.1.1. Relevance of Tracking Resource Statuses

These days, many employees are confronted with very high work demands (Parent-Thirion et al., 2017). High workloads, complex and knowledge-intense tasks and

[1] The content of this chapter has already been published as follows:
Lambusch, F.; Weigelt, O.; Fellmann, M.; Siestrup, K. (2020): Application of a Pictorial Scale of Human Energy in Ecological Momentary Assessment Research. In: Engineering Psychology and Cognitive Ergonomics. Mental Workload, Human Physiology, and Human Energy. HCII 2020. Lecture Notes in Computer Science, vol 12186, pp. 171–189. Springer, Cham. https://doi.org/10.1007/978-3-030-49044-7_16

increased expectations for flexibility intensify the work. Of concern in this context is that the boundaries between life domains are becoming increasingly blurred, while the intensification of work continues. Due to an extensive use of information and communication technology, multitasking and interruptions of the workflow have become daily business in many companies. All these circumstances can induce long-term stress, which can result in serious health problems. Worldwide, mental health problems are a major contributor to the overall burden of disease and are particularly concentrated in the working population, possibly leading to a loss of human capital (James et al., 2018).
In order to prevent such negative consequences and promote a sustainable management of personal resources, it is desirable that individuals reflect on their own behavior to discover strength as well as necessary changes. Observations of the own behavior constitute a basis for self-evaluation, which is in turn necessary for reinforcing desired behaviors (Manz and Sims, 1980). While keeping a diary might be a good practice for gathering data, it might be time-consuming and impractical in many cases. Valid measures in combination with information technology (IT) could act as facilitators to keep track of the own resource status and desirable behaviors. IT can be supportive by collecting personally relevant information e.g. through mobile apps (Rapp and Cena, 2014). Such apps can incorporate self-assessments as well as mechanisms to automatically capture some data e.g. on the physical activity of the user. On the basis of data collected, visualizations can be generated that might help people in self-reflection (Choe et al., 2017). Furthermore, tracking a person's state enables to create and trigger situational interventions. IT-based interventions were, for example, already used for promoting relaxation (Fallon et al., 2018). Thus, tracking of a person's state constitutes a fundament to provide support in reflection and development processes.

13.1.2. Dynamics in Individual Resource Status: Human Energy

The literature on occupational stress considers a broad range of aspects of individual well-being as reflected in states like fatigue (Frone and Tidwell, 2015), thriving (Kleine et al., 2019), work-related rumination (Weigelt et al., 2019a; Wendsche and Lohmann-Haislah, 2017) or engagement and burnout (Crawford et al., 2010). Studying these phenomena is important to promote and sustain health and quality of life (Reilly et al., 2012) of individual workers and whole organizations in the long run. Given the major impact of resource theories (Hobfoll, 1989) in industrial and organizational psychology (Halbesleben et al., 2014), well-being is often conceptualized in terms of individual resource status (Ragsdale and Beehr, 2016). In this sense, processes of strain and recovery from work are reflected in decreases and increases of individual resource status over time (Zijlstra et al., 2014) – expending specific resources during work and returning to pre-stressor levels of functioning during breaks (Meijman and Mulder, 1998; Zijlstra and Sonnentag, 2006). Individual resource status is usually operationalized in terms of fatigue, (emotional) exhaustion, need for recovery, self-control capacity or vitality (Sonnentag et al., 2017). A common theme inherent in the aforementioned states is that they refer to different aspects of human energy (Quinn et al., 2012). Building on research in social and personality psychology (Thayer et al., 1994), the literature on work breaks and energy management has focused on human energy in terms of high levels of subjective vitality and low levels of fatigue (Fritz et al., 2011; Zacher et al., 2014). According to Ryan and Frederick (1997) subjective vitality encompasses a feeling of aliveness and energy. By contrast, the terms fatigue and exhaustion refer to states of low energy. A common theme in definitions of fatigue is extreme tiredness and reduced functional capacity (Frone and Tidwell, 2015). Therefore, valid indicators of human energy should tap into the experience of subjective vitality and fatigue.

13.2. Development of a Pictorial Scale of Human Energy

13.2.1. The Value of Valid Measures in Experience Sampling Research

Experience sampling methodology has become a major approach to studying human affect, cognition, and behavior in various disciplines, such as psychology and management (Ilies et al., 2016). In a typical experience sampling study participants provide self-reports on focal variables multiple times over a period of several days. Recently, ecological momentary assessment has gained currency (Syrek et al., 2018). Ecological momentary assessment is a specific form of research within experience sampling methodology usually including hourly self-reports over the course of a day. Tracking individual experiences over time is highly relevant not only in psychology and behavioral sciences. Measuring the subjective experience is often required to facilitate the interpretation of objective indicators of individual health (e.g., blood pressure) or to put individual behavior (e.g., time spent on twitter during work) into context. Although, research in information technology has adopted experience sampling methodology alongside tracking objective user activity, the measures or scales applied are often taken for granted. It is quite common to shorten scales or adapt scales to the purposes of the study. Unfortunately, the adapted scales rarely undergo rigorous scrutiny regarding reliability and validity, although any changes to the original instruction and items might change the meaning of the construct. In other words, we cannot be certain that adapted scales meant to capture specific aspects of current affect (i.e., moods or emotions), such as exhaustion and vigor, actually reflect these subjective states as accurately as the original scales do. Accordingly, examination of validity and reliability should precede the application of adapted or new scales in experience sampling or ecological momentary assessment research. Of note, reliability and validity of measurement instruments in experience sampling research is crucial both from a theoretical and a practical perspective. For instance, if the scales applied lack reliability and validity, we may not only draw faulty conclusion regarding the antecedents of individual well-being, we may also risk giving wrong advice to end-users within recommender systems applying feedback from self-reports.

13.2.2. Developing a Brief and Valid Measure: A Pictorial Scale

Usually, experience sampling research precludes the application of comprehensive scales because of time constraints (Ohly et al., 2010). For one, comprehensive scales would put a high burden on participants increasing the risk of non-participation or dropout from the study. For the other, given that an experience sampling study

consists of five, ten or more self-reports per participant, the length of each daily or momentary self-report might accumulate over time to produce reactivity of the study. In other words, a study originally planned to capture life unobtrusively may become a major disturbance in its own right. Accordingly, experience sampling researchers have to rely on shortened scales or brief measures to capture the variables of interest. The need for brief measures applies even more for ecological momentary assessment research which aims to capture life in situ by sampling individual experiences multiple times a day. Given the need for brevity particularly in applied field research, there is a long tradition in psychology applying pictorial scales to measure variables of interest. Probably the first pictorial scale in (applied) psychology was developed by Kunin to capture overall job satisfaction (Kunin, 1955). In the Kunin or faces-scale individuals choose one of five faces ranging from (1) a frowning face to (5) a smiling face to describe their level of job satisfaction. There is meta-analytic evidence that the Kunin pictorial scale is a reliable and valid measure of job satisfaction as reflected in a correlation of $p = .67$ with verbal scales of overall job satisfaction (Wanous et al., 1997).
Pictorial scales have also been applied in research on affect. For instance, the self-assessment manikin scales are among the most popular pictorial scales. Originally developed to assess pleasure arousal, and dominance of presented stimuli in lab experiments (Bradley and Lang, 1994), the self-assessment manikin scale has been adapted to measure momentary affect. Recently, Weigelt et al. (2019b) have proposed a pictorial scale to capture human energy. These authors have drawn on the metaphor of batteries that is dominant in lay theories of well-being and the scientific discourse on aspects of human energy. For instance, the literature on recovery from job stress frequently refers to "charging the batteries" (Zijlstra and Sonnentag, 2006). Drawing on the analogy between individuals and batteries, in the pictorial scale of human energy, participants may choose one of five symbols of a battery to describe their levels of energy. The battery scale ranges from (1) an almost empty battery to (5) a fully charged battery. In a cross-sectional survey study among 189 workers Weigelt et al. (2019b) found that the battery scale is reliable and valid as reflected in high correlations with several indicators of human energy. More specifically, the battery scale correlates highly with verbal scales of vigor (r = .73), fatigue (r = -.72), subjective vitality (r = .69), self-control capacity (r = .68), and emotional exhaustion (r = -.66). Retest-reliability across six weeks was rather low (r = .40). While low retest-reliabilities of trait measures are problematic, the rather high volatility of the battery scale suggests that this pictorial scale may be sensitive to situational factors, and hence, be particularly suited in settings where researcher strive for tracking and understanding within-person changes in subjective states or behaviors (e.g., experience sampling research). Although, these initial findings from survey research are encouraging, so far, the battery scale has not been examined in the context of experience sampling research. Given that the battery scale holds promise to be particularly valuable in ecological momentary assessment settings, we set out to scrutinize the reliability and validity of the battery scale in an experience sampling study.

13.3. Examination of the Pictorial Scale in the Context of Experience Sampling Research

13.3.1. Aims and Scope

Prior research on the battery scale has referred to general or "chronic" levels of human energy in the context of a self-report survey study. Hence, in this study we aim to adapt the battery scale from a chronic (or trait) version to a state version. Of note, it is neither certain nor trivial that the battery scale will fare equally well in experience sampling research. Accordingly, we explicitly examine the psychometric properties of the battery scale referring to momentary levels of human energy. Importantly, experience sampling data allow for analyzing associations among focal variables at different levels. In experience sampling research, researchers usually distinguish the within-person level of analysis from the between-person level of analysis (Gabriel et al., 2019). The within-person level of analysis refers to fluctuation in human energy within an individual over time (high energy vs. low energy days). By contrast, the between-person level of analysis refers to differences between persons as reflected in different average levels of energy across all days (high energy persons vs. low energy persons).

In this study, we consider correlations of the battery scale with subjective vitality and fatigue as measured by established verbal scales. This is consistent with the description and operationalization of human energy in terms of high levels of vitality and low levels of fatigue (Fritz et al., 2011; Zacher et al., 2014). In line with the cross-sectional evidence reported above, we expect the battery scale to yield high positive correlations with subjective vitality and high negative correlations with fatigue at the within-person level and at the between-person level. We examine these associations at the two levels of analysis (within-person and between-person) applying multilevel structural equation modeling. Unlike classic structural equation modeling, multilevel (structural equation) modeling accounts for the nested data structure and allows separation of within-person variance from between-person variance (McCormick et al., 2020; West et al., 2011). Hence, multilevel (structural equation) modeling allows for modeling associations among variables separately at different levels of analysis (within-person vs. between-person).

Furthermore, we examine the battery scale regarding the level of variability (or stability) across days by analyzing intra-class correlations coefficients ICC(1). We compare intra-class correlations as a measure of stability across the battery scale, the vitality-scale, and the fatigue-scale. We expect the battery scale to yield an ICC similar to those of vitality and fatigue. In other words, the battery scale should be equally sensitive to capture changes in human energy within person over time as the verbal scales do.

13.3.2. Methods

Procedure. This study is part of a larger project on occupational stress and recovery in leisure time. The study was pre-registered. We provide details through the open science framework[2]. We made sure that the study materials comply with

[2]Study details at `https://doi.org/10.17605/OSF.IO/QBS8J`

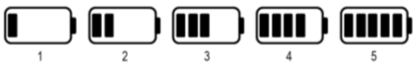


Figure 13.1.: Battery icons applied to capture momentary level of human energy

the declaration of Helsinki. Our study fully complied with the ethical guidelines of the Department of Psychology at the University of Hagen, the university where this study was hosted. We obtained informed-consent from each participant before the study started. Participation was voluntary and participants were free to quit whenever they wanted to. We conducted an experience sampling study across 12 consecutive days beginning on a Monday and ending on a Friday. The self-reports covered a broad range of topics such as daily job demands, recovery activities, and recovery experiences. Participants provided self-reports of momentary energy level three times a day: In the morning upon getting up, in the afternoon upon leaving the workplace, and in the evening before going to bed. For each of the 36 surveys we sent participants an invitation via email containing a personalized link. Participants responded online to our electronic surveys through their web browser on their (mobile) electronic devices (computers, tablets, mobile phones).

Measures. We measured different aspects of energetic well-being to examine the convergent validity of the battery scale. First, we measured subjective vitality with three items of the subjective vitality scale developed by Ryan and Frederick (1997). The scale has been adapted to German and applied in an experience sampling methodology setting, recently (Schmitt et al., 2017). A sample item is "Right now, I feel alive and vital." Second, we measured fatigue with three items of the profile of mood states (POMS) scales (McNair et al., 1992). The POMS has been adapted to German (Albani et al., 2005). We selected items from the fatigue-subscale and asked participants to describe how they felt right now. The selected items were "exhausted", "worn out", and "weary". The response format for subjective vitality and fatigue ranged from 1 (*strongly disagree*) to 5 (*strongly agree*). Third, we measured human energy applying the battery scale. We applied the following instruction: "People often describe how they feel right now referring to the metaphor of a battery ranging from exhausted to full of energy. Please indicate which of the following battery icons describes your current state best." The battery icons are displayed in Figure 13.1.

Sample. Our sample consisted of 57 workers from diverse organizations, occupations, and industries. The majority was female (79 %). Age ranged from 20 to 57 years (M = 35.19, SD = 10.21). Average tenure with the organization was 7 years (M = 6.99, SD = 8.55). On average, they worked 35 hours per week (M = 35.52, SD = 11.16). Participants came mainly from healthcare (21 %), industry (14 %), public administration, (12 %), commerce (11 %), and the service sector (11 %). Eighteen persons had a leadership position (31.6 %). In total 599 complete self-reports in the morning, 535 self-reports in the afternoon, and 565 self-reports in the evening from 57 individuals were available for the focal analyses (1699 of the theoretically possible 2052 of self-reports ~ 83 % response rate).

Analytic Strategy. We analyzed data applying multilevel structural equation modeling in the “lavaan” package for R. In a first step, we examined the measurement model of the verbal scales. Accordingly, we specified a set of confirmatory factor analyses to examine the reliabilities of the verbal scales of energetic well-being (subjective vitality and fatigue). In a second step, we added a structural model by including regression paths from the battery scale to the subjective vitality-factor and the fatigue-factor. In a third step, we ran multilevel regression models in the “nlme” package for R. More specifically, we specified a null model to infer intraclass correlation coefficients from the variance components. The ICC reflects the degree of agreement between ratings from the same person across time. A value of 1 would suggest that the variable is totally invariant (i.e., perfectly constant) across the repeated measurements within person. A value of 0 would indicate that the variable of interest varies complete randomly within person. We estimated alpha reliabilities separately at the within-person and at the between-person level of analysis for subjective vitality and fatigue as proposed by Geldhof et al. (2014). We applied procedures proposed by Huang to estimate Alpha in R (Huang, 2016). To avoid running three-level structural equation models (self-reports nested in days, days nested in persons), a feature currently supported by only few statistics packages, we ran analyses for the morning survey, the afternoon survey, and the evening survey separately. Besides pragmatic aspects, our approach provides the opportunity to examine whether the validity of the battery scale varies systematically over the course of the day.

13.3.3. Results

Preliminary analyses. The correlations among the focal variables are presented Table 13.1. Correlations below the diagonal refer to correlations at the within-person level (uncentered or raw correlations). Correlations above the diagonal refer to the between-person level (person-mean values across self-reports person).
Table 13.1 also contains the means, standard deviations, and ICCs of all scales across surveys (morning, afternoon, evening). We also included coefficient alphas as a measure of reliability for the multi-item verbal scales. Of note, standard deviations and ICCs of the battery scale are very similar to the respective values of vitality and fatigue. The means of the battery scale and the vitality verbal scale were very similar. Applying confirmatory factor analysis, we compared a single-factor model in which vitality items and fatigue items loaded on a common factor with a two-factor model in which vitality items loaded on one factor and fatigue items loaded on the other factor. We specified homologous models (Chen et al., 2005). That is, we assumed the same structure at the within-person level and at the between-person level. Although, the two-factor models fit better than the single-factor models, the absolute fit of these models was poor according to most fit indices (CFI $< .90$, TLI $< .80$, RMSEA $> .15$, SRMR $_{\text{Level 1}} > .08$, SRMR $_{\text{Level 2}} > .13$).

Modification of the measurement models. Inspection of the output and the modification indices suggested that the item “weary” yielded low loadings on the fatigue factor. Accordingly, we excluded this indicator from the fatigue-factor and retained it as a manifest indicator besides the latent factors (vitality and fatigue).

Table 13.1.: Correlations, means, standard deviations, reliabilities, and intra-class correlation coefficients among the focal variables

		Morning survey			Afternoon survey			Evening survey		
Variable	Sex	Battery	Vitality	Fatigue	Battery	Vitality	Fatigue	Battery	Vitality	Fatigue
Baseline survey (N = 57)										
Age	.02	.08	.16	-.26	.21	.18	**-.38**	.04	.01	-.24
Sex	--	-.17	-.18	.08	-.02	-.16	.10	-.21	**-.33**	.22
Morning survey (N = 599)										
Battery	--		**.83**	**-.81**	**.59**	**.36**	**-.44**	**.38**	**.29**	**-.29**
Vitality	--	**.77**		**-.82**	**.57**	**.54**	**-.52**	.26	**.35**	**-.31**
Fatigue	--	**-.72**	**-.74**		**-.53**	**-.41**	**.63**	-.25	-.22	**.41**
Afternoon survey (N = 535)										
Battery	--	**.46**	**.43**	**-.40**		**.75**	**-.63**	**.57**	**.54**	**-.54**
Vitality	--	**.37**	**.48**	**-.38**	**.78**		**-.77**	**.41**	**.61**	**-.56**
Fatigue	--	**-.37**	**-.45**	**.47**	**-.70**	**-.77**		**-.33**	**-.44**	**.66**
Evening survey (N = 565)										
Battery	--	**.26**	**.16**	**-.15**	**.37**	**.28**	**-.22**		**.86**	**-.78**
Vitality	--	**.18**	**.18**	**-.12**	**.31**	**.34**	**-.26**	**.79**		**-.81**
Fatigue	--	**-.23**	**-.22**	**.28**	**-.33**	**-.31**	**.39**	**-.73**	**-.76**	
M		3.30	3.18	2.23	3.20	3.34	2.24	2.76	2.93	2.61
SD Level 1		1.02	0.96	0.96	1.01	0.94	1.01	1.04	1.03	1.07
SD Level 2		0.76	0.69	0.62	0.63	0.63	0.64	0.72	0.72	0.74
Alpha Level 1		--	.86	.78	--	.89	.83	--	.88	.79
Alpha at Level 2		--	.96	.92	--	.98	.94	--	.97	.89
ICC(1)		.46	.45	.34	.31	.32	.31	.41	.40	.37

Note. Correlations below the diagonal refer to the within-person level (n = ranges from 535 to 599 occasions). Correlations above the diagonal refer to the between-person level (n = 57 individuals). Correlations in bold are significant at p = .05. ICC(1) = intra-class correlation coefficient.

Furthermore, we freely estimated the covariance of the third vitality item (alert and awake) and "weary" because the content of both items referred to the aspect of tiredness (the German item "muede" of the POMS actually corresponds better to the English word "tired"). This modified model fits considerably better and achieved excellent model fit. Accordingly, we treated vitality, fatigue and weariness as three distinct outcome variables.

Focal multilevel structural equation models. In the final models, vitality, fatigue and weariness were regressed on the battery scale. We ran separate models for the morning survey, afternoon survey, and evening survey. The three resulting models are depicted in Figure 13.2, 13.3, and 13.4 respectively. All fit indices for all models are reported in Table 13.2. Factor loadings and standardized covariances among factors are displayed in Figure 13.2 through Figure 13.4. The focal models yielded excellent model fit according to common criteria for assessing model fit (Schermelleh-Engel et al., 2003), such as:

- comparative fit index (CFI, values above .97 reflect good fit),
- Tucker Lewis index (TLI, values above .97 reflect good fit),
- root mean square error of approximation (RMSEA, values below .05 reflect good fit),
- standardized root mean square residual (SRMR, values below .05 reflect good fit).

Consistently across surveys (morning, afternoon, evening) all items yielded high loadings on their respective factors ($\lambda >.71$). The subjective vitality factor, the fatigue factor and the "weary"-item correlated moderately.

Associations of the battery scale with vitality and fatigue. Our focus in this study was examining the links between the battery scale and the prototypical indicators of human energy, namely subjective vitality and fatigue. Accordingly, the regression coefficients of the battery scale predicting vitality and fatigue were of major interest. In essence, the battery scale yielded high standardized regression coefficients predicting subjective vitality, fatigue, and tiredness as reflected in the weary-item at the within-person and the between-person level of analysis.

At the within-person level, regression coefficients ranged from .71 to .84 for subjective vitality and -.62 to -.72 for fatigue. The regression coefficients predicting tiredness as reflected in the weary-item ranged from -.59 to -.64. That is, momentary status as measured with the battery scale is strongly linked to momentary perceptions of vitality, fatigue, and tiredness as captured through established verbal scales of human energy. At the between-person level, the regression coefficients of the battery scale ranged from .84 to .89 predicting subjective vitality and ranged from -.62 to -.79 predicting fatigue. The battery scale was strongly associated with tiredness as reflected in the weary-item as evidenced in standardized regression coefficients ranging from -.54 to -.73. In other words, the average status within person across time or the person-mean of momentary status as captured with the battery

Table 13.2.: Overview of model fit statistics for the confirmatory factor analyses and the focal structural equation models

Model	Survey	Chi-square	Df	CFI	TLI	RMSEA	SRMR Level 1	SRMR Level 2	AIC	BIC
Single-Factor-Model										
	Morning	365.4	18	.808	.679	.180	.079	.097	8023.3	8155.2
	Afternoon	315.3	18	.852	.753	.176	.063	.010	7021.6	7150.1
	Evening	362.2	18	.824	.707	.184	.074	.094	7912.6	8042.7
2-Factor-Model										
	Morning	216.6	16	.897	.807	.145	.079	.132	7878.5	8019.2
	Afternoon	187.7	16	.920	.849	.142	.066	.060	6898,0	7035.1
	Evening	238.1	16	.893	.800	.157	.081	.119	7792.4	7931.2
Modified 2-Factor-Model										
	Morning	14.1	12	.999	.998	.017	.011	.019	7684.0	7842.2
	Afternoon	18.3	12	.997	.993	.031	.010	.026	6736.7	6890.8
	Evening	15.6	12	.998	.996	.023	.010	.024	7577.9	7734.1
Final Structural Equation Model (Figures 2 to 4)										
	Morning	31.4	18	.995	.988	.035	.015	.020	8643.3	8827.9
	Afternoon	35.9	18	.994	.985	.043	.014	.024	7598.9	7778.7
	Evening	34.7	18	.994	.986	.040	.014	.025	8516.2	8698.3

Note. CFI = comparative fit index, TLI = Tucker Lewis index, RMSEA = root mean square error of approximation, SRMR = standardized root mean square residual, AIC = Akaike information criterion, BIC = Bayesian information criterion. Level 1 refers the within-person level. Level 2 refers to the between-person level.

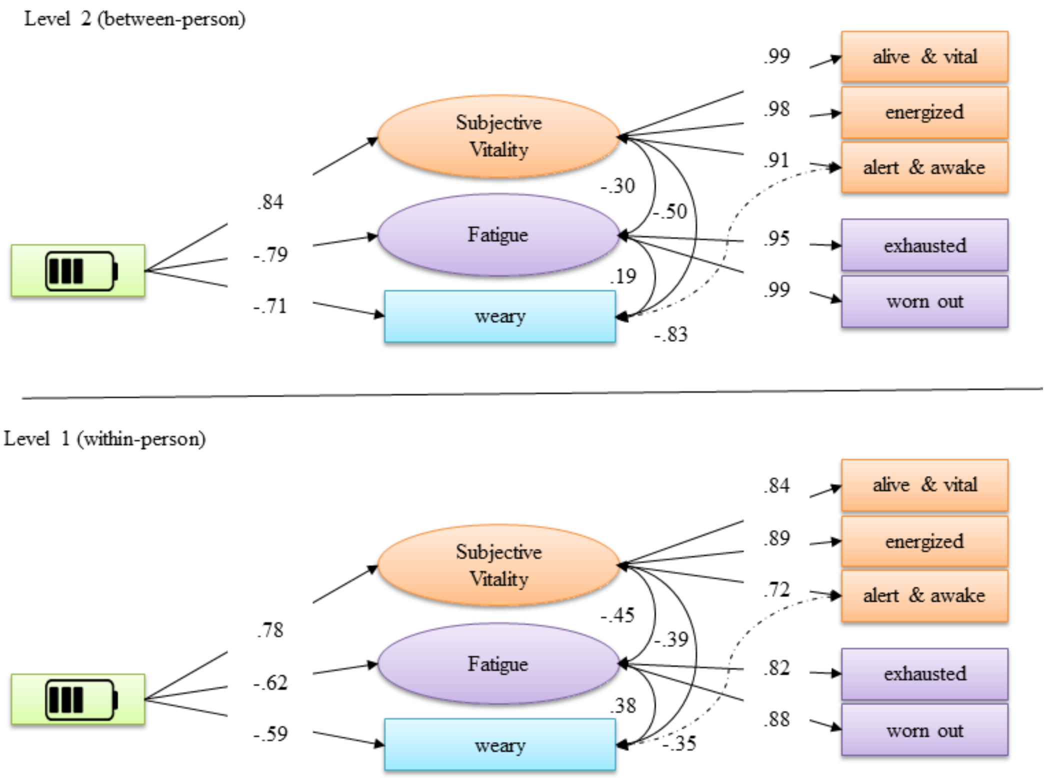


Figure 13.2.: Standardized loadings, covariances, and regression coefficients of the morning survey at the between-person level (top) and at the within-person level of analysis (bottom)

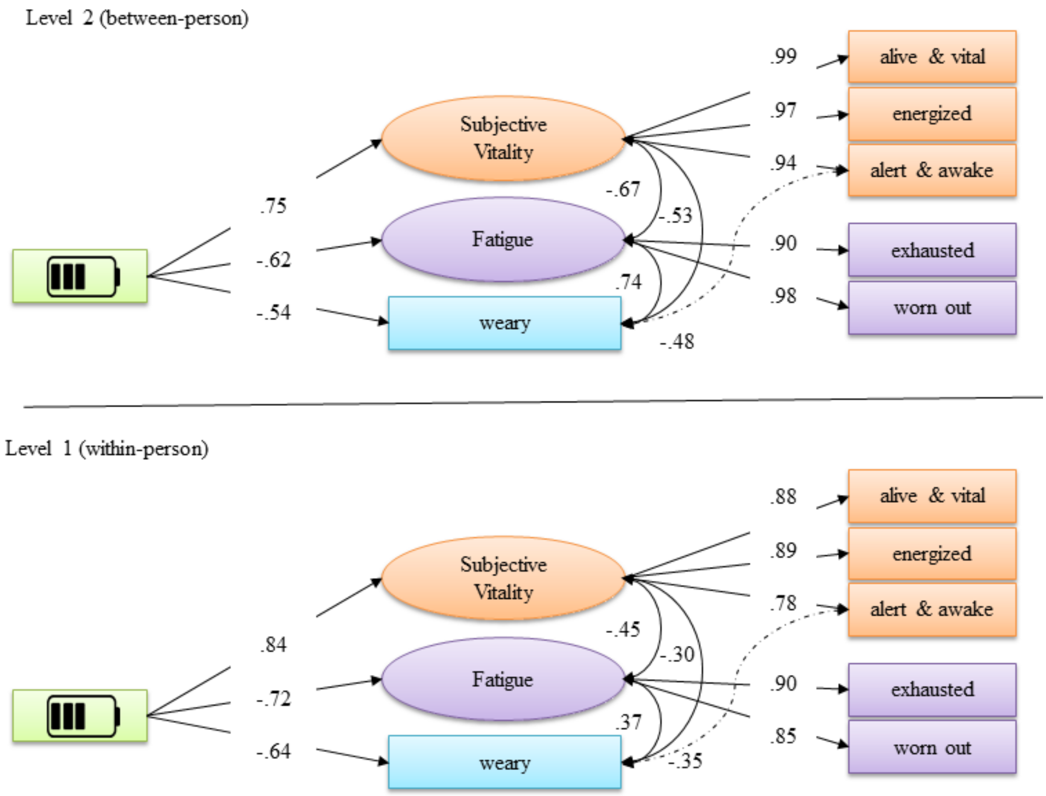


Figure 13.3.: Standardized loadings, covariances, and regression coefficients of the afternoon survey at the between-person level (top) and at the within-person level of analysis (bottom)

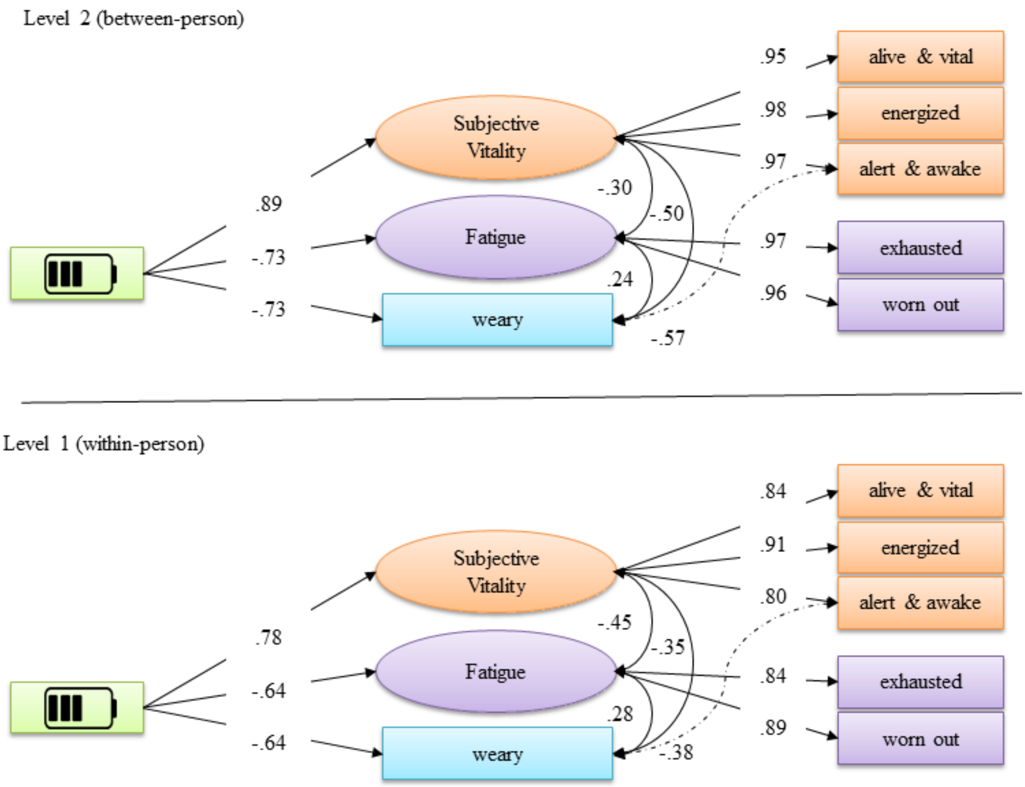


Figure 13.4.: Standardized loadings, covariances, and regression coefficients of the evening survey at the between-person level (top) and at the within-person level of analysis (bottom)

scale corresponds highly to the person-mean in vitality, fatigue, and tiredness. Of note, the associations at the within-person level were a bit weaker than the associations at the between-person level. The strongest links across levels of analyses emerged between the battery scale and subjective vitality. In sum, although the battery scale provides a rather broad (or unspecific) assessment of momentary human energy status reflecting aspects of vitality, fatigue, and tiredness, the battery scale corresponds most closely to subjective vitality that is feeling energetic, alive, and alert.

13.3.4. Implications

In sum, our results suggest that the battery-scale is a reliable and valid measure of human energy when applied to capture momentary energetic state in experience sampling methodology studies. The links between ratings through the battery scale on the one hand and ratings through verbal scales of vitality and fatigue on the other hand are in line with prior research at the between-person level of analysis (Weigelt et al., 2019b). The strong associations of the battery scale with the other indicators of human energy seem to be homologous across levels. Hence, the battery scale is a useful and valid tool to track differences in energetic well-being between persons at a given point in time. At the same time, the battery scale is almost equally valid and sensitive to measure changes in energetic well-being within an individual over time, as reflected in the high correlations with vitality and fatigue and the ICCs, very similar to those of the verbal scales. Drawing on these findings, we discuss next how our pictorial scale can be applied for managing energy on an individual and organizational level.

13.4. Application on an Individual Level

The developed single-item measure is particularly useful in ecological momentary assessment research in order to survey people multiple times over the course of a day without a need for the people to spend too much time to it. Tools such as formr[3] not only offer the possibility of surveying participants online, but even to automatically analyze and visualize the data according to different aspects (Arslan et al., 2019b). Thus, it is possible to generate and provide to the user individual feedback based on the collected data, such as individual energetic peaks and troughs. The pictorial scale offers the opportunity of collecting more data points by means of short, fast surveys. Due to the higher data density, trajectories relevant for the user can be examined not only in the long term, but even down to the course of a day. The pictorial scale thus provides the basis for observing the development of the individual energy level over time, gaining insights into individual patterns of human energy and supporting personal energy management through IT. In the following the motivation and approach for technology-assisted self-management in the area of human energy are presented.

[3] `https://formr.org/`

13.4.1. Importance of Personal Energy Management

As human energy is experienced as a high level of subjective vitality and low level of fatigue, it is a limited and depletable, but also renewable resource. An effective energy management could enable people to reach their goals in life while maintaining their energy (Schippers and Hogenes, 2011). There are several phenomena connected to higher human energy that might be desirable for the individual, and often at the same time for the organization a person works for. As humans want to feel competent and effective functioning (Ryan and Frederick, 1997), it is worth noting that higher levels of energy are connected to more productivity and creativity (Schippers and Hogenes, 2011). Furthermore, research suggests that high levels of subjective energy are related to well-being, both in its psychological and physical part (Ryan and Frederick, 1997). It is shown that there is a positive relationship between subjective vitality and mental health, as well as a negative relationship to ill-being (Ryan and Frederick, 1997). In contrast, a lack of energy might be a problem to health. For example, Schippers and Hogenes (2011) associate burnout with a lack of energy. Mental health problems contribute substantially to the overall disease burden worldwide and are especially concentrated in the working population, potentially leading also to a loss in human capital (James et al., 2018). Thus, promoting sustained personal human energy might be an important aspect in future countermeasures, which are not only relevant to the individual, but in the larger context also to e.g. health insurances and employers.
However, handling one's own energy effectively is not easy, because there are several things to consider. For example, even if a person is experiencing high levels of energy, it is important that this energy is held stable and furthermore has a targeted direction rather than being depleted randomly (Schippers and Hogenes, 2011). In order to avoid problems resulting from a suboptimal use of personal resources, there are approaches to self-management that can also be utilized with regard to human energy. Kleinmann and König define self-management as "all efforts of a person to influence the own behavior in a targeted way" (Kleinmann and König, 2018). Thus, self-management is necessary, whenever many alternatives of behavior are available. Given a set of behavioral alternatives with different consequences, self-management actions are usually maintained by desirable long-term consequences (Manz and Sims, 1980). In line with these characteristics, we define personal energy management as all efforts of a person to influence behaviors associated with energy depletion and recovery in a targeted way that take into account desirable long-term consequences of behavioral alternatives on the own energy status.

13.4.2. Key Competences Self-Reflection and Self-Development

Self-management does not mean to change oneself, but to find and improve the own individual way to perform - and thus, it is essential to analyze and become aware of one's own behaviors (Drucker, 2005). For many people it is challenging to determine the activities, which help them to energize, and even more to reinforce them in order to change a situation actively (Schippers and Hogenes, 2011). However, reflecting on one's own behavior and utilizing the gained insights to implement changes represent two fundamental levels of self-management competence in which it is also possible to evolve (Graf, 2012). Based on these both levels, we use the terms *self-reflection* and *self-development* for the corresponding competences, which can be developed by using different self-management procedures. Self-reflection can be promoted through the procedure of self-observation, which "involves systematic data gathering about one's own behavior" (Manz and Sims, 1980). On the basis of observations and goals set, self-evaluation can take place (Manz and Sims, 1980), which we also consider a part of self-reflection. While achievements and strengths can be discovered through self-reflection, also potentials for improvement and necessary steps for change can be determined. When managing human energy, a person could e.g. reflect on the personal energy curve over the day in order to discover energizing and exhausting activities as well as influencing factors such as the time of day. This knowledge could then, for example, be used to increase the proportion of energizing activities, to utilize energy peaks for important tasks, or to establish recovery phases for energy troughs. Several self-management procedures are proposed that support implementing envisaged improvements for self-development. An example is cueing, which means altering the exposure to certain stimuli in a way that desirable behaviors are promoted while undesirable are limited (Manz and Sims, 1980). One could e.g. place a picture or text in a prominent place as a reminder of regular recovery activities.

13.4.3. The Role of Technology

Since managing energy effectively can be challenging, information technology could act as a facilitator, both in self-reflection and self-development. The first step in self-reflection is to systematically gather data as a basis for later self-evaluation. Using validated instruments may help focusing the data collection on targeted aspects like the personal energy. As such, the developed battery scale provides the opportunity to regularly assess the levels of human energy without a need for the people to spend too much time to it. In order to minimize the effort and introduce a stimulus for self-assessment, a digital version of the scale e.g. as an application with a reminder could be used. As can be seen from the quantified self movement, IT can also be supportive by automatically collecting personally relevant information like physical activity, e.g. through mobile apps or smart devices (Rapp and Cena, 2014). This could constitute a good complement for personal energy management with context data or even reduce the need for self-assessments, where reliable measurements are possible.

As a next step, the data collected has to be prepared to be useful for self-evaluation. Choe et al. (2017) propose to provide rich visualizations to help people in self-reflection. For energy management, a very simple approach is to visualize the personal energy curve over time. Similar to using a tool like formr in momentary assessment research, where it is possible to survey participants and automatically create plots based on the data (Arslan et al., 2019b), an application for personal purposes could collect data and generate visualizations. In order to create rich visualizations for personal energy management, further research is necessary to determine other relevant data in conjunction with the "battery status", which can be collected and integrated appropriately in order to reveal the contingencies between individual behaviors and energetic well-being to end-users.

In addition to supporting self-reflection, IT can also promote self-development, e.g. by cueing through alerts or recommendations. Such interventions should be created on the basis of the individual data collected, so that they are personalized. Alerts were already used, for example, in the form of changing light colors depending on mental workload of a person performing a task (Maior et al., 2018). The use of recommendations is studied, among others, for promoting relaxation (Fallon et al., 2018) or physical activity (see (Ghanvatkar et al., 2019) for a review). Such IT-supported triggers might help people in implementing their targeted improvements. With regard to human energy further research is necessary to determine, which kind and combination of feedback procedures are appropriate to effectively support managing personal energy through IT.

13.5. Application on an Organizational Level

In the previous section, we emphasized the importance of managing human energy from the perspective of the individual. In a similar way, energy is also important for organizations as acknowledged by Bruch and Ghoshal (2003). The authors state that "without a high level of energy, a company cannot achieve radical productivity improvements, cannot grow fast and cannot create major innovations". Since organizations typically involve multiple persons, the construct of human energy has to be viewed on a collective level leading to a construct of organizational energy (Hannah et al., 2010). In the following approaches to the measurement, aggregation and mapping of organizational energy are discussed.

13.5.1. Measurements and Aggregation

Schiuma et al. (2007) state that "the energy of employees is recognized as an important factor in their performance and in maximizing their overall contribution to the organization. Organizational energy is dynamic in nature; it is more than just the sum of the energy of its employees. It also includes the interaction and dynamics of teams and the organization as a whole" (Schiuma et al., 2007). What all considerations of organizational energy have in common is that human energy forms an important component of organizational energy. Hence applying the concept of human energy on an organizational level implies to integrate it and melt it into organizational energy. Measuring energy within organizations has already been discussed previously e.g. in regard to energy assessments (Schiuma et al., 2007) or as part of research reviews on organizational energy (Schippers and Hogenes, 2011). Different kinds and models of energy may be relevant such as individual energy, relational energy, or productive energy, to name only a few (Baker, 2019). The developed battery scale can be used to capture the individual energy level of a person ranging from exhausted to full of energy. As a brief measure, it could be integrated in information systems of organizations allowing to diagnose the employees' energy level at several moments at work, while requiring much less time than comprehensive scales. As mentioned above, organizational energy also includes aspects like team dynamics, so that assessments via the battery scale could be complemented with other scales like the productive energy scale by Cole et al. (2012). While brief

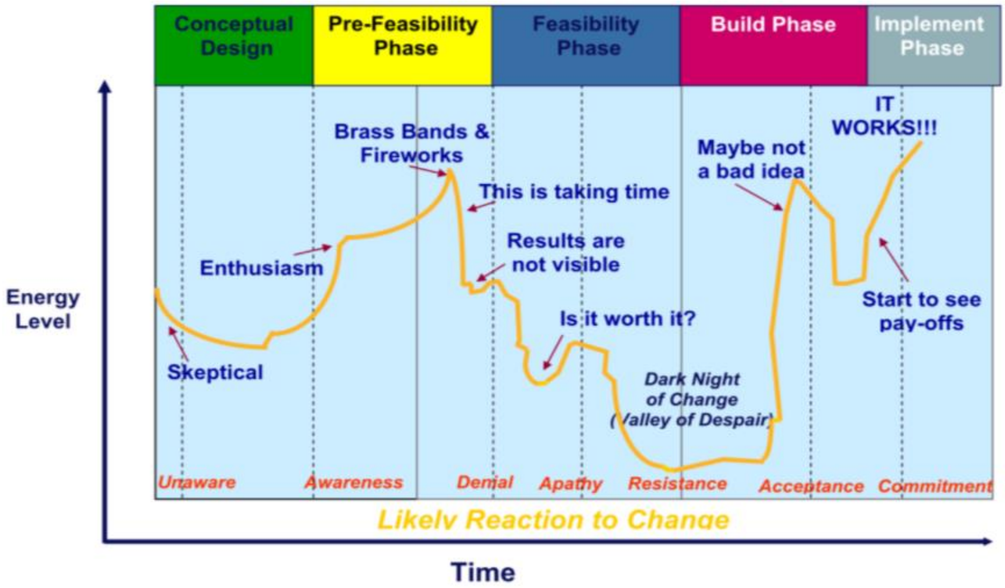


Figure 13.5.: Mapping of energy along typical phases of projects (source: Matthias (2009)[p. 154])

measures as the battery scale could then be used for regular assessments, more comprehensive scales could be used mainly at certain points in time, e.g. at times of organizational changes. Furthermore, self-assessments could be complemented by automated IT-based data analysis tools that try to infer the level of energy e.g. based on the duration of concentrated uninterrupted work on single content objects such as documents, presentations, or code. Next, according to Baker (2019), “individual-level measures can be aggregated to the group level as the sum, mean, or variability of individual members’ energy”. After measuring the organizational energy at various levels of aggregation, mapping it might be relevant in order to reflect on the current level of energy at various level of details (e.g. group level, department level, organization-wide) and to find ways of sustainably improving the energy level.

13.5.2. Energy Mapping and Analysis

An aggregated level of team energy could be mapped along the typical phases of a project showing the average level of energy of all involved team members (cf. Figure 13.5). This will give insights into the current state of the project and the energy increases or decreases. The latter might depend on the project or on factors outside the project which in either case must be analyzed when energy is lacking. In this direction, mappings and comparisons between different teams and departments might help team leaders and managers to identify needs for intervention and to help them reflect on their leadership style.

Furthermore, energy trajectories could be mapped to phases of organizational changes or interventions. Depending on the scope of changes such mappings could be created and analyzed on several aggregation levels of energy ranging from the team level to the departmental level up to the organizational level. In this way it would be possible to determine which managerial strategies are favorable or dysfunctional in the long term in order to unfold and promote human potential. On this basis, organizations can develop and achieve sustainable organizational energy.

13.6. Conclusions

Human energy is an important construct that is connected to a person's well-being, health, creativity, and productivity. Thus, the energy of employees is an important factor for organizations regarding their innovations, overall productivity, and growth. Taking the battery-metaphor literally, we have developed a pictorial scale to capture momentary levels of human energy. We present empirical results demonstrating high correlations of the pictorial scale with momentary ratings of subjective vitality and fatigue at the intraindividual and the interindividual level. Hence, the battery scale is a useful and valid tool to track differences in energetic well-being between persons at a given point in time and is almost equally valid and sensitive to measure changes in energetic well-being within an individual over time. A brief and face-valid single-item measure is particularly useful in ecological momentary assessment research, e.g. surveying employees multiple times over the course of a day. By enabling higher data density, the battery scale provides the basis to examine the development of the energy level even down to the course of a day and to gain insights into individual patterns of human energy in greater detail. Furthermore, it could be applied for technology-assisted management of energy at the individual and organizational level. As the battery scale is a very brief measure, it could conveniently be integrated into personal applications of an individual or information systems of organizations in order to capture momentary energetic states over time and thus, provide the basis for reflection and development processes.

14 Human Energy Diary Studies with Personalized Feedback[1]

Abstract. While the current pandemic amplifies the trend of highly self-responsible and flexible work, many employees still struggle addressing the resulting self-management challenges like balancing strain and recovery. Maintaining health of employees is a major concern of organizations to remain competitive, but in the context of highly individual work, this can hardly be supported with classical occupational health initiatives. Thus, it is crucial to develop tools that provide individuals with personal insights on their everyday work and help them determine applicable health behaviors. Towards this goal, we report on our design and implementation of diary studies with personalized feedback about persons' energetic well-being. Whereas such studies enable to research phenomena at the collective level, they can additionally act as intervention at the individual level. This is especially relevant to 1) provide a motivational incentive for continued participation and 2) raise awareness about recent topics in occupational health and promote healthy behaviors, while advancing research concerns. We provide insights from several studies regarding the generated feedback, the perception of the participants and IT-related improvement potentials. Hopefully, this will inspire further research that takes advantage of the win-win situation conducting studies, which simultaneously provide participants with individual insights.

14.1. Introduction

In the past decades, working conditions shifted more and more towards complex and knowledge-intense tasks, increased expectations for flexibility, and high speed (Green and McIntosh, 2001; Parent-Thirion et al., 2017; Eurofound, 2021). Thus, managing balance in life became more challenging for individuals (Green and McIntosh, 2001; Barber and Jenkins, 2014). In this context, the so-called *human energy* plays a major

[1]The content of this chapter has already been published as follows:
Lambusch, F.; Richter, H. D.; Fellmann, M.; Weigelt, O., Kiechle, A.-K. (2022). Human Energy Diary Studies with Personalized Feedback: A Proof of Concept with formr. In: Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies, vol 5 HEALTHINF: Scale-IT-up, pp. 789-800). https://doi.org/10.5220/0010974100003123

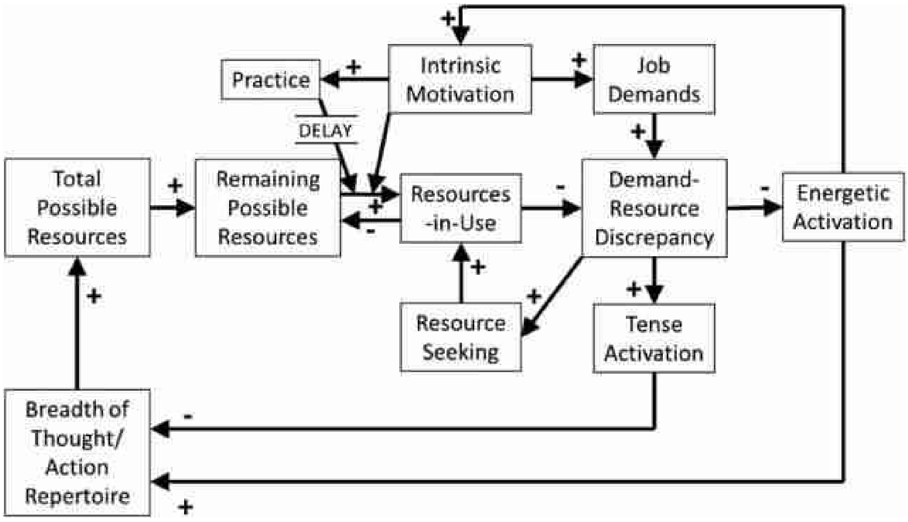


Figure 14.1.: The integrated model of human energy over time in a work context (Quinn et al., 2012), which is a theoretical basis of the presented studies with feedback on human energy

role. Quinn et al. (2012) describe human energy as an organizational resource that increases employees' ability to act by motivating them to do their work and achieve their goals. Human energy is an umbrella term that comprises physical aspects, like the available glucose in the blood enabling humans to act, and subjective aspects, like the degree of feeling alive. Quinn et al. call these two components physical energy and energetic activation and present an integrated model of human energy at work that can be seen in Figure 14.1. Yet, research provides only scattered indications of which factors influence especially the subjective component of energetic activation and how an employee can proactively improve energy management on an individual level (i.e. energy self-management). Although prior research investigated the fields of job design (Grant and Parker, 2009), leaderships (Inceoglu et al., 2018; Skakon et al., 2010) and interventions (Tetrick and Winslow, 2015) in order to foster employee well-being, addressing self-management challenges via digital solutions has not yet received much attention (Li and Vogel, 2021). Self-management is key to find and improve the own individual way to perform (Drucker, 2005). It means controlling the own actions in a way that prefers behaviors with consequences desirable in the longer-term over short-term outcomes (Manz and Sims, 1980). Self-management skills are essential for work characterized by high degrees of freedom (Kleinmann and König, 2018). In order to manage oneself, several strategies can be used. Self-observation, where a person systematically gathers data about the own behaviour (Manz and Sims, 1980), is an exemplary strategy that is especially relevant in our context. Indeed, designing and implementing IT-based tools that support employees in the collection and analysis of data relevant for self-reflection is a promising avenue of research (Choe et al., 2017; Rapp and Cena, 2014; Fallon et al., 2018). Specifically for human energy, there is yet no technical support assisting individuals in identifying how different factors like micro-breaks (Kim et al.,

2018) influence their energy level. Determining the influencing factors that are particularly relevant within the own working day would be highly valuable in order to proactively increase the own energy level or prevent a decrease.
Diary studies help to regularly gather data about peoples' situation, especially if there is no established automatic measurement instrument like sensors for the targeted phenomena yet. They provide gaining insights over a certain period of time by requiring the participants to submit protocols of their activities independently and frequently (Janssens et al., 2018). The character of a diary study enables combining research with the provision of early and individual feedback to the participants of the studies, even before the detailed scientific analyses take place that focus more on generalizable results. Overall, diary studies are very reasonable to keep track of dynamics in experiences of and between employees in organizations (Ohly et al., 2010). As diary studies can require much time from the participants depending on how frequently and deeply they are asked to assess their situation, providing individual feedback may raise the intrinsic motivation for regular participation (de Vries et al., 2021). With this, the participants expect and receive insights, they are likely interested in. Through generating personalized feedback on human energy during work days, we furthermore strive to empower employees to better understand their energy and improve their management in such a way that enables overload prevention and lasting work pleasure. This would create added value for the individual as well as the organization, which in addition might lead to a better feasibility of implementing diary studies for research purposes in organizational contexts.
However, the design and implementation of IT-supported diary studies with personalized feedback remain challenging in terms of the technical infrastructure required and the existing sample cases described in sufficient detail to learn from. In addition, there is also a lack of research how participants perceive personalized feedback in diary studies. Against this gap, we report on the design, implementation and execution of our IT-supported diary studies on human energy using the established tool *formr*. Our results thus can inform the design and implementation of future IT-supported diary studies that emphasize personalized feedback.

14.2. Related Work

In this section, we provide information on related studies and tools starting with ambulatory assessment studies more generally and proceeding with electronic diary studies with feedback and the digital tool we used for our diary studies.

14.2.1. Ecological Momentary Assessment and Intervention Studies

A term commonly used in diary research is ecological momentary assessment (EMA), which includes diverse ambulatory assessment methods (Janssens et al., 2018). EMA refers to methods involving repeated sampling of subjects' current behaviors and experiences in real time (= "momentary") in the natural environment (= "ecological"). Thus, EMA comprises not only methods using diaries, but also such using e.g. physiological sensors (Shiffman et al., 2008). Existing electronic EMA studies are often focused towards researching interesting phenomena such as (clinical) symptoms, behaviors or perceptions and their interplay. For example, there are numerous studies that focus on understanding basic psychological need fulfillment at the workplace, as summarized by Coxen et al. (2021) in their analysis on 20 diary studies. Giving participants feedback is not at the heart of such studies. Rather, data is collected for understanding and gaining scientific knowledge about the phenomenon under consideration. de Vries et al. (2021) focus in their review on smartphone-based EMA studies on well-being and explicitly recommend providing feedback to the subjects at the end of the study in order to motivate them for continued participation. Even though about half of the analyzed 53 smartphone-based EMA studies additionally integrate passive sensor data, nearly all studies also use the collected data for their research analyses only. The review mentions just one exemplary study, in which participants got feedback in form of personalized graphs about their happiness. We will look at this study in the next section, as its approach is quite similar to what we propose.

In addition to the more insight-oriented studies described so far, there are also intervention-oriented studies. In the mobile context, such studies aim at delivering just-in-time prompts as treatments, as indicated in a review on 27 ecological momentary intervention (EMI) studies with mobile technology support (Heron and Smyth, 2010). This sort of feedback often is directive in its nature and presented e.g. in the form of small textual messages. Alternatively, interventions are offered by questions, conversational interaction, or multimedia content as described in a review study on 64 EMI studies by Balaskas et al. (2021). Four of the analyzed studies actually provided participants feedback in form of graphical data visualizations of past entries. These studies are addressed in the next section together with others including visual feedback. However, the feedback provided seems to be a bye-product of the actual goal to deliver and research momentary interventions that are used as treatments and is often just roughly mentioned. In contrast to EMI designs, we propose to utilize the integration of rich visualizations of participant data for reflective purposes and higher participation motivation even for studies that have mainly an assessment character and do not necessarily aim at intervening in opportune moments.

To summarize, while previous work mostly focused on insight-oriented or intervention-oriented studies, we specifically focus on a study type between these that enables assessments for research purposes, but includes a reflective benefit for the participants providing rich and personalized feedback. Besides the benefit for participants, this approach also provides the perfect basis to evolve an insight-oriented study later into an intervention-oriented study using the feedback as an intervention for reflection or adding other interventions. This would also promote the connection of EMA and EMI techniques that remained largely separate, but would enable better tailoring and delivery of interventions (Heron and Smyth, 2010). In the next section, we analyze the few works that are closer to our approach by providing reflective visual feedback on the collected data.

14.2.2. Electronic Diary Studies with Feedback Generation

According to Narciss (2006), *feedback* is an information given to a person during or after a process in order to have a regulating effect on that process. Zannella et al. (2020) state a beneficial effect caused by feedback, if used cautiously. They argue that providing participants with personalized feedback may not be generally feasible, especially where results can be sensitive or easily misinterpreted as a wrong psychological diagnosis. Thus, they suggest carefully deciding which captured data is considered for feedback and how it is presented to decrease the risk of misconstruing.

Unfortunately, many research documentations about diary studies with feedback generation neither describe the design nor the impact of the generated feedback. The authors then just mention that feedback was provided for the participants, but do not explain more on that (Rentzsch et al., 2021; Richter and Hunecke, 2022; Arslan et al., 2019a, 2021; Holzleitner et al., 2019; Pusch et al., 2020; Depp et al., 2015; Kazemi et al., 2019).

Few works at least shortly describe the feedback they generated for their participants. For example, Burns et al. (2011) provided participants visual feedback related to depression, e.g. a graph showing the frequency of the locations they were at together with their average reported mood in each location. Kroska et al. (2020) developed an application for assessment and intervention in their study that can visualize data collected regarding mood and activity. Participants can access graphs e.g. on their depressive symptoms, perceived stress symptoms, or certain behavior over three days. Advanced visual feedback on health and well-being was provided to participants in the study by van der Krieke et al. (2017). Besides some rather basic graphs like frequency of certain activities ranked by perceived pleasantness, also personal networks showing concurrent and dynamic relationships between mood, health behaviors, and emotions over time were presented to participants. While the aforementioned studies can well inspire the design of feedback to be generated for the participants, they all lack describing their technical infrastructure and corresponding study design in sufficient detail for reuse. Researchers conducting EMA studies often use applications, which were specifically developed for their research and thus the development costs a lot of time and money (de Vries et al., 2021). For studies with feedback generation, it is even more important to build on an existing infrastructure to reduce complexity of implementation. Non-commercial tools that provide functionality for conducting a diary study as well as generating comprehensive personalized feedback while fulfilling research demands (e.g., reproducibility, traceability, privacy guaranteed or extensibility), are still rarely found. Furthermore, non-commercial software is often poorly maintained due to limited resources (Arslan et al., 2019b).

Arslan et al. (2019b) developed a study framework and an open-source software tool that tackles this gap, namely formr (see next section for more information). They describe in their paper three case studies with automatized feedback illustrating the capabilities of their tool. One exemplary diary study with personalized feedback aimed to investigate daily habits and sexuality of women over a period of 70 days. The participants received various personalized feedback at the end of this study. In addition to personality feedback, the study provided them with visualizations of the variation of their mood, desire and stress level during their menstrual cycle. The participants could even investigate several visualized correlations between the quality of their sleep and mood level and their alcohol consumption on the previous day. Additionally, an interactive display provided the participants the possibility to

retrace their mood level over time and investigate their answers from a specific day. Moreover, the participants were also provided with a spider diagram showing the distribution of activities in portions during the week and the weekend.
Conducting a study with formr that uses diverse of its features, is still challenging due to the complexity of possibilities and the still rather short information on exemplary cases. With this article, we contribute an exemplary case with descriptions of study designs, implementation choices, participant perceptions, technical challenges, and learnings from our study on human energy, specifically focusing on combining EMA and personalized feedback. We provide with this a proof of concept for future studies and hope to reduce barriers other researchers may face when conducting a similar study.

14.2.3. formr – A Tool for Diary Studies

Arslan et al. (2019b) developed formr, a study framework and an open-source software tool supporting researchers in conducting a wide range of studies (i.e., from simple surveys to even more intricate research). Thereby, it allows to automatically send email or SMS notifications to registered participants. Researchers can thus determine a specific time schedule formr follows. The notifications embody an external trigger to remind and motivate participants to do their self-assessments. Furthermore, formr supports the coding language R to execute more complex tasks like generating personalized feedback. Through coding in R, a wide range of different visualizations can be created for the feedback. For instance, a participant's data can be shown in a table, pie chart, bar chart, line graph or radar chart.
Overall, the formr framework consists of three main elements: 1) the survey framework, 2) the study framework (aka "run") and 3) the R package. In the survey, researchers can define questions and to correspondingly gather data from participants. The "run" provides researchers the possibility to actively manage and drive the survey (i.e., researchers can manage access to a study, define when which questions are answered by whom, send emails or text messages to remind or invite the participants and provide feedback to the users). Whereas those two main components of formr are coded in PHP, the third one is the utility R package and thus independent from the other PHP code. This should ensure common operations (like cleaning and aggregating data or setting timeouts for analyzing purposes) becoming easier to implement for the researchers. The R package is connected to the PHP software via a RESTful API allowing researchers to use many familiar packages directly in formr (e.g., for displaying graphical feedback to the users. Overall, those features seem to perfectly fit the requirements of performing longitudinal studies and thus also diary studies. That is, data can be gathered from participants by creating surveys, the execution of those surveys can be maintained in the runs (e.g., by reminding inactive users to continue participating) and the gathered data can be precisely analyzed afterwards using the R packages.

14.3. Study Designs

Based on positive response of participants in first studies, we conducted three diary studies on human energy over the last three years where we combined researching human energy in terms of energetic activation and its influencing factors with developing a flexible study procedure and valuable feedback for the participants of the studies. In this, we iteratively improved the personalized feedback provided to the participants and added more and more complexity to it in order to maximize knowledge gain. All studies had a similar procedure design, but with different frequencies of requested self-assessments per day and different influencing factors and corresponding scales. While our procedure design could function as a blueprint for future studies, the things we changed from study to study are the key elements to adjust for each new context, in which a diary study based on our design shall be conducted. The key concept and influencing factors depend on the objective of the research and on the demands of the studied domain or organization. Furthermore, an essential lesson learned from conducting our studies is that feedback on influencing factors is relevant mainly, if the assessed factors are actionable in terms of a possibility for the participants to change the manifestation of the factor. Thus, we shifted the items assessed in the last study more to behavioral strategies. From a research point of view, the frequencies of assessments should be as high as possible to collect a large data set for subsequent analyses. However, in practice the frequencies of self-assessments and number of items used for assessment strongly rely on the feasibility in terms of the time needed by the participants to answer the surveys. This is especially true in case of assessments during the work day as in our study designs. In the following, the commonalities of the study designs are described first and then illustrated by the exemplary procedure of our latest study. Each design consisted of:

- An initial questionnaire for contact and demographic data
- Individual survey days including only work days
- A number of surveys per day with a designated e-mail reminder
- A short energy-related measurement at each measurement point for the momentary state
- Scales for retrospective assessments of different influencing factors, e.g. sleep quality, work characteristics, recovery activities, and used work strategies
- Feedback generated from the individual data

Two of our three studies included ten survey days with up to four surveys per day at meaningful time points for work and leisure – in the morning, noon, afternoon, and evening. In one study considering an average working day with eight hours, there were even up to eight surveys a day to complete, but just for three days of participation then and with the same questionnaire for all diaries. In the last studies, a final questionnaire asked for the participants' perception of the study and generated feedback. The rest of this section describes the so-called formr run (cf.

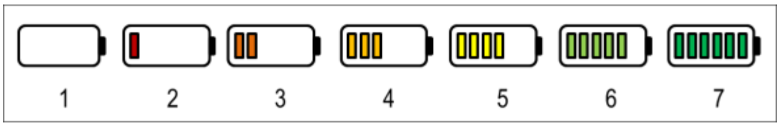


Figure 14.2.: Pictorial scale of human energy with seven response options ranging from a depleted to a fully-charged battery according to Weigelt et al. (2022)

Section 14.2.3) of our latest study in order to illustrate with a concrete example, how the procedure of further studies can look like. The procedure is as follows:
When entering the study link, the questionnaire shown first is for meta data like the email address for further invitations, the favored starting day, typical start time of the working day, and some demographic data. Furthermore, the participants are asked to estimate how their energy might develop throughout a typical day. For this, we used a pictorial scale of human energy (Lambusch et al., 2020; Weigelt et al., 2022) as shown in Figure 14.2, because it is more natural estimating a status with just one visual item.
The main study starts with an invitation link to the first diary entry after a waiting time that lasts until the chosen starting day one hour after the participant's individual work begin. Every diary contained a short energy-related measurement comprising the pictorial scale of human energy and a few items of verbal scales.
As energetic activation represents the subjective experience of human energy, it includes all facets of experiencing the presence or absence of energy, e.g. vitality or zest, fatigue or exhaustion. With the diversity of focal aspects of the phenomenon, there are many common instruments that can be used to measure sub-concepts of human energy in terms of energetic activation. In order to keep the diaries as short as possible, we had to decide for few focal aspects to measure. We chose to use three items of the vigor-subscale of POMS (Albani et al., 2005). In earlier studies we used Ryan and Frederick's subjective vitality scale as adapted by Schmitt et al. (2017). Furthermore, we used three items of the tension-subscale of POMS (Wyrwich and Yu, 2011) for every diary in this study. The morning diary, to which the mentioned invitation link leads, complements the energy measurement with questions about sleep, including e.g. the Insomnia Severity Index (Bastien, 2001) and the day so far, e.g. morning reattachment (Sonnentag and Kühnel, 2016), and items for planning and goal setting of the German version of the revised self-leadership questionnaire (Andreßen and Konradt, 2007). The run waits 90 minutes for the participant to click the invitation link and complete this diary entry and skips it in case the participant doesn't click the link. In any case the next module is to wait until the individually chosen lunch time, where the next invitation email with a link to the noon diary is sent. In the noon diary questions about e.g. job crafting (Lopper et al., 2020) complement the energy measurement. As this entry shall be completed after lunch and the invitation is sent at the given lunch time, we wait a bit longer here for the participant to complete the diary entry, namely 120 minutes, before this diary is skipped. The afternoon diary is always sent at 4 pm with a waiting time of 90 minutes and the evening diary at 7 pm with a waiting time until

11:59 pm before the entry is skipped. In the afternoon questions are posed about e.g. autonomy (Stegmann et al., 2010), elective selection (Schmitt et al., 2012) and micro-breaks (Kim et al., 2018). while in the evening we ask for concepts like work-life-balance (Syrek et al., 2011) and progress through supplemental work (Weigelt and Syrek, 2017).
The described daily procedure starting with a morning diary and ending with an evening diary is a loop repeated over the course of the study. However, invitations for diary entries are only sent on workdays, not on weekends. Thus, on weekends a waiting time takes effect. After five days of diary entries, the participants of the second group get their intermediate feedback after completing or skipping the evening entry. After ten days of diary entries, all participants get final feedback. After a pause, an invitation to a closing survey is sent to the participants to ask for perception of the study and generated feedback. After completing this survey, the participants have again access to their final feedback via the link. Explanations and exemplary excerpts of the generated feedback are given in the next section on feedback development.

14.4. Development of Personalized Human Energy Feedback

The feedback generated in our studies is intended to empower employees to better understand their energy levels and improve their energy self-management. In this way, we strive to enable overload prevention and promote lasting work pleasure. Instead of providing just general information and tips, the feedback is created personalized from the individual data, e.g. showing a selection of only those influencing factors most relevant for the specific person. The diary study feedback can be seen as a step towards a comprehensive tool helping people to identify those factors, which have a major influence on their individual energy level. To date, our study results already indicate how highly individual energy curves and factors are, supporting our endeavor and the necessity for individual feedback complementing rather general recommendations on energy self-management.
When designing the feedback, we decided that the it should at least include graphs visualizing the development of the participant's energy and representations of how the different scales correlate with it. In our latest feedback design, we additionally provide information on the development of the person's tension as well as on the manifestations of the assessed influencing factors in the everyday work life of the participant. Researchers should carefully elaborate how to visualize which data in advance to a run. For instance, visualizing a user's level of human energy over the time of a day in a line graph seems more suitable than showing its portions in a radar chart. Oppositely, visualizing the manifestations of a user's different working characteristics in comparison seems to be more reasonable with a radar chart than with a line graph (cf. e.g. Chapter 6.3 in Skiena (2017) on chart types). As it is very important to enable the participants to understand what the feedback means, descriptive texts should explain the feedback data and limitations in interpretation. The generated feedback actually addresses critical data in the sense of Zannella et al. (2020). Thus, its presentation was carefully elaborated in collaboration with

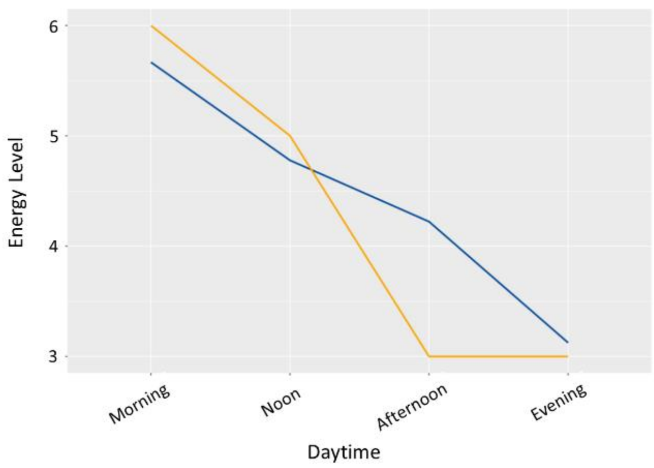


Figure 14.3.: Exemplary formr feedback diagram of a participant's estimated (orange) and actual (blue) mean energy (1 to 7) over the course of a day

psychologists and cautionary notes were included, e.g. for the influencing factors regarding the difference between correlations and causality. In order to visualize the development of the participant's energy level, two time contexts are important according to existing research: 1) the day level (Golder and Macy, 2011) and 2) the week level (Weigelt et al., 2021). Thus, we provide the participants with a diagram for both levels. For the day level the participants were requested to estimate their mean energy throughout a typical work day with the pictorial scale. In the feedback, we show them their estimation together with their actual mean energy curve over a day (cf. Figure 14.3). For the week level, we provide the participants a graph with their mean vigor (as one of the manifestations of human energy) of each day during the whole study period (cf. Figure 14.4). The figures shown in this section are the graphs generated by formr, only texts in the figures are changed in sizes and have been translated from German. A similar curve as in Figure 14.4 is shown for the participant's tension over the diary study period. Furthermore, we provide information on the daytime with the minimum and maximum mean values for energy and tension, e.g. maximum tension was in the morning with a mean value of 2,2. Next, a series of radar charts illustrates how strongly the possible influencing factors assessed are pronounced in the participant's everyday working life (see Figure 14.5). The last diagram of the provided feedback represents a core element for energy self-management, namely the four strongest correlations of the influencing factors with the participant's vigor (cf. Figure 14.6). In case the participants are interested in reviewing the course of the four strongest correlating factors over the study period in comparison to their energy, it would be possible to create for future studies a graph similar to Figure 14.4, complementing it with four other line graphs for the correlating factors.

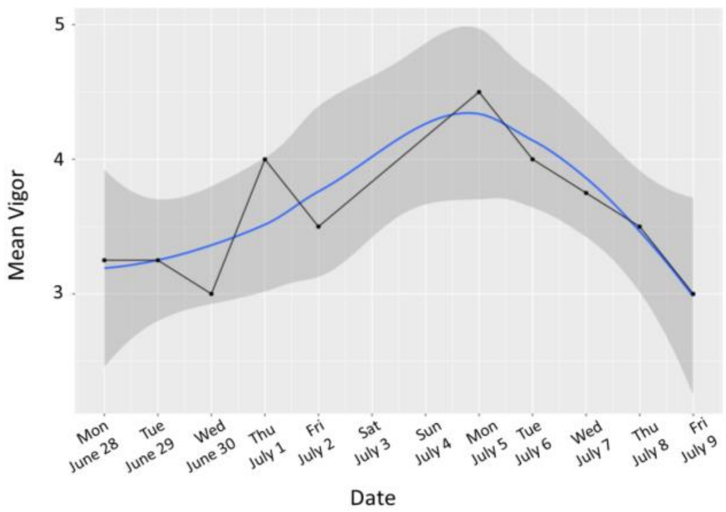


Figure 14.4.: Exemplary formr feedback diagram of individual vigor (1 to 5) over the course of the study. The black graph shows the connected measurement values, whereas the blue graph represents a smoothed curve with an enclosing grey area highlighting the general trend

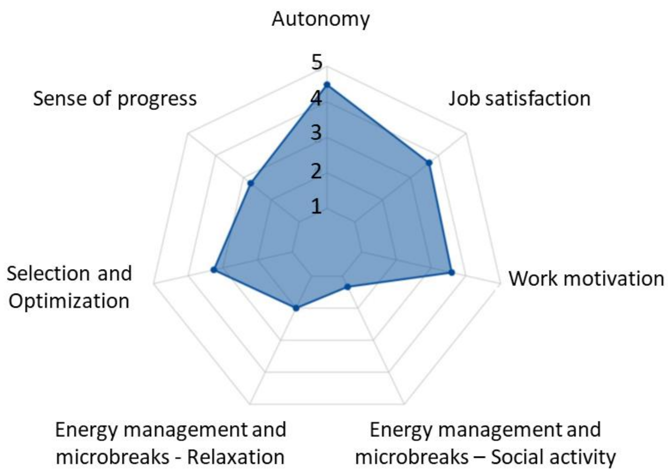


Figure 14.5.: Exemplary formr radar chart for characteristics of a participant's typical day assessed in the noon. It shows the mean assessment value for the factors across all days of participation

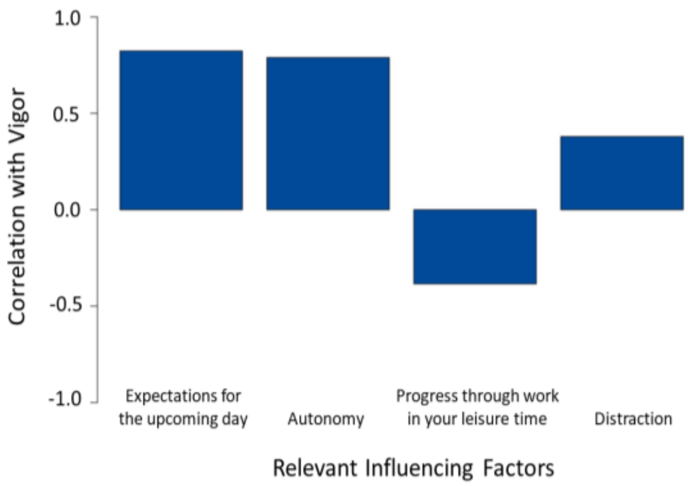


Figure 14.6.: Exemplary formr bar chart displaying the four strongest correlation coefficients of the personal vigor to possible influencing factors

14.5. Insights from Proof of Concept Studies

We conducted a series of diary studies that implemented the analyses and feedback we described on a conceptual level in the previous chapter. Participants were recruited using a convenience sampling strategy, i.e. the invitation was spread through word-of-mouth recommendation and social media (e.g. posted on the platform Xing in a forum about self-management and self-coaching). In sum, 74 persons participated in the studies. In the following, we report on our insights during the studies regarding feedback generation, participants' perceptions and IT-support.

14.5.1. Observations from Data Analysis

Our study results show how much energy curves and high correlating factors differ on an individual level, which supports the need for personalized feedback in addition to more general recommendations for energy self-management. We illustrate the differences of participants in daily energy in Figure 14.7. Also for the high correlating factors, we observed that these are largely different between subjects. An explanation for this could be that participants differ in terms of e.g. personality, cognition and also their working conditions. An example for the latter is that postpone or delegation behaviors are not possible if work-related autonomy is rather small.
Furthermore, we were able to derive interesting insights by analyzing the collected data. Since the studies varied slightly and due to space limitations, we are not able to report on all of our findings. A sample finding is e.g. that negative correlations were found for time spent in meetings and subjective vitality. In regard to the factors influencing human energy, it was e.g. discovered that strength use is positively correlated with vitality. From this it can be deduced that tasks should be favored where personal strengths can be applied and that time spent in meetings should be reduced.

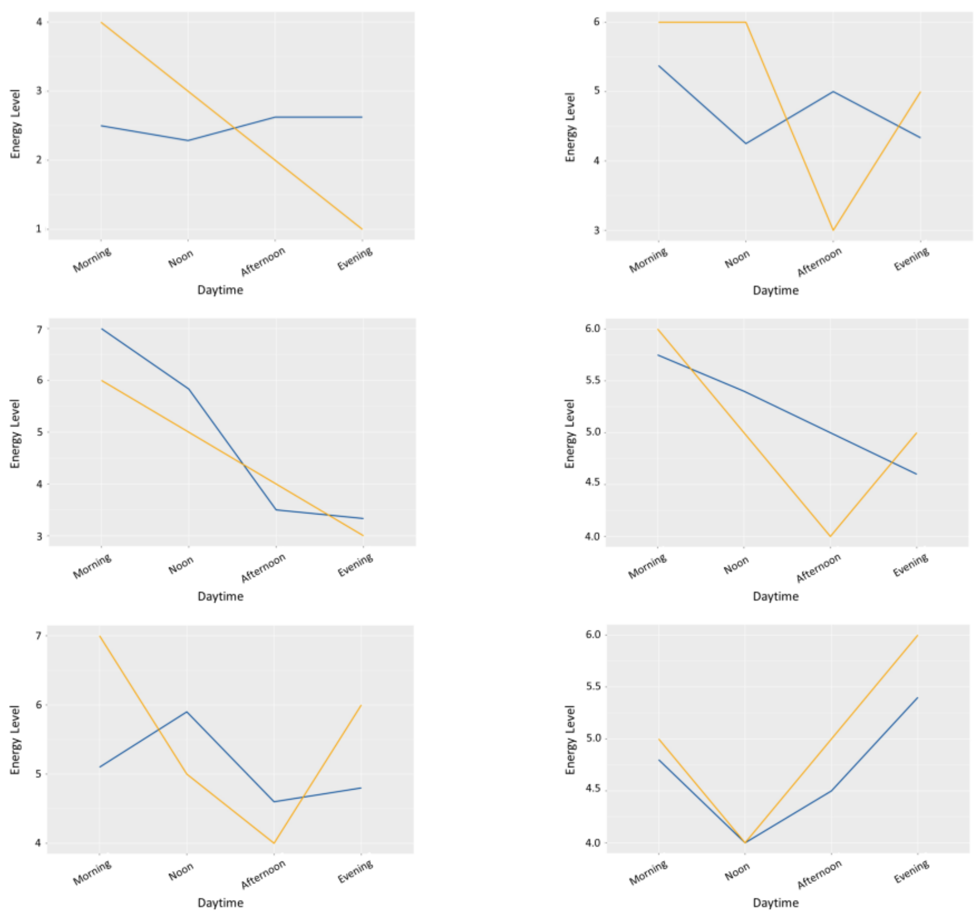


Figure 14.7.: Comparison of energy curves of different participants on the day level. Orange lines represent the participants' estimated energy curve and blue lines the actual energy

14.5.2. Preliminary Insights on how the Participants Perceived the Study

In the studies we conducted, we collected both qualitative and quantitative feedback from our participants which we summarize below.
Comments to the applied scales. In general, we did not receive negative feedback regarding the understandability (with rare exceptions). However, some new items were suggested by the participants such as work tasks that were assigned at short notice in the evening through mail, SMS or even phone calls and that cause sleep problems or doing sports. A point of criticism was that inapplicable questions could not be omitted.
Feedback to the study execution. Concerning the general study, there were only criticisms about the procedure of the study. According to this, the study should provide more flexibility, i.e. participants wished to determine the time of the questionnaires being sent and to limit questions to a subset they find applicable for their daily life. Also, integration with task calendar, e.g. in Outlook, was suggested in order to not to miss questionnaires. Another idea was to send funny and therefore encouraging messages to the participants during the study in order to avoid the "stiff" character of the questionnaires over time. Furthermore, the issue of time-lag effects was raised, e.g. to measure whether or not there is a drop in performance after overproductive days.
General comments on the impact on personal life. For many of the participants, these questionnaires seemed to have a positive impact on their thoughts. In some cases, it was reported that it stimulated reflection and helped to gain insights into everyday work and how different aspects affect work. In this sense, the studies were able to provide "food for thought". Of course, some more critical remarks occurred too. Predominantly, these were about questions that were felt to be repetitive or irrelevant. Also, the "one-off" nature of the feedback was criticized, i.e. a more incremental feedback was preferred.
Perceived relevance and usefulness of the feedback. We included a final questionnaire at the end of the last two studies to ask for participants' perceptions of the feedback. In one of the studies, participants (n=27) had to specify their agreement on a 5 point Likert scale ranging from disagreement (1) to complete agreement (5). In regard to the proposition that *the feedback is useful for everyday work*, most of the participants answered with 3-4 with approx. 42 % for each value. In regard the assertion that *the time invested in the study is useful*, approx. 68 % of the participants highly or even completely agreed to this (4-5). Moreover, more than 60 % of the participants answered with 3-5 regarding the question of being *able to integrate the content of the feedback into their everyday work.* Furthermore, being *able to derive personal benefit from the feedback of the study* was highly agreed (4) by approx. 37 %. In regard *whether the participant's knowledge could be expanded in the long term with the help of the feedback*, this question was mostly answered with 2 (21.1 %) and 3 (52.6 %). Finally, in regard to the statements that *new knowledge could be generated by the study and that something could be learned through the study*, most participants somewhat or highly agreed (3-4). This is also consistent with the overall average, as the most common response options for the entire final questionnaire were 3 with 33.1 % and 4 with 32.3 %. In sum, over 60 % of the

participants responded positively to the study evaluation form.

14.5.3. Challenges and Learnings regarding the IT-Support

Regarding the technical implementation of the study, the most important learning was that timing problems should be handled with caution. There is a so-called "expiry date", which can be set in the settings of each questionnaire. It determines how long a questionnaire can be filled in. However, only when this period is exceeded, the participant can receive the invitation for the next questionnaire. The period between the questionnaire in the morning and at noon, for example, was set to 300 minutes first. However, this did not take into account that often questionnaires do not arrive on time at 7 am, but also sometimes later. If this is the case, the "expiry date" overlaps with the invitation time of the following questionnaire and an error occurs where participants get stuck in the run and do not receive any further invitations. The problem could be solved by subtracting 10 minutes from the expiry date. Such timing problems may be caused due to the computational load of the server that is hosting the study. We currently explore this issue further. Another logical error found was that after entering the last questionnaire of a day, the participants jumped via the rewind module to the invitation on the next morning. However, this only works if the respondent completes the questionnaire on the same day. If this does not happen, the run skips a day. This problem was also solved by implementing an if-statement before the last questionnaire.

14.6. Conclusion and Outlook

Today's working world can be characterized by increased flexibility and ever growing complexity of products and services in highly dynamic markets. This induces high workloads, constant time-pressure as well as blurring borderlines between different life-domains. For individuals as well as organizations, it can be hard to keep pace. Hence, good self-management capabilities in terms of controlling the own behaviors in a long-term desirable way are of vital importance for promoting productivity as well as sustainable health management. In this direction, we suggest to combine researching phenomena with the generation of personalized feedback as an integral part of a study. In order to do so, we design and implement IT-supported diary studies that provide comprehensive and personalized feedback. In the paper at hand, our contribution is that we (i) identify and describe characteristics of such studies together with the corresponding infrastructure (Section 14.3), (ii) provide examples and suggestions for individual feedback generation (Section 14.4) and finally (iii) provide preliminary insights based on several studies we already implemented and executed (Section 14.5).

A limitation of our research is the still small amount of participants in our studies (n=74). In addition, all of our studies were centered on working behaviors and attitudes and their influence on psychological constructs measured by established scales, most notably "human energy". Hence, generalizations to other study topics have to be made with caution so far. However, our results are quite promising since in all studies, we were able to collect required data, analyze the data and provide

meaningful feedback, according to our participants.
For the future, we want to develop our assessment study with feedback further into a more intervention-oriented study. In the first step, we will do this by using the feedback as an intervention itself. Thus, while we collected initial perceptions of the participants on the generated feedback so far, we plan to culminate the optimized conceptual and technical realization focused in this article with a larger study examining specifically the psychological effects of our diary study with feedback on the participants. As a next step, it could be decided, if further interventions might be interesting to add and research. Such interventions might be intended to support behavior change. For example, if a person is regularly low in energy after a meeting, the system could suggest recovery strategies like taking a short walk after meetings, so that this might become a habit little by little.
Our approach may also be helpful in the domain of eCoaching. Since coaching activities often imply to explore and experiment with different interventions and study their effect over a period of time, the impact of different interventions could be tested. Furthermore, an essential part of coaching activities often is to identify contingencies between variables, e.g. to identify how the interplay of certain behaviors affects clinical symptoms or perceived outcomes on target variables. Due to the powerful statistical data analysis capabilities of R, such contingencies could be identified in an automated way and included in the personal feedback. Hence, an avenue of future research would be to develop our design more in the direction of coaching activities.
In summary, there is much opportunity for further exciting developments and we hope that our results will inform and inspire future IT-supported diary studies that include personalized feedback as an integral part of the study.

15 Evaluation of Energy Feedback: Randomized Controlled Trial[1]

Abstract. Higher levels of personal energy are related to higher well-being, productivity, creativity, and better mental health. Thus, systems supporting employees to self-manage their energy at work might be a straightforward instrument of sustainable health promotion and performance maintenance. However, assistance for energy self-management is still in its infancy and requires further research on energy trajectories, individual factors involved, and the implications for behavioral recommendations. In order to investigate day-to-day fluctuations, experience sampling is a common assessment instrument. In recent years, experience sampling researchers have begun to provide their participants personalized feedback reports. Mostly, however, feedback only serves to motivate participation and is therefore provided at the end of a study. Accordingly, the potential benefits inherent in the personalized feedback on phenomena still being investigated are understudied. Taking into account individual variability, we developed personalized feedback on energy trajectories and associated behaviors. This feedback is automatically created from the self-reported data of each participant during daily diaries. We conducted a comprehensive randomized controlled study across four weeks with a sample of 136 employees from diverse occupational contexts to evaluate the effectiveness of this personalized feedback. Our analyses show promising opportunities for utilizing feedback to benefit experienced energy and for deepening research in IT-supported energy self management.

15.1. Introduction

In the past decades, working conditions have shifted more and more towards complex and knowledge-intense tasks, increased expectations for flexibility, and higher speed (Eurofound, 2021; Green and McIntosh, 2001). Thus, managing balance in

[1] The content of this chapter has already been published as follows:
Lambusch, F.; Weigelt, O.; Fellmann, M.; Fischer, J.; Kiechle, A.-K. (2023). Towards Personalized Feedback as an Energizer: A Randomized Controlled Trial. In: 2023 IEEE 25th Conference on Business Informatics (CBI), pp. 1-9. https://doi.org/10.1109/CBI58679.2023.10187545

life has become more challenging for individuals (Green and McIntosh, 2001; Barber and Jenkins, 2014). To better understand this challenge and the factors involved, research has suggested to assess individual behaviors, well-being, and even health-status via pulse surveys and has identified self-reflection effects about the contingencies underlying well-being from day-to-day (Spreitzer and Grant, 2012). Self-reported data on behaviors and experiences are commonly assessed in scientific studies using experience sampling methodology (ESM) (Gabriel et al., 2019). Given that such studies usually consist of five, ten, or more repeated self-reports per person, the data gathered provide rich information on the fluctuation of variables across time and trajectories within persons compared to other self-report methods. Moreover, if more than one variable is measured over time, contingencies between the variables can be identified as reflected in a correlation. While there are numerous variables that are important for managing balance in life, a person's *energy* plays a major role, most notably in the interplay between personal and professional life. According to Quinn et al. (2012), human energy describes an organizational resource that increases employees' ability to act by raising their motivation to do their work and to achieve their goals. The outstanding importance in the organizational context is also underlined by research suggesting the critical role of energy in regard to dynamics of groups for a person's performance (Cross et al., 2003) and even the association of employees' energy with the long-term survival of companies (Welbourne, 2014). Furthermore, personal energy plays also a prominent role in regard to mental well-being (Ryan and Frederick, 1997). Nowadays, mental problems are on the rise and are even the number one reason for sick leave in many industries (Grobe and Frerk, 2020). Among the mental problems, a large portion in turn consists of burnout and depression (Grobe and Frerk, 2020), both of which share symptoms of lowered energy (Shirom et al., 2005). Especially burnout is associated with a lack of human energy (Schippers and Hogenes, 2011), whereby depletion of energetic resources is even regarded as the "unique core of burnout" (Shirom et al., 2005). Taken together, personal energy might be a highly relevant variable.

However, providing support for self-management, e.g., via digital solutions has not yet received much attention (Li and Vogel, 2021). Specifically, there is yet no technical support assisting individuals in identifying how different factors like micro-breaks (Kim et al., 2018) influence their energy level in everyday life. *Determining the influencing factors that are particularly relevant within the own working day* would be highly valuable in order to proactively increase the own energy level or prevent a decrease (Kosenkranius et al., 2023). Thus, researchers may study the link between individual behaviors and momentary levels of well-being. For instance, Müller and Niessen (2019) studied links between self-leadership and energetic well-being in a daily diary study and found that *on average* self-leadership may be associated with impaired rather than improved energetic well-being at the day-level. Although the data collected are analyzed to provide an estimate of the link between the variables (e.g., self-leadership and energetic well-being) that exists on average in the sample studied (fixed effects in a multilevel model), empirically there may be *considerable variation* of this link *across persons* (random effects, slope variance in a multilevel model). That is, the strength of association between daily self-leadership behaviors and daily energetic well-being may range from a negative link for some individuals (self-leadership incurs costs) to a negligible (self-leadership has no net effect on energy) or even a positive link for others (self-leadership energizes). Drawing on the idea that participants may find a personalized report on the trajectories and contingencies of variables tracked in ESM studies valuable, researchers have begun developing survey tools that facilitate providing personalized feedback to participants (Arslan et al., 2019b). However, up to now personalized feedback reports in most cases are only used to motivate for participation and thus, provided at the end of an ESM study. Furthermore, most feedback in such studies is rather descriptive (e.g., mean values of reported data). Accordingly, the potential benefits to participants inherent in personalized feedback on complex, innovative topics under research are (1) underutilized from a practical perspective and (2) not well understood from a theoretical and empirical perspective.

To address these gaps, we suggest and evaluate a specific form of personalized feedback. More precisely, in our study we provide individuals with a *personalized report on their energy derived from their daily self-reports.* The report especially depicts the person-specific energy curves, characteristics of the workdays, and correlations between different behaviors and personal energy that manifested themselves during the study. Given that the reports are *tailored to each individual*, we point to idiosyncratic rather than universal leverage points for individuals' energy self-management. Through a comparative presentation of the strongest correlating behaviors in the reports, we point to levers that may be particularly effective for individuals in enhancing (promote positive correlates) or sustaining (avoid negative correlates) their own energy from day to day. As a result, the recommended levers may differ considerably from person to person. In an earlier publication (Lambusch et al., 2022), we report on the design and implementation of ESM studies with personalized feedback regarding personal energy. The article also provides examples of several participants' daily energy curves in our initial studies, which have been demonstrating the large differences in individuals and pointing out the need for more research on individual energy specificities rather than just on one size-fits-all recommendations.

In the present article, we report on findings evaluating the effectiveness of the personalized feedback based on data from a randomized controlled study with 136 participants. More specifically, we describe analyses for an *evaluation in terms of perceived enjoyment, usefulness, and especially for improving individual energy as reflected in changes of energetic activation*, that is the experience of vitality, vigor, enthusiasm, or zest (Quinn et al., 2012; Weigelt et al., 2022). In this manuscript, we use the terms energy and energetic activation synonymously. The participants, who were assigned to one of two groups, provided up to four daily self reports on their energetic activation across ten workdays. One of the groups received a personalized feedback report as an intervention already in the middle of the study period. After the ten workdays, all participants received feedback. By aiming to evaluate the effectiveness of the feedback, we present comparative analyses of changes in energetic activation between the two groups. In contrast, perceived enjoyment and usefulness were examined through one questionnaire at the end of the study, after both groups received final feedback reports. Thus, the answers describe the participants' perception of the personalized feedback they received during the study.

The remainder of the paper is organized as follows. The next section presents related work in terms of feedback mechanisms, energy observations, and ESM studies with feedback generation. Section 15.3 details our sample and method for conducting and analyzing the study for improving proactive energetic self-management via personalized feedback. In Section 15.4, we illustrate sample energy feedback generated for the participants, before we present the preliminary results of our approach in terms of participants' perceptions and the observed effects of the generated feedback on their experienced energy in Section 15.5. Finally, we discuss our results and provide a conclusion and outlook in Section 15.6.

15.2. Related Work

Against earlier assumptions, people fail to make best choices in their own interest (Hsee and Hastie, 2006). In order to manage balance in life, the individual has to assess an actual and a target state. If there is a discrepancy between a current state of behavior and a desired target state, this discrepancy can lead to active action to approach the target state (Burkert and Sniehotta, 2009). It is information that enables the comparison of the current state with a target state in the first place. This comparison can be referred to as self-regulation or feedback control (Burkert and Sniehotta, 2009). The information can be gathered, for example, via self-observation (Manz and Sims, 1980) or via feedback. Feedback in the cognitivist approach serves as a source of information (Krause, 2007), which can be used to support the control of learning activities (Fischer and Mandl, 1988). In self-observation, however, it is difficult to construct trajectories retrospectively, as well as to find out individual patterns or correlations. Thus, technical support for close observations and following analyses (i.e. created feedback) can lead to surprising insights for the individual (Pammer and Bratic, 2013). Such analyses might be essential for developing oneself to reach desired targets, but also tedious and error-prone when done without assistance. Especially, the experience of energy and external events or specific behaviors that may have caused ups and downs in energy levels might not be obvious to individuals.

In this direction, Spreitzer and Grant (2012) propose an energy audit, i.e. a self-observation and intervention class to improve energy management. In their article, they describe how students manually recorded their energy trajectories and identified behaviors that benefit or impair personal energy. The authors report positive learning experiences by students, i.e. a clearer understanding of their energy trajectories, energy depleting or promoting factors, and even strategies to improve their energy. Actually, the class led to surprising insights for students like their low energy in the afternoon. They were also able to identify behaviors to be improved for better recovery, e.g., sleep practices and break activities, behaviors that are not sustainable, e.g., using energy drinks, and even behavioral strategies that could help them use their energy peaks, e.g., planning important work according to their typical energy curve. Spreitzer and Grant furthermore describe how already the increased awareness for the individual energy levels caused some students to change their behavior for improved energy management. They explicitly suggest using ESM in the future to automatically request energy assessments from the students at different

points in time in comparison to their manual method. With our study presented, we fill this gap and even more, add personalized feedback reports generated from the ESM data. These may present information about contingencies underlying well-being during the period studied. This provides an opportunity to reflect on external events or specific behaviors that may have caused ups and downs in energy.
While our *focus on energy for automatized feedback is innovative* and while we are among the first to *explicitly evaluate the effectiveness of energy feedback*, we build on research that has provided feedback reports to participants of ESM studies in other domains. Several researchers report on the use of electronic studies with automatized feedback generation. However, few works at least shortly describe the feedback they generated for their participants. For example, Burns et al. (2011) provided participants visual feedback related to depression, e.g., a graph showing the frequency of the locations they were at together with their average reported mood in each location. Kroska et al. (2020) developed an application for assessment and intervention in their study that can visualize data collected regarding mood and activity. Participants can access graphs, e.g., on their depressive symptoms, perceived stress symptoms, or certain behavior over three days. Advanced visual feedback on health and well being was provided to participants in the study by van der Krieke et al. (2017). Besides some rather basic graphs like frequency of certain activities ranked by perceived pleasantness, also personal networks showing concurrent and dynamic relationships between mood, health behaviors, and emotions over time were presented to participants. Arslan et al. (2019b) describe in their paper three case studies with automatized feedback illustrating the capabilities of their tool formr. One exemplary ESM study with personalized feedback aimed to investigate daily habits and sexuality of women over a period of 70 days. The participants received various personalized feedback at the end of this study. In addition to personality feedback, the study provided them with visualizations of the variation of their mood, desire and stress level during their menstrual cycle. The participants could even investigate several visualized correlations between the quality of their sleep and mood level and their alcohol consumption on the previous day. Additionally, an interactive display provided the participants the possibility to retrace their mood level over time and investigate their answers from a specific day. Moreover, the participants were also provided with a spider diagram showing the distribution of activities in portions during the week and the weekend.
In our study, we connect the two streams of using an energy audit to assist for better energy self-management and using electronic diary studies with feedback generated from the individual data. In combination, we not only provide a digital version of the energy audit approach, but also add the opportunity for participants to receive highly individualized, directed feedback, which even enables identifying contingencies between variables like behavioral strategies based on momentary data. Most importantly, we evaluate the effects of the generated feedback as a critical step towards assistance tools for energy self-management.

15.3. Methods

We conducted a comprehensive randomized controlled study across four weeks. The study was carried out in German. Our sample consists of 136 employees from diverse occupational contexts. The participants were mainly recruited via the virtual lab of the University of Hagen that provides a platform to reach participants for scientific online studies, but also through available social networks. The sample consists of about 21 % men, 78 % women, and 1 % non-binary. The average age of the sample is 32.6 years with a standard deviation of about 8.4 years. Age range is from 18 to 57 years. 48 % of the participants reported working from home all or part of the time during the study, whereas the remaining 52 % did not work from home during the study. We used the open-source software formr (Arslan et al., 2019b) to conduct the study and to provide feedback generated from each participant's individual data. This tool supports researchers in implementing studies with complex designs through chaining simple online surveys into long runs with an elaborated time schedule. It allows to automatically send email notifications to participants, e.g., to remind of assessments at several points in time. Furthermore, formr supports the coding language R that enables, among others, the creation of visualizations from participants' data in formats like HTML or PDF. With this, complex feedback with texts and graphs can be generated and displayed online, but also sent via email.

We combined surveys based on ESM with weekly surveys covering more general self-assessments. The dense ESM data constitute the fundament for the personalized feedback as they reflect the higher-resolution trajectories in daily life. More specifically, the ESM part consisted of four daily surveys across two workweeks (in the morning during the first hour of work, at noon during the lunch break, in the afternoon upon leaving work, at bedtime). In other words, the participants provided up to 40 self-reports on their energetic activation and up to 10 self-reports on a broad range of self-management behaviors across ten workdays. Besides energetic activation, we captured a broad set of variables encompassing various facets of self-leadership, like imagining successful performance and self-reward (Knotts et al., 2022), reattachment (Sonnentag and Kühnel, 2016), self-management like making a to-do list in the morning, effort (Rich et al., 2010), job crafting (Zhang and Parker, 2019), and micro-breaks (Fritz et al., 2011). We provide an overview of all constructs captured and scales applied in the supplemental materials[2]. Our emphasis was on behaviors in the discretion of employees. However, we also captured sleep quality in the morning, workload, job autonomy, and work goal progress (Koopman et al., 2016) during work, and work-related rumination after work (Weigelt et al., 2019a; Jimenez et al., 2022) to set the role of self-management in a broad sense into context of other variables likely to affect personal energy.

The weekly surveys encompassed a selection of the variables captured in the ESM-part of the study (e.g., energetic activation, self-leadership, micro-breaks), but referred to the past week in retrospect instead of the moment or day. Participants filled in a weekly survey during the weekends starting on the weekend preceding the ESM-part and spanning four consecutive weekends. Thus, the weekly surveys encompassed a total of up to four self-reports:

[2] https://osf.io/drqph/?view_only=01e9bb7a0c4345d0a20f4113aa60e84a

1. Week 0 – Pre-ESM
2. Week 1 – Interim (after 5 ESM days)
3. Week 2 – Post-ESM (after 10 ESM days)
4. Week 3 – Follow up (one week after the ESM-part)

We randomly assigned participants to one of two groups: (1) the focal intervention group receiving feedback after five workdays and then again after ten workdays and (2) a waitlist group receiving feedback after ten workdays. Hence, all participants received the feedback. However, the point in time was different. The waitlist group received the first feedback report at the end of week 2.

In this article, we focus on analyzing the weekly self-reports to examine trajectories of energetic activation across four weeks comparing the two groups. We captured energetic activation with three items from the vigor-subscale of the Profile of Mood States (McNair et al., 1992; Albani et al., 2005), a validated psychological questionnaire to measure six specific facets of affect (mood or emotions), namely anger, anxiety, confusion, depression, fatigue, and vigor. This set of items has been adapted to German and to ESM research and yielded excellent reliability and validity (Weigelt et al., 2022). We asked participants how they felt right now. Participants rated to what extent they felt "lively", "energetic", and "full of life" on a scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Factor loadings ranged from 0.81 to 0.89 at the within-person level. After checking the multilevel reliability of the scale as reflected in Cronbach's alpha ($\alpha_{within-person} = 0.87$, $\alpha_{between-person} = 0.92$), we formed a composite score from the items.

The final weekly questionnaire at the end of the study (Week 3 – follow-up) explored, among other aspects, the participants' perception of the personalized feedback they received during the study. We used two items from the subjective enjoyment subscale of Training Evaluation Inventory TEI (Ritzmann et al., 2014), a questionnaire to measure training outcome dimensions. An example is 'Overall, I liked the personalized feedback.' Cronbach's alpha was 0.86. Furthermore, we chose to use three items from the perceived usefulness subscale of TEI. An example is 'I can apply the content of this generated feedback in my daily life.' Cronbach's alpha was 0.87. All items of the TEI were adapted for this study and had to be answered on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

Based on the data from the weekly surveys at the end of week 0, week 1, week 2, and week 3, we evaluated the effectiveness of the feedback by focusing on trajectories of energetic activation within person over time and across groups. More specifically, we applied discontinuous growth modeling (Bliese and Lang, 2016; Bliese et al., 2020) and specified three time contrasts:

1. Transition 1 capturing a discontinuous change in energetic activation immediately after receiving the first feedback report.
2. Transition 2 capturing a discontinuous change in energetic activation one week after receiving the first feedback report.
3. Time linear capturing time passed since the Pre-ESM survey (week 0).

Table 15.1.: Time contrasts applied in the discontinuous growth models predicting trajectories of energetic activation across weeks

ID	Group	Wave No.	Provision of Feedback	Time linear	Transition1	Transition2
4	0	1		0	**0**	0
4	0	2	x	1	**1**	**0**
4	0	3	x	2	1	**1**
4	0	4		3	1	1
…						
23	1	1		0	0	0
23	1	2		1	**0**	0
23	1	3	x	2	**1**	**0**
23	1	4		3	1	**1**

Note. ID = Participant identification number. Group variable (0 = intervention group, 1 = waitlist group). Time linear is time in weeks since the first weekend.

Of note, we centered the transitions around the receipt of the feedback report. That is, the Transition 1-contrast counted up between the first (Pre-ESM) and the second (Interim) weekly survey in the intervention group. By contrast, the Transition 1-contrast counted up between the second (Interim) and the third (Post-ESM) weekly survey in the waitlist group. We applied the same strategy for Transition 2. Transition 2 counted between the second (Interim) and the third (Post-ESM) weekly survey in the intervention group and between the third (Post-ESM) and the fourth (Follow-up) weekly survey in the waitlist group. Centering the transitions this way utilizes the fact that all participants received the feedback at some point in time. Our approach maximizes test power, because all participants contribute to estimate the transition slopes. We centered the linear slope around the first weekly survey (Pre-ESM). Hence, the intercept of the discontinuous growth model is equivalent to the baseline level of energetic activation in the first weekly survey. We illustrate how time was coded in Table 15.1.

The transition slope reflects a discrete shift in energetic activation upon receiving the first feedback report. Given that the two groups differed in the number of ESM self-reports provided when receiving the first feedback report (intervention group: up to 20 self-reports; waitlist group: up to 40 self-reports), we included treatment (0 = intervention, 1 = waitlist) as a covariate and moderator of the first transition effect to model the changes in energetic activation unique to participants of the intervention group receiving the feedback after day 5 vs. day 10 of the ESM part. Including group as a covariate is also conducive to identifying (and accounting for) eventual differences in baseline levels of energetic activation across groups. In other words, we expected that energetic activation might increase upon receiving the first feedback report. Given that, we had assigned participants randomly to one of the two groups and hence, the time of the presentation of feedback was manipulated experimentally, a significant transition effect can be interpreted in terms of a causal effect.

We captured 444 weekly self-reports of energetic activation from 136 persons. On average, participants provided 3.2 out of 4 theoretically possible weekly self-reports (81.6 % response rate). Given that self-reports were nested in persons, applying multilevel modeling is straightforward. The intra-class correlation (ICC1) for weekly self-reports of energetic activation was ICC(1) = 0.393. In other words, more than one third of the variance in this variable can be attributed to the between-person level. Given the non-trivial degree of nesting (ICC1) within persons, running discontinuous growth models utilizing multilevel models is warranted.

15.4. Exemplary Feedback

The feedback generated individually for each participant is described in more detail in Lambusch et al. (2022). Brief explanations and exemplary excerpts of the feedback are given below. The feedback generated in our study is intended to empower employees to better understand their energy levels and improve their energy self-management. In order to visualize the development of the participant's energy level, two time contexts are important according to existing research: 1) the day level (Golder and Macy, 2011) and 2) the week level (Weigelt et al., 2021). Thus, we provided the participants with a diagram for both levels. For the day level the participants were requested to estimate their mean energy throughout a typical workday with the battery scale – a single item pictorial scale of energetic activation (Weigelt et al., 2022). In the feedback, we showed them their estimation (captured prior to the ESM part) together with their actual mean energy curve over the course of a day as reported in the ESM part of the study. For the week level, we provided the participants a graph with their mean level of energy of each day like the one shown in Figure 15.1. The black graph shows the measurement values, whereas the blue graph represents a smoothed curve with an enclosing grey area highlighting the general trend. Furthermore, we provided information on the daytime with the minimum and maximum mean values for energy and tension. Next, a series of radar charts illustrated how strongly the possible influencing factors that were assessed are pronounced in the participant's everyday working life. The last diagram of the provided feedback represented a core element for energy self-management, namely the four strongest correlations of the influencing factors with the participant's energy as shown by the example in Figure 15.2.
We used descriptive texts to explain the feedback data and limitations in interpretation. The generated feedback actually addressed critical data in the sense of Zannella et al. (2020). Thus, its presentation was carefully elaborated in collaboration with psychologists and cautionary notes were included, e.g., for the influencing factors regarding the difference between correlations and causality.

15.5. Results

We aim to evaluate the effectiveness of the personalized feedback in terms of participants' perceptions and especially for improving individual energy. First, we present our findings on the perceptions in terms of perceived enjoyment and usefulness of

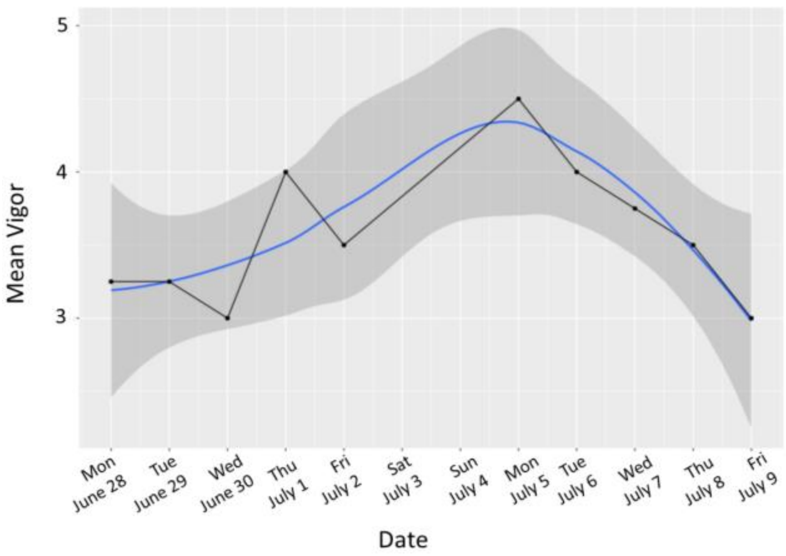


Figure 15.1.: Sample feedback diagram of individual vigor over the course of the study

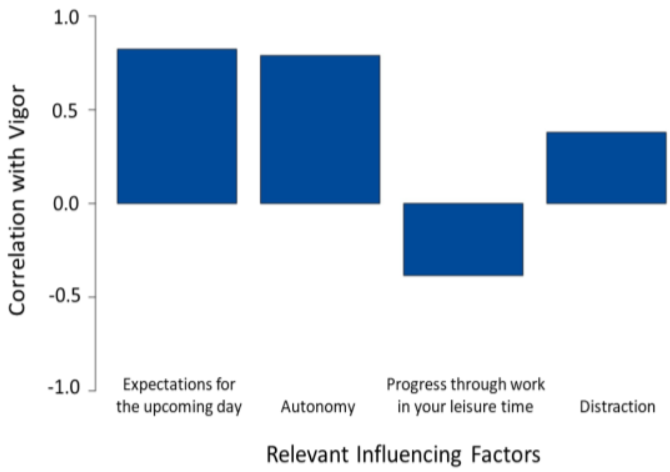


Figure 15.2.: Sample bar chart with the strongest correlation coefficients between personal vigor to possible influence factors

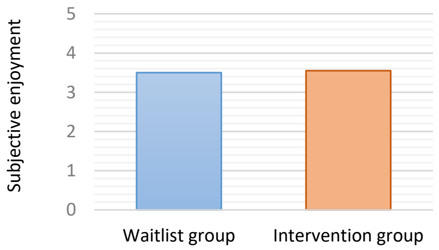


Figure 15.3.: Subjective enjoyment between both groups

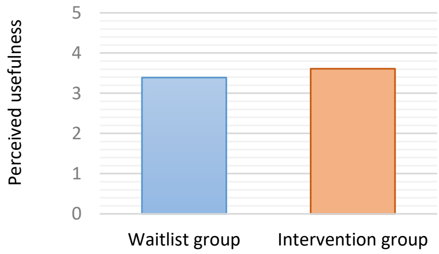


Figure 15.4.: Perceived usefulness between both groups

the feedback. Afterwards, we describe the results of analyzing changes in the participants' actual trajectories of energetic activation.

15.5.1. Participants' Perceptions

Out of the 136 participants, 101 persons rated the user experience of the feedback reports. Across the entire sample (n = 101) subjective enjoyment and perceived usefulness averaged approximately 3.5 each on a scale ranging from 1 to 5. Thus, participants tended to enjoy the feedback and to find it useful, even though there is still room for improvement. With a focus on the general perceptions concerning the feedback reports, differences between the groups are not decisive. Nevertheless, we wanted to examine whether the difference between the groups in receiving intermediate feedback affected how much participants enjoyed the feedback and found it useful. Figure 15.3 presents the comparison of means for subjective enjoyment between the intervention group IG(n = 54) and the waitlist group WG(n = 47). Figure 15.4 shows the comparison of means for perceived usefulness between IG and WG, respectively. Concerning participants' perception of the personalized feedback between the two groups, there was not a significant difference in subjective enjoyment between IG ($M = 3.55$, $SD = 0.78$) and WG ($M = 3.5$, $SD = 0.91$); $t(100) = 0.58$, $p = 0.56$, $d = 0.12$. There was also no significant difference in perceived usefulness between IG ($M = 3.61$, $SD = 0.94$) and WG ($M = 3.39$, $SD = 0.89$); $t(100) = -1.20$, $p = 0.23$, $d = 0.24$. Thus, although participants received feedback at different points in time (intervention group: at the end of week 1 and 2; waitlist group or at the end of week 2 only), perceptions of the feedback did not differ across groups.

15.5.2. Changes in Energy across the Weekly Surveys

We applied discontinuous growth modeling applying multilevel regression models in the nlme-package (Pinheiro and Bates, 2000) in the R statistics environment to analyze the weekly survey data on energetic activation. We followed the procedures suggested in Bliese and Ployhart (2002) and Bliese et al. (2020). We added the focal time contrasts as predictors step by step. In the final model, we included the group variable as a predictor of the intercept and the Transition 1-slope. We present the coefficients of the focal discontinuous growth model in Table 15.2. We found evidence

Table 15.2.: Results of discontinuous growth modeling predicting energetic activation across weeks

			Energetic activation			
			Estimate	*SE*	*t*	
Level 2 (between-person)						
	Intercept		3,11	0,11	28,21	
	Group (0 = intervention group, 1 = waitlist group)		0,18	0,15	1,21	
Time contrasts						
	Time linear		-0,01	0,07	-0,07	
	Transition 1		0,32	0,15	2,13	*
	Transition 2		0,09	0,12	0,82	
Interactions with covariate						
-	Transition 1 x Group	-	-0,18	0,16	-1,10	-
Variance components						
Between-person variance						
	Intercept variance		0,47			
	Transition 1		0,41			
Within-person variance						
	Residual variance		0,27			
Deviance			988,74			
AIC			1008,74			
BIC			1049,70			

Note. Transition 1 refers to change immediately after receiving the first feedback report. Transition 2 refers to eventual changes one week after receiving the first feedback report. *SE* = standard error. *df* = degrees of freedom. † $p < 0.10$. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$. Deviance = (-2 Residual Log Likelihood). Sample size: 444 self-reports nested in 136 persons.

for a significant Transition 1 slope (γ_{10} = 0.32, SE = 0.15, t = 2.13, p = 0.034). Neither the Transition 2-slope (γ_{20} = 0.09, SE = 0.12, t = 0.82, p = 0.413) nor the linear time slope (γ_{30} = -0.01, SE = 0.07, t = 0.07, p = 0.941) were significant. That is, there was an increase in energetic activation upon receiving the first feedback report, but there were no further changes after this transition.

Status as a member of the intervention vs. waitlist group was not associated with the intercept (γ_{01} = 0.18, SE = 0.15, t = 1.21, p = 0.227). Hence, levels of energetic activation did not differ across groups at the beginning of the study at Pre-ESM (when all time contrast were 0). Group status did not predict variance in the Transition 1-slope (γ_{11} = 0.18, SE = 0.16, t = 1.10, p = 0.274). Hence, although participants in the intervention group vs. the waitlist group differed in the specific point in time when they received the feedback reports relative to the beginning of the ESM part of the study (after 5 days vs. after 10 days), participants in both groups benefited equally upon receiving the feedback reports. We illustrate the trajectories of ener-

getic activation for the intervention group vs. the waitlist group as derived from model equations in Figure 15.5.
As evident from the figure, in the intervention group there is a sizable increase in energetic activation upon receiving the feedback from Pre-ESM to Interim. A similar pattern occurs for the waitlist group one week later: Energetic activation increases upon receiving the feedback report between Interim and Post-ESM. This pattern of results suggests that the receipt of the feedback report is associated with an increase of energetic activation. In sum, there are immediate benefits for experienced energy upon receiving the feedback.

15.6. Discussion and Future Work

We found evidence that participants experienced the feedback provided as useful and that receiving the feedback is associated with upward shifts in energy. Thereby, our study features several strengths, such as applying rigorous analyses on weekly survey data from a large sample. However, our results should be interpreted in the light of the limitations of the present research. We reported the correlations of different behaviors and energetic activation in the feedback reports drawing on a sample size of n = 10 self-reports per person at the maximum (each behavior was captured once per day), but cannot be certain how precise the correlation coefficient is with this few self-reports. Hence, capturing more than ten days would be a straightforward next step. On a related note, correlations might, but do not necessarily reflect contingencies. Therefore correlations in our feedback reports must not be interpreted causally (Antonakis et al., 2014) and we emphasized this point in our communication with participants. Our feedback focused on day-to-day fluctuation of energetic activation and its correlates rather than differences in habitual behavior between persons. In other words, if a person engages in high levels of self-management all the time, this behavior likely contributes to experience higher levels of energetic activation than others do. At the same time, if there is barely any day-to-day fluctuation in this behavior, the correlation with energetic activation at the within-person level as reported in the feedback will be small. However, pointing to specific potential levers is meant to be the starting point for individual hypothesis generation and experimentation on which levers actually work. We covered a relatively short period of four weeks. Hence, our study is mute on whether there is a sustained change in energetic activation. However, previous research on energy management with students (Spreitzer and Grant, 2012) suggests that the benefits may stick over longer periods. In summary, our contribution is that we provide first empirical evidence that gains in energetic activation are possible due to the participation in a technology-assisted personalized energy management audit. More specifically, *based on 444 self-reports nested in 136 persons we found out that personalized feedback on the contingencies underlying the individual energetic activation indeed has immediate effects that last over the entire period of the study.* The richness of our study offers much potential for further investigation. For instance, the weekly surveys provide the opportunity to examine trajectories of self-reported behaviors (e.g., self-leadership, taking micro-breaks). In our future research, we plan to run longer studies, include follow-up surveys to explore long-term effects,

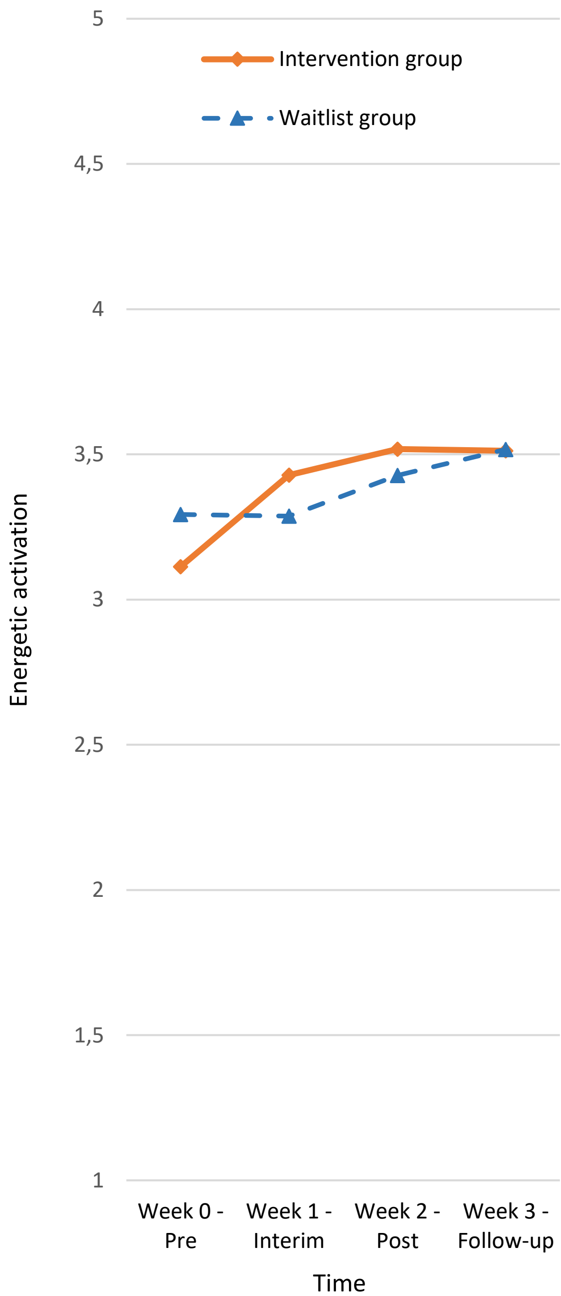


Figure 15.5.: Trajectories of energetic activation for the intervention group vs. the waitlist group receiving the feedback report one week later than the intervention group

and complement the self-assessments with tracking physiological variables.
First, we are in the process of running a longer study that also incorporates a follow-up to explore possible long-term effects of diary studies on energy self-management with personalized feedback. This is inspired by studies such as the energy audit from Spreitzer and Grant (2012) who conducted a follow-up survey after 6 and 12 months (with identical results). In their follow-up, it was shown that "77 % of the respondents reported better understanding of the factors that deplete human energy while 62 % reported they better understood the factors that sustain human energy". Studies in the area of self-tracking corroborate similar effects. Even in the absence of the tracking device, participants behave differently, which the authors coined as "It doesn't just 'stop'", since self-tracking "continues to shape individuals' daily practices, routines and health and fitness-related understandings even after discontinued use of digital self-trackers" (Clark et al., 2022). Taken together, these findings imply that also diary studies with feedback can have a lasting influence on the participants, which calls for further research regarding the long-term effects. It also raises the question whether narrow approaches of evaluating the "efficacy" or "outcome" of technology-supported self-reflection tools are appropriate.
Second, we plan further research to better understand the mechanisms behind the increased energetic activation. Although this result is encouraging, at present, we lack a clear understanding of how the feedback benefits energetic activation. One plausible explanation might be that the feedback triggered adaptive energy management behaviors like engaging in more micro-breaks. However, the benefits of these behaviors may not take effect immediately, but may take some time to unfold. Individuals likely face constraints to engaging in specific behaviors, for instance if job autonomy is low (Humphrey et al., 2007). More importantly, the most effective levers to improve experienced energy are unlikely to be the same across persons. In other words, some participants might benefit most from taking micro-breaks (Albulescu et al., 2022), others might benefit most from engaging in specific self-leadership (Knotts et al., 2022), or job crafting behaviors (Zhang and Parker, 2019). Consequently, instead of heading for a "one size fits all"-approach to human energy management, we take a person-centric perspective and focus on mechanisms that put the individual in the center. Given our emphasis on personalized levers to manage one's energy, users are unlikely to focus on the same set of behaviors. In line with this, the energy management audit introduced here is meant to inspire reflection on and exploration of contingencies underlying one's energetic activation in everyday work life by means of experimenting. Loops of individual hypothesis generation (micro-breaks might matter) and testing (engaging in more micro-breaks than usual) may unfold over time and the most relevant levers may even change over time, which just becomes visible, if feedback is provided more than once.
Hence, third, our future research might examine the individual learning processes in more detail and should explore to what extent participants actually start experimenting with energy management behaviors. Documenting the individual learnings derived from taking the energy management audit might be relevant, too. We confined to self-reported behaviors and experiences as a first step, because our priority were behaviors in the discretion of employees.
Fourth and finally, the inclusion of physiological data might advance the energy

management audit even more towards revealing contingencies underlying energetic activation that are not already obvious from introspection alone. For this, we currently work towards integrating sensor devices via a time series database to the formr diary study tool. Sensor data could comprise, e.g., sleep quality as inferred from actigraphy with wristband sensors as well as heart rate variability (HRV), steps, and calories burnt that can be read with consumer devices. Integrating these tracking data yields the potential to obtain an even more holistic view of human energy self-management variables and their contingencies.

16 The Relationship between Levels of Energy and Blood Glucose[1]

Abstract. Nowadays, many organizations steadily have to face new challenges due to an increasing competition, new technologies and manpower shortage. While dealing with this growth of challenges and confronting employees with higher demands, organizations have to pay attention to employees' personal resources that are connected to their well-being and health. Human energy is a psychological construct connected to different states of experiencing e.g. vigor and vitality, or otherwise fatigue. The subjective experience of human energy varies during the working day. In order to promote employees' health and well-being, an objective measure to determine human energy levels is needed. In this paper, we report on first insights from a pilot study with 12 healthy participants investigating if human's glucose concentration can serve as an objective measure of human energy. We analyze the possible interplay between subjective human energy perception during work and sensor-based blood sugar levels, assessed by a continuous glucose monitoring (CGM) system in healthy adults.

16.1. Introduction

Drawing on well-being in terms of individual resource status (Ragsdale and Beehr, 2016), processes of strain and recovery from work are reflected in decreases and increases of individual resource status over time (Zijlstra et al., 2014). Individual resource status is usually operationalized in terms of fatigue, (emotional) exhaustion, need for recovery, self-control capacity or vitality (Sonnentag et al., 2017). A common theme inherent in the aforementioned states is that they refer to different aspects of human energy (Quinn et al., 2012). High human energy can be understood as high levels of subjective vitality and low levels of fatigue (Fritz et al., 2011; Zacher et al., 2014). Fritz et al. (2011, p. 28) state: "Human energy is a 'fuel' that helps organizations run successfully". Nevertheless, today's job demands of many work systems are leading to high levels of fatigue and rapid depletion of human

[1] The content of this chapter has already been published as follows:
Lambusch, F.; Knoblich, J.; Weigelt, O.; Kraft, D.; Fellmann, M.; Bieber, G. (2022). Does my glucose level tell how energetic I feel? In: Proceedings of the 7th International Workshop on Sensor-based Activity Recognition and Artificial Intelligence (iWOAR '22), article no. 8, pp. 1–9. https://doi.org/10.1145/3558884.3558894

energy during work (Fritz et al., 2011; Jiandong et al., 2020). Many employees are faced with long work hours, information overloads and heightened job insecurities. Furthermore, many employees have a hard time to switch off from work completely due to the non-stop availability, e.g. via call or e-mail (Fritz et al., 2011). Previous research associates such work stressors even with an elevated risk of cardiovascular disease (Kivimäki and Kawachi, 2015). In order to prevent overburdening employees, organizations and research are focusing on strategies to reduce the job demands, e.g. shorter work time (Kivimäki and Kawachi, 2015), and to recover from job demands, e.g. taking microbreaks (Kim et al., 2017; Zacher et al., 2014). However, such strategies are rarely rooted and practiced sufficiently in organizational cultures so far, so that strain can still accumulate and make workers ill. The measurement and forecast of individual energy levels could assist workers better manage their energy based on their individual rhythms and behaviors, e.g. by pointing out situations in which they over-exhaust their resources or, on the other hand, in which they recover well or engage in energy-boosting activities. This opportunity might help organizations to support their employees' in promoting their health and thus, could help organizations to run successfully.
Unfortunately, human energy levels have to be tracked through self-reports so far, which is very cumbersome. Thus, a sensor-based measure for the umbrella concept of human energy would reduce the burden for measurement. Furthermore, the amount of data points would enable more precise analysis as for forecasts that point out trends in future trajectories. In research, glucose is considered as one resource of human energy (Quinn et al., 2012) and is thus a relevant variable to be investigated as a subject of measurement. In recent years, diabetes healthcare took a large step by developing continuous glucose monitoring systems. Such systems are able to measure glucose concentrations in short intervals without interrupting the patients' activities. In contrast to prior methods, where glucose levels usually were measured just two or three times a day, this method allows researchers to detect relations to glucose levels without overloading participants (Kontou et al., 2021).
In this article, we present first insights from a field study with 12 healthy participants investigating if human's glucose concentration can serve as an objective measure of human energy. The remainder of the paper is organized as follows. The next section presents important background information on personal resources in form of glucose and energy levels. Section 16.3 presents the field study and discusses the results. We summarize the paper and give a concluding reflection on the results in Section 16.4.

16.2. Related Work

This section describes the background on glucose levels, human energy, and resource depletion.

16.2.1. Glucose Concentration and its Measurement

Every human cell needs energy, especially muscles and brain. The central nervous system covers its energy requirement to 90 % with glucose (Krey, 2017). The provisioning of energy is possible by transporting glucose through the blood. In recent

Figure 16.1.: Continuous measurement of a person's glucose concentration using a Dexcom G6 on the upper arm

years, continuous glucose monitoring (CGM) has become a crucial part in diabetic healthcare (Shah et al., 2018; Sørgård et al., 2019). CGM devices measure the glucose concentration in interstitial fluid using a sensor implanted in the subcutaneous tissue (Forlenza et al., 2019; Kontou et al., 2021; Pickup et al., 2011). While the use of CGM devices is frequently analyzed when used by patients with diabetes, the use and functionality in settings with healthy subjects is just researched recently. Kontou et al., for example, performed oral glucose tolerance tests with a total of 124 healthy participants in order to validate the use of CGM devices in such settings (Kontou et al., 2021). Besides, latest factory-calibrated CGM devices make the additional self-monitoring of blood glucose (e.g. via finger prick) almost negligible. In our presented study, glucose was measured by using the Dexcom G6 (see Figure 16.1), which is a real-time factory-calibrated continuous glucose monitoring system published in 2018 (Forlenza et al., 2019). As CGM systems do not measure the blood glucose itself, but the glucose concentration in interstitial fluid, time delay has to be considered. In research referring to the G6 CGM system the average time delay observed was 3.7 ± 3.1 min (Shah et al., 2018) respectively 4.5 ± 3.3 min (Wadwa et al., 2018).

The aim of the presented study is to have an accurate view on glucose as a biological variable and determine if it can serve as a predictor for human energy.

16.2.2. Human Energy

Quinn et al. (2012) reviewed several energy-related literature and developed an integrated model of human energy. The model differentiates between two types of human energy: physical energy and energetic activation (see Figure 16.2). The physical energy is furthermore classified into potential energy (ATP and glucose) and kinetic energy.

Energetic activation is "the degree to which people feel energised" (Quinn et al., 2012, p. 342) and is pictured on the right side of the model. It is "experienced as feelings of vitality, vigor or enthusiasm" (Quinn et al., 2012, p. 342). Energetic activation leads to intrinsic motivation, which makes people seek new challenges. Thus, the discrepancy between demands and resources is increasing, which leads to a decline of the energetic activation. Quinn et al. state that the energetic activation is the limiting factor whether we invest our energy into an activity or not. Thus, if we feel energetically activated for an activity, we decide to put our possible resources,

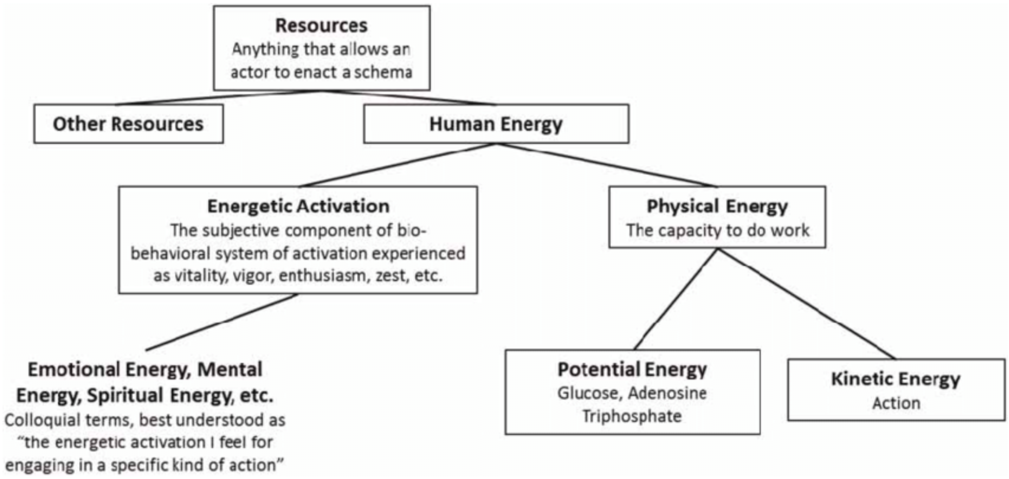


Figure 16.2.: Hierarchy of types of human energy (Quinn et al., 2012)

such as glucose, into resources-in-use. In contrast, if our energetic activation is low we probably will not engage into this activity and invest our resources into another activity, with different demands and with different resources that are required. Although glucose is seen as one of the main resources in the model of human energy and several assumptions have been made how glucose could possibly interact in the model, the model is missing accurate specifications about the functionality of glucose in the construct. If glucose is one of the main resources in terms of human energy, it is expected that the glucose concentration of persons correlates with their perceived level of human energy.

16.2.3. The Role of Blood Glucose in Resource Depletion

In research on Ego-Depletion, the correlation between glucose and energy in form of self-control has already been analyzed. In the late 1990s, Baumeister et al. (1998) suggest that acts of self-control draw on the same, limited resource. In experiments, they figured out that acts of volition interfere with following similar acts. Based on these findings the assumption has been made that some resource becomes depleted performing self-control. Yet, it was unclear what kind of nature that resource is. In the 2000s researchers suggested that glucose is used to perform self-control. Gailliot et al. (2007) investigated the relation between acts of self-control and the level of glucose in the bloodstream. They identified a significant drop of blood glucose following acts of self-control as well as a poor performance in subsequent tasks if the participants blood glucose was low after performing a previous self-control task.
However, in the 2010s many articles have been published disproving glucose as the underlying resource of self-control (Finley et al., 2019; Vadillo et al., 2016; Lange and Eggert, 2014). The controversy and current state in the field of ego-depletion is reviewed by Inzlicht and Friese (2019). In summary, glucose failed to predict self-control in previous research. Nevertheless, by now research only focused on glucose as a predictor for self-control. If glucose can serve as a predictor for human energy still has to be determined.

16.3. Field Study

In order to test if humans glucose concentration could serve as an objective measure of human energy, we conducted a field study that is described in the following.

16.3.1. Subjects and Settings

Participants were primarily recruited from the University of Rostock and the Fraunhofer IGD Rostock. The resulting 12 participants were according to their own statement healthy, non-diabetic adults, working at least 30 h the week (6 female, 6 male, age 24–56 years, body mass index 22.7 ± 3.2 kg/m2). Additional inclusion criteria was the possession of a smart device compatible with the Dexcom G6 as well as no planned holiday during their participation. Participants provided a signed, informed consent before start of study. The study was furthermore approved by the ethic commission of the Medical Faculty of the University of Rostock. The sensor of the G6 lasts for a period of 10 days before it has to be changed. Subjects were asked to participate for a total of 10 days. Participation was voluntary and the participants were free to withdraw from the study at any time, but there was no withdraw from participation and all participants completed the study. The participation took place from January until March 2022 and was divided into 3 blocks of 4 people participating for 10 days.

16.3.2. Method

In this study, participants' glucose concentration was measured with a Dexcom G6 CGM device (see Section 16.2.1) in parallel to self-reports on human energy. The Dexcom G6 sensor measures a glucose value every 5 min and lasts for a period of 10 days. The glucose values are reported to the participant's smartphone in real-time via Bluetooth and participants could observe their glucose values in the app. The data could later be downloaded as CSV-files.
In order to track human energy fluctuations over time, experience sampling methodology (ESM) in form of a diary study was conducted. Compared to traditional survey studies, diary studies have the advantage that participants can be asked several times a day and the risk of retrospective bias is reduced (Ohly et al., 2010). Additionally, "the situational context can be taken into account when studying feelings, cognitions, and behavior" (Ohly et al., 2010, p. 85). All participants registered online to receive digital surveys created via the formr[2] survey framework (Arslan et al., 2019b). The study was conducted in German language. In each survey, participants were asked about their present energy by using the battery scale of human energy shown in Figure 16.3.
The single item battery scale was used rather than using multiple verbal item scales because of its time efficiency. Performing studies under everyday conditions and tracking the human energy multiple times a day, participants may become overloaded and energy could be reduced due to participation. By using the battery scale this risk was reduced, e.g. participants did not have to interrupt their daily activities over longer periods. Besides using the battery scale in order to measure human

[2] `https://formr.org/`

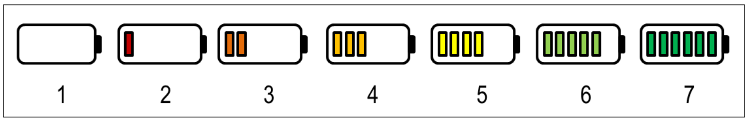


Figure 16.3.: Battery scale of human energy with response options ranging from a depleted to a fully-charged battery (Weigelt et al., 2022)

energy, surveys included items, which have been considered as having potential effects on the human energy that are not observed by the battery scale (e.g. workload, microbreaks), or which are expected to correlate with the battery scale (e.g. vitality, fatigue). The selection of additional items is not exhaustive and several additional items could be included, e.g. enthusiasm, fear, anger, weariness etc. However, adding too much items would increase the risk of overloading participants.
The overall procedure for participation was as follows. On the evening before the start of the study, the Dexcom G6 glucose monitoring system was inserted into the back of the participant's upper arm. In addition, every participant registered online to receive surveys starting the next day. On workdays participants received an e-mail invitation every hour between 9:00–16:00 as well as one e-mail at 18:00 and one at 20:00. At the weekend participants received an e-mail at 10:00, 14:00 and 18:00. Participants were asked to answer the survey as soon as possible after receiving the invitation. Whether the previous survey was answered or not, the next survey was sent. After 10 days the CGM was removed and participation was finished. For the analyses, each participant is assigned a unique letter as a pseudonym and identifier. Glucose and survey data are merged according to the respective participant and datetime. Since self-reports are received less frequently than glucose levels, for most of the analyses only pairs of self-reports with a glucose measurement timely matching the self-report are considered and the rest of the glucose values are discarded. In order to create pairs of self-reports and glucose measurements, timestamps had to be rounded to be exact the same. The timestamp of the energy was rounded up every 5 min and the datetime of the glucose was rounded down by every 5 min, so that a battery value at 18:07 is rounded up to 18:10 and a glucose value at 18:12 is rounded down to 18:10. By doing so, also the time delay of the glucose values (see Section 16.2.1) is minimized. Compared to the assumed time delay of 0.6–7.8 min of the Dexcom G6 in this study, the time shift due to rounding the timestamps is almost matched perfectly. However, it has to be mentioned that in the study no evidence can be made about the individual time delay. Besides the rather exact pairs of a self-report and a glucose measurement, we also conducted analyses using more glucose data, e.g. the mean value within 1 hour, to ensure comprehensive analyses of the data. In these cases, we mention in the results, if more glucose values were used. The analyses were performed on data of the 9 days on which each participant carried the G6 the whole day. Data analysis was performed with the Statistical Analysis Software (SAS).

16.3.3. Hypotheses

Human energy is measured in our study using the battery scale, which represents particularly vitality and fatigue (Weigelt et al., 2022). Hence, the first hypothesis has been formulated according to this in order to prove plausibility of our battery data. The second hypothesis is formulated assuming direct correlations between battery and glucose states on two levels: correlations within persons across days and correlations of the average values of a person comparing between persons, which would mean that persons with different battery rating would also have a correspondingly different concentration of glucose. Based on the existing literature, we furthermore hypothesize that at least the battery is describing a specific diurnal pattern (cf. (Adan and Sánchez-Turet, 2001)). Regarding glucose, research only observed diurnal variation based on meal intake (Saad et al., 2012; Holmstrup et al., 2010). It is expected that glucose excursions are higher in the afternoon and evening than in the morning. Yet, it is unclear if a specific diurnal pattern in glucose exists under everyday life conditions, so we hypothesize it. Finally, regardless of whether hypotheses 2 on direct correlations is rejected or supported, we want to examine whether possible diurnal patterns reveal correlations, what we assume. In summary, our hypotheses are:

1. Self-reported states of the battery scale correlate with self-reported states of vitality and fatigue
2. Glucose concentration correlates with self-reported states of the battery scale within-person and between-person
3. Perceived human energy and glucose concentration each have a certain (average) diurnal pattern
4. Diurnal patterns of glucose concentration and human energy correlate

16.3.4. Results

Overall, 828 surveys were completed and 33,734 glucose values were reported during the study. On average participants completed 81.14 % of surveys. Regarding the glucose level, most of the participants recorded a continuous data line without any loss. There was just one participant with some missing parts and 3 participants with abnormal glucose values within the first hours after inserting the G6, which have thus been excluded. After excluding outliers and rounding timestamps, data consisted of a total of 29,192 glucose values, 737 rated battery scales and 729 timestamps with paired battery and glucose values. Overall the 24-hour mean glucose concentration was 107 mg/dL with a standard deviation (SD) of 19. The mean human energy level was 5.3 with a SD of 0.9. The battery scale ranges from 1 (battery empty) to 7 (battery full). While the maximum was reported multiple times, an empty battery never was reported and the lowest observation in the study was 2.

Hypothesis 1 (correlation of the battery with vitality and fatigue)

Self-reported states of the battery scale should correlate with self-reported states of vitality and fatigue based on existing literature. Table 16.1 shows the results

Table 16.1.: Correlations between battery/glucose and vitality/fatigue with number of self-reports for the verbal items. For vitality, the items in descending order are: “I feel alive and vital”, “I feel full of energy”, and “I feel awake and alert”. For fatigue, the items are: “I feel exhausted”, “I feel worn out”, and “I feel weary”

	N	Battery	Glucose
Vitality 1	135	**.62 (< .001)**	.13 (.137)
Vitality 2	135	**.73 (< .001)**	-.01 (.922)
Vitality 3	135	**.66 (< .001)**	.01 (.945)
Fatigue 1	135	**-.65 (< .001)**	-.07 (.414)
Fatigue 2	135	**-.63 (< .001)**	**-.18 (.033)**
Fatigue 3	135	**-.63 (< .001)**	-.13 (.141)

examining the relationship of these constructs to the battery values over all subjects. In addition, correlations of the constructs and glucose levels were computed.
The strongest association appeared between the battery and vitality 2 (“I feel full of energy”). Between battery and all items of fatigue there was a strong linear negative correlation ($r = -.65$ to $-.63$). Therefore, feeling fatigue is associated with low states of the battery. All correlations between battery and vitality/fatigue were statistically significant ($p < .001$). Given the results of the computed correlations, hypothesis 1 is supported as expected from the literature and it can be assumed that the battery values are plausible.

Hypothesis 2 (glucose correlates with the battery)

In order to test whether glucose concentration correlates with self-reported states of the battery scale within-person and between-person, Pearson’s correlation coefficient (Pearson’s r) was computed and results were interpreted according to Cohen’s convention to interpret effect sizes (Cohen, 1988). We analyzed the data at within-person level as well as at between-person level. At within-person level, the data was analyzed for all days and separately for weekdays and weekend. In addition, we conducted analyses differentiating between women and men, because literature on diurnal patterns of energy suggests that energy variations over the course of the day are different between women and men (Adan and Sánchez-Turet, 2001). The correlations were computed with two types of data: 1) pairs of raw glucose and battery values over all subjects and 2) pairs of centered glucose and raw battery data. By centering, every glucose value is centered at the glucose mean of each subject and the centered glucose value is then correlated with the corresponding battery value in order to eliminate height differences and variability between subjects. Table 16.2 shows the results of the correlation analyses.
On weekdays, the human energy of the participants did not appear to be associated with the glucose concentration of the participants, neither on raw data nor on glucose-centered data. At the weekend, there is a weak negative correlation between glucose and battery. However, the correlation is not statistically significant. It is

Table 16.2.: Correlation analyses for glucose and battery levels. At within-person level, correlations below the diagonal are based on raw data. Correlations computed above the diagonal are based on glucose-centered data and raw data of the battery. On the between-person level correlations are based on the subject-mean of glucose and battery

	N	Mean	SD	Glucose	Battery
Within-person level					
On weekdays					
Glucose	667	109	20		.03 (.371)
Battery	667	5.3	0.9	.04 (.348)	
At the weekend					
Glucose	62	108	18		-.12 (.371)
Battery	62	5.7	0.8	-.09 (.475)	
All days					
Glucose	729	109	20		.02 (.515)
Battery	729	5.3	0.9	.03 (.491)	
Men (all days)					
Glucose	377	111	23		.07 (.182)
Battery	377	5.4	0.9	.08 (.010)	
Women (all days)					
Glucose	352	107	17		-.03 (.566)
Battery	352	5.3	1.0	-.06 (.262)	
Between-person level					
All days					
Glucose	12	108	7		.05 (.207)
Battery	12	5.3	0.3	.05 (.207)	

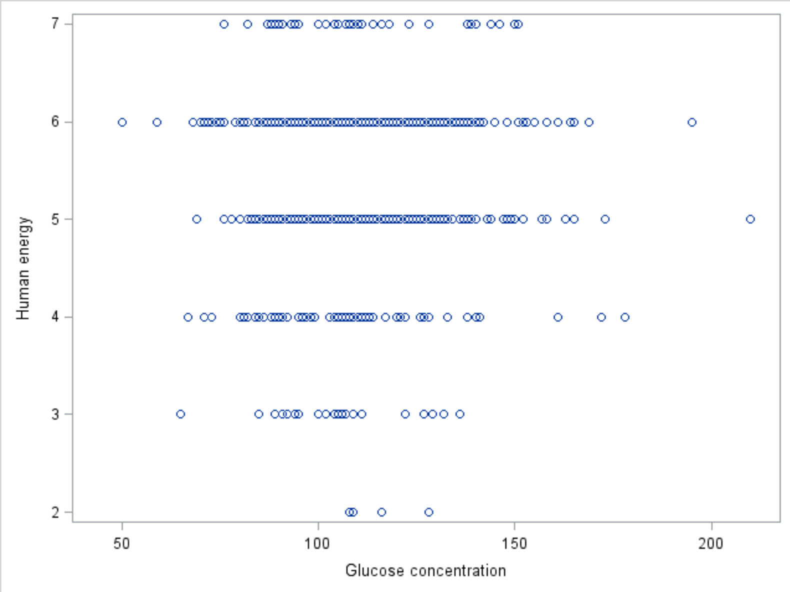


Figure 16.4.: Scatter plot of human energy and glucose

noteworthy that mean glucose at the weekend (108) is even nearly the same as on weekdays (109). Mean battery is slightly higher (7.5 %) at the weekend (5.7) than on weekdays (5.3). However, sample size on weekends is rather small (n=62). Considering all participation days, no linear relationship was examined between glucose and battery. Human energy did not appear to be associated with glucose for neither men nor women ($r < .01$). In addition to within-person analyses, differences between individuals are examined (between-person level). The mean of glucose as well as of battery of each subject was calculated. When observing the linear correlation between the subject-mean of glucose and battery, results are indicating that there is no.

For further investigation, a scatter plot of the relationship between battery data and glucose was created. This scatter plot is pictured in Figure 16.4. The scatter plot supports findings of the computed correlations, since there is no linear relationship illustrated by the dots. Furthermore, the scatter plot does not indicate the existence of any nonlinear relationship either. Most of the dots are pictured at an energy level of 5 and 6, but have a long range in glucose concentration. Additionally, there is no evidence that low glucose concentrations are linked to low states of human energy or high glucose concentrations are linked to high levels of human energy.

Assuming that biological processes and psychological processes might show time lagged effects, we also examine correlations considering time delays. The biological process could react faster while the psychological process might be more lazy. Reviewing literature on glucose and energy trends after intake of snacks, the previous assumption can also be inverted. Thus, we analyzed both options as well as we performed a computation based on aggregation of glucose values within a time interval. The results are shown in Table 16.3. “Glucose - 5 min”, for example, indicates that battery values are correlated to glucose values that occur 5 minutes before, while “Battery - 10 min” indicates that glucose values are correlated to battery values

Table 16.3.: Correlation analyses on all days assuming time-lagged effects in glucose or battery levels or for the battery with aggregation of one hour of glucose values

	Glucose - 5 min	- 10 min	- 15 min	- 20 min	average 1 h	Battery - 10 min	- 20 min
r	.03	.02	.04	-.01	.02	.04	$< .01$
p	.576	.548	.366	.824	.580	0.270	.954

that occur 10 minutes before. Additionally, each battery value was correlated to the average of glucose values reported in between 1 hour before the battery value. Data analysis was performed over all subjects. No significant correlations could be found. Based on these correlation analyses, hypothesis 2 can not be confirmed. There is no significant linear correlation between glucose concentration and self-reported states of the battery scale at within-person or between-person level. Also, there is no evidence for any nonlinear relations as well as there is no evidence for delayed reactions of the perceived human energy to the glucose concentration or vice versa.

Hypotheses 3 (human energy and glucose have a diurnal pattern)

In order to analyze if perceived human energy and glucose concentration each have a certain (average) diurnal pattern, diurnal patterns were generated for both, the glucose levels and the battery levels. Before plotting the graph, glucose/battery values were averaged over multiple days and all subjects. Since participants only reported a maximum of 3 batteries per day at the weekend and battery values were slightly higher than on weekdays, diurnal patterns were computed exclusively with data on weekdays. The diurnal patterns of human energy (blue) and glucose (red) over all subjects of the study as interpolated graphs are shown in Figure 16.5. Since there were no reported battery values during the night, the graphs show both patterns only between 9:00–20:00. In summary, the graphs are describing diurnal variations of human energy/glucose as a mean of all weekdays along all subjects.
Human energy seems to have a certain diurnal pattern, since there is an almost linear drop during daytime. The graph of glucose concentration indicates that glucose may generally increase during the morning, peaks shortly after midday, remains on the same level in the afternoon and drops during the night. Nevertheless, since the glucose graph has multiple fluctuations during the day, in the following diurnal patterns of individuals are examined in order to proof the existence of a general pattern. Exemplary diurnal patterns of subject C, D, and G are shown in Figure 16.6. Subject C (blue) has a similar pattern throughout the day to the pattern over all subjects. Glucose is increasing during the morning, is higher in its mean during the afternoon and drops during the night. Only the peak of glucose is delayed and occurs at short past 16:00. In contrast, the glucose patterns of subject D and subject G are different. Subject D (red) has nearly the same peaks in the morning, short past midday and in the evening. Additionally, glucose is already dropping in the late evening and remains on the same level during the night. Glucose concentration of subject

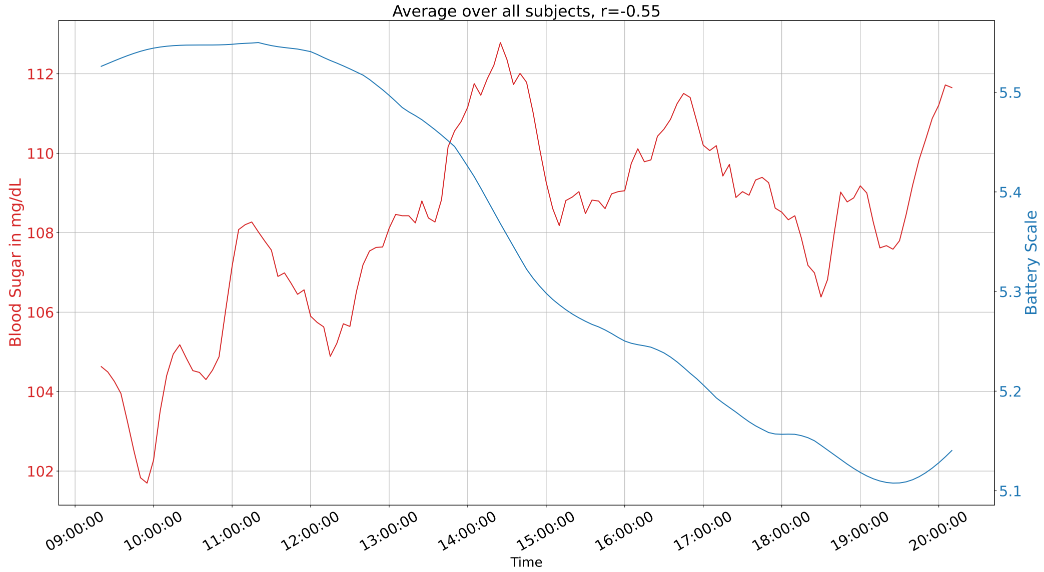


Figure 16.5.: Mean diurnal patterns of human energy and glucose over all subjects of the study as interpolated graphs

G (green) is peaking short past midnight and decreasing afterwards until midday. In reverse to the trend over all subjects where glucose was peaking around midday, glucose of subject G has its through at midday. Reviewing individual glucose trends, there is no evidence for a general pattern in glucose.
Observing diurnal patterns on an individual level, patterns were different between subjects in glucose, but in human energy as well. Literature on diurnal variation of energy suggest that there exist disparities of energy throughout the day between women and men, e.g. for vigor (Adan and Sánchez-Turet, 2001). Thus, we additionally generated diurnal patterns with the data of our 6 male participants and 6 female participants separately. Differences in the diurnal variation in *perceived human energy* over all men in comparison to over all women are observed. Diurnal patterns of human energy are pictured in Figure 16.7a. Women's energy was on average highest at the first daily self-report at 9:00 and decreased continuously throughout the morning. In contrast men's energy was highest between 12:00–13:00. Findings support the assumption made by Adan and Sánchez-Turet (2001) that women's energy (measured as vigor) is peaking earlier than men's energy. Furthermore, they observed that energy of women was lowest at their last measurement of the day (9:00) while energy of men was lowest at 16:00 and was increasing again afterwards. Similar findings were made in this study, although men's energy was lowest two hours later. Considering diurnal patterns of women's and men's *glucose concentration* shown in Figure 16.7b, there exist major height differences during the morning as well as during the afternoon and evening. At midday women's glucose is strongly increasing and shortly afterwards strongly decreasing, remaining on a higher level during the afternoon and evening than during the morning. In contrast, men's glucose remains on a generally higher level than women's glucose without significant drops. Women's glucose is by far highest at 14:00 compared to the rest of the day, whereas men's

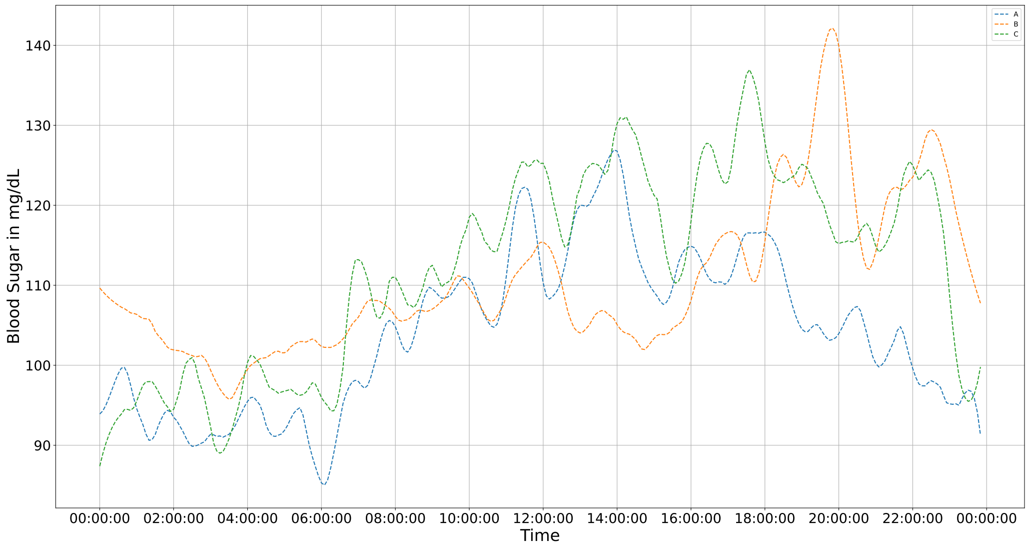
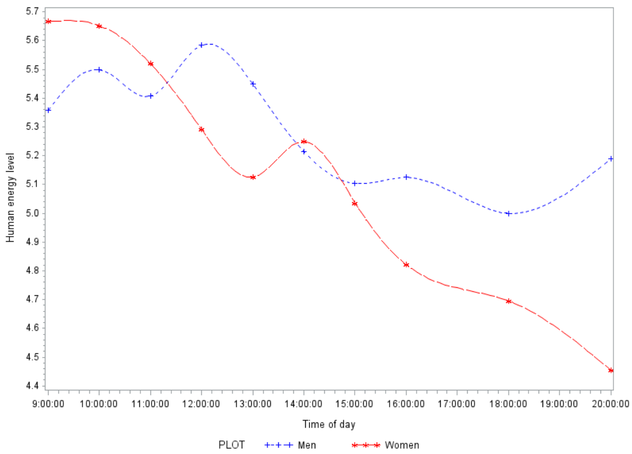


Figure 16.6.: Diurnal patterns of glucose concentration of subject A, B, and C averaged over all days

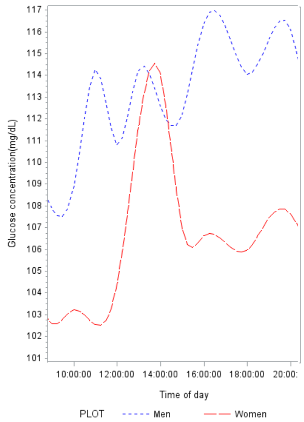
glucose is highest at 16:00, but nearly at the same level at 20:00 again. These findings agree with diurnal variations of human energy where women experienced less energy during the afternoon and evening than men.
In summary, findings suggest that human energy as well as glucose levels vary significantly between women and men. Yet, it is unclear if differences are caused by varying behavior, biological differences or even other effects. If future research is able to replicate the findings of this study with a larger sample and identify reasons for variations, this might provide important knowledge about the regulation of glucose levels. While there is indication that at least when differentiating between genders a diurnal pattern in glucose levels could exist, hypothesis 3 can not clearly be supported regarding glucose patterns.

Hypothesis 4 (diurnal patterns of glucose and human energy correlate)

In contrast to the computed values in hypothesis 2, the diurnal patterns in Figure 16.5 show a medium and also statistically significant negative correlation with each other ($r = -.5$, $p < .001$). Furthermore, it seems that the graphs representing energy and glucose patterns differentiated according to gender (Figure 16.7a and 16.7b) also contain some indicators for relations between the constructs, e.g. effects of peaks in glucose. However, it is not clear yet if the mean values over several subjects for certain points in time are meaningful as individual glucose patterns also show a heterogeneous picture and even if there are correlations, these might not be causal. It needs further analyses to investigate the relationship of the two constructs, perceived human energy and glucose. Thus, we cannot yet make a final judgment, but will perform deeper analyses on that.



(a) Diurnal pattern of human energy of women and men between 9:00–20:00



(b) Diurnal pattern of glucose concentration of women and men

Figure 16.7.: Diurnal patterns of of women and men

16.3.5. Discussion

Diurnal patterns of glucose and energy examined over all subjects in this study suggest that energy is decreasing throughout the day, while glucose is fluctuating at daytime and is decreasing throughout the night. Fluctuations of glucose at daytime can be primary explained with mealtimes of participants. Increases of glucose in the morning are in line with breakfast times. Participants reported having snacks twice as often at 11:00–15:00 and 15:00–20:00 than at 6:00–11:00. This may represent the higher average glucose concentration during the afternoon compared to the concentration during the morning. The results also agree with research in diurnal tolerance of glucose. Saad et al. (2012) observed postprandial glucose concentration after breakfast, lunch and dinner. They investigated a greater glucose excursion after lunch and dinner than after breakfast. Findings were caused by a better glucose tolerance during the morning as a result of better β-cell responsiveness and insulin action. While glucose is increasing and decreasing multiple times the day, energy seems to be a limited resource, which (all in all) gets depleted over the course of the day and gets refilled by sleeping during the night. The assumption is made due to the almost linear drop of the human energy level as an average over all subjects in between 10:00–19:00 and the major higher level of human energy in the morning (5,5) than in the evening (4,8). The hypothesis is supported by the correlation examined in this study between sleep quality and following daily mean human energy ($r = -.44$, $p < .001$). The average human energy level was higher at days where participants reported to have had a good sleep during the previous night. However, diurnal patterns of human energy are varying considerably between subjects. Some participants' human energy increased during the morning. Additionally, some participants had an increase of their energy after end of work. Also, a few participants had multiple increases and drops during the day.

Overall, findings suggest that human energy is very subjective and is rather controlled

by sleep, relaxation, and work time than by glucose concentrations. However, looking at the results on the diurnal patterns of energy and glucose, there still could be connections. We will further investigate, if stronger correlations only or at least exist at certain points in time, e.g. if peaks of glucose weaken the drop of energy.
Key limitation of this study is the small sample size of 12 participants. Future research might want to replicate the findings of this study with a larger sample size and with a focus on effects of food intake as well as on differences between women and men. Some further things should then also be considered. CGM devices measure the subcutaneous tissue glucose. Measurement errors might remained undiscovered. Data were excluded if they were significant abnormal in comparison to the rest of the data, but in order to make precise assumptions about measurement errors an additional blood glucose measurement would be necessary. In addition, examined glucose data of some participants were similar to typical data of person with prediabetes, which could have distorted the data set. Since this is the first study examining the relationship between perceived human energy – primarily in form of vigor, vitality and fatigue – and glucose concentration, further analyses and studies are necessary to investigate the topic in more detail.

16.4. Conclusion and Outlook

The purpose of the present study was to determine whether perceived human energy correlates with the measurement of continuous glucose data of healthy subjects. For this purpose, battery ratings and glucose data were tracked along 12 subjects during their everyday life over a period of 10 days. Findings of this study show a mixed picture. Correlation analyses between measurements of the battery scale and vitality as well as fatigue are consistent with research, showing that measurements of the battery scale converge with vitality and fatigue. However, regarding a connection between human energy and glucose data, we cannot make a clear statement. Although some of the analyses suggest that there is no (direct) relationship between energy and glucose trajectories, correlations of diurnal patterns, peculiarities in certain situations such as glucose peaks, or differences by gender indicate that further analyses of these data and future more detailed studies with more participants may be worthwhile to come to a richer understanding of the phenomena.
In this study the main point of interest was the relation between human energy and glucose in occupational contexts over the course of the day. Since food intake is one of the main factors of glucose fluctuations (Saad et al., 2012; Holmstrup et al., 2010) and has different impact on e.g. vitality and well-being (no effect) (Fritz et al., 2011; Kim et al., 2017) as well as exhaustion and tension (increase) (Fritz et al., 2011; Thayer, 1987), future research could examine human energy and glucose in detail after food intake. Furthermore, future research should consider the potential effect of subject's gender. Examining diurnal patterns in this study, it is assumed that variations are different between women and men. For human energy, these findings are already supported by previous research (Adan and Sánchez-Turet, 2001), but glucose levels of healthy subjects and their effects on cognition are still underresearched.

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Appendix: Contributions in Publications

In the following paragraphs, the contributions of the author of this dissertation to each of the included peer-reviewed publications are described.

Articles of Part II

Publication in Chapter 5: I conceived and guided the literature analysis presented in the article. As the corresponding author of the publication, I conceptualized and compiled the paper. Thereby, I reviewed the literature again, refined contents from co-authors, and wrote complementary texts. Especially, I reworked the central systematization proposed in the article together with the explanations referencing to the literature.

Publication in Chapter 6: For this article, I reviewed the literature and discussed the research. I planned, structured, and compiled the article. Especially, I wrote parts of Sections 1-3 as well as mainly compiled Section 4-5 on the empirical investigation from a co-author's written work. I also created some new figures for it. Furthermore, I reviewed and edited drafts of the article.

Publication in Chapter 7: I contributed to this article by discussing, structuring, and editing the contents, reviewing literature, and compiling the article. In particular, I reworked the presented framework for IT-supported stress-management and created the figures presenting the survey results. I wrote especially parts of the abstract, Sections 1, 2, and 6. I created Section 3-5 mainly based on a co-author's written work. Furthermore, I reviewed and revised the article.

Publication in Chapter 10: This was the initial article presenting the vision and core idea of the self-management assistance. As such, I hold responsibility for the proposed concept and grounding in literature. As corresponding author, I critically discussed the research with the co-author, conceived and largely wrote the article, except for the second section that I mainly refined based on a co-author's draft.

Publication in Chapter 11: I devised and discussed the architecture presented in this article as well as developed the respective figure. Furthermore, I initiated and supervised the conduct of the survey, on which Section 3 is based. I wrote parts of the article, critically reviewed and revised it.

Publication in Chapter 12: The architectural concept presented in the article is a revised version and extension of my proposed architecture mentioned in the previous paragraph. I intensively discussed the ideas behind the article and the central figure, supported the writing, and critically reviewed the article.

Publication in Chapter 8: As the corresponding author of the publication, I planned, structured, and discussed the paper. I wrote parts of the abstract, Section 1 and 4, and created figures for Section 3. I conceived and guided the literature analysis presented in Section 2 and translated it from an earlier version published in German. I reviewed and revised the article.

Publication in Chapter 9: I conceived and initiated the research underlying the article. I conducted initial literature searches, planned the research scope, and co-supervised the research. Regarding article writing, I critically reviewed, discussed, and edited versions.

Articles of Part III:

Articles in this part are based on numerous intensive research discussions and investigations together with the organizational psychology. I was integral in initiating, manifesting, and advancing the collaboration, which continues now for years and yields joint research.

Publication in Chapter 13: The second author and I shared responsibility for the article and structured the paper together. I contributed especially Section 4 on energy self-management and wrote parts of Section 1.1 and 6. As corresponding author, I also reviewed and revised versions of the article.

Publication in Chapter 14: As corresponding author, I planned and largely wrote the article. Mainly Section 2 and 5 were in larger parts compiled from co-authors' writings. I furthermore revised versions of the article.

Publication in Chapter 15: In discussion with the co-authors, I structured and compiled the article. I wrote portions of the paper, partly using input from co-authors. As corresponding author, I reviewed, intensively discussed, and several times revised the article.

Publication in Chapter 16: I conceived and guided the research presented in the article together with the last author. I planned the research scope and intensively discussed the research with the co-authors. As corresponding author, I conceptualized, compiled, and revised the paper.

Eidesstattliche Erklärung (Statutory Declaration)

Hiermit bestätige ich, dass ich die vorliegende Arbeit selbständig und ohne fremde Hilfe verfasst, sowie keine anderen als die angegebenen Hilfsmittel benutzt habe. Die Stellen der Arbeit, die dem Wortlaut oder dem Sinn nach anderen Werken entnommen sind, wurden unter Angabe der Quelle kenntlich gemacht.