Personal Productivity Management in the Digital Age: Measures from Research and Use of Conventional Tools

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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.

Keywords: productivity, measurement, literature review, survey, application usage.

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 [1]. Such conditions can lead to stress and a long-term exposure to stress can lead to serious health problems [2]. 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 [3]. 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 collect information and support the user, e.g. [4, 5]. One advantage of these devices is that

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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 [6, 7], 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 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 3, the procedure and results of the survey study are described. Finally, we discuss our results and draw conclusions in Section 4.

2 Systematic Literature Review

The literature review that is presented in an initial German version in [8] serves to present the state of research on productivity factors that are unobtrusively measurable

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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.

2.1 Method

The literature research was carried out according to the structured approach of Kitchenham [9]. The literature database Scopus[1] 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 [10, 11] 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 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 and productivity factors of workers was described. There remained 32 publications relevant to this work.

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

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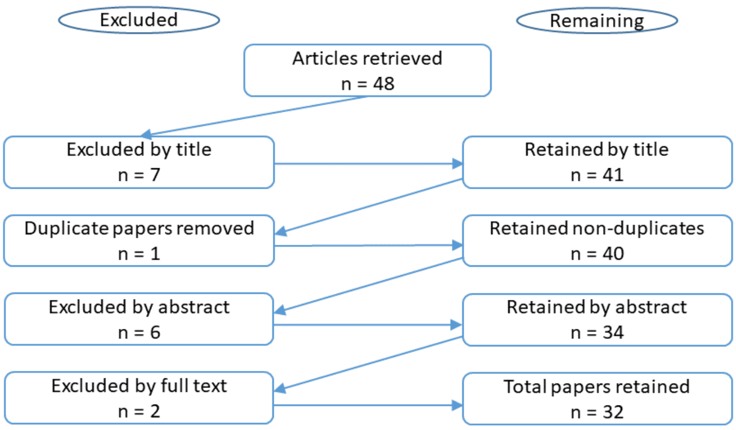

Figure 1. Article exclusion process

2.2 Results

The concept-oriented approach according to Webster & Watson was chosen for the investigation of the research topics [12]. With this approach, the literature sources examined were mapped to concepts that are shown in Table 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 [10]. Some authors also describe the development of a method for predicting stress or cognitive performance.

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.

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Table 1. Concept matrix

Article	Concept																	
	Objective			Subject of Consideration					Parameter of State Detection									
	Measurement	Data Analysis	Prediction	Cognitive Performance	Stress	Wellbeing	Work Setting	Happiness	HRV	Blood Pressure	Skin Conductance	Brain Activity	Phys. Activity	E-Mail	Personal Interaction	PC Interaction	Air Quality	Light
2018 [13]	X	X			X						X							
[15]	X	X					X										X	X
[16]	X	X		X		X					X							
[17]	X	X	X			X	X		X									X
[18]	X	X			X							X						
[19]	X	X			X							X						
[20]	X	X			X							X						
[21]	X	X		X	X				X		X							
[22]	X	X		X	X				X									
[23]	X	X	X		X						X							
[14]		X	X	X					X				X					
2017 [24]		X		X		X	X		X									X
[25]			X		X								X			X		
[10]			X	X					X									
2016 [26]		X				X							X					
[27]		X	X	X	X									X		X		
[28]		X			X								X					
[29]	X	X		X			X		X				X					
[30]		X		X			X						X		X			
[31]			X	X					X									
2015 [32]			X	X					X									
[11]	X	X						X					X					
[33]	X							X					X					
2014 [34]	X	X		X	X				X	X								
2013 [35]		X		X		X											X	
[36]	X	X			X				X									
[37]			X	X	X	X		X							X			
2011 [38]		X		X					X				X					
[39]		X			X						X							
[40]				X					X									
[41]	X							X										
2010 [42]		X		X	X						X							
Total	16	24	9	17	15	6	5	4	14	1	6	3	9	1	2	2	2	3

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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 [25]. 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 [27]. 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 [39, 42]. 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 [13, 14].

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 [18–20]. 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 [19]. However, some work also deals with issues that do not examine the way people work, but rather the effects of changes in the working environment. 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 [29]. 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 [24].

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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 [43], and two facets of functional perfectionism [44], as these dispositions tap into the motivation to perform well and to constantly improve one's performance.

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

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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 2 and Figure 3, we present the specific self-tracking and self-management activities with their associated frequencies of use, respectively, which are described in Section 3.3. To measure the acceptance of technology we used 9 items from [45] tapping into perceived ease of use and perceived usability of ICT devices. We gauged ICT privacy concerns with 4 items from [45]. We applied 5 Items to capture proactive personality [46], and 4 items each to capture the personal standards facet and the organization facet of functional perfectionism as a personality trait [47]. 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 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).

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

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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.

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 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 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 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 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.

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

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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.

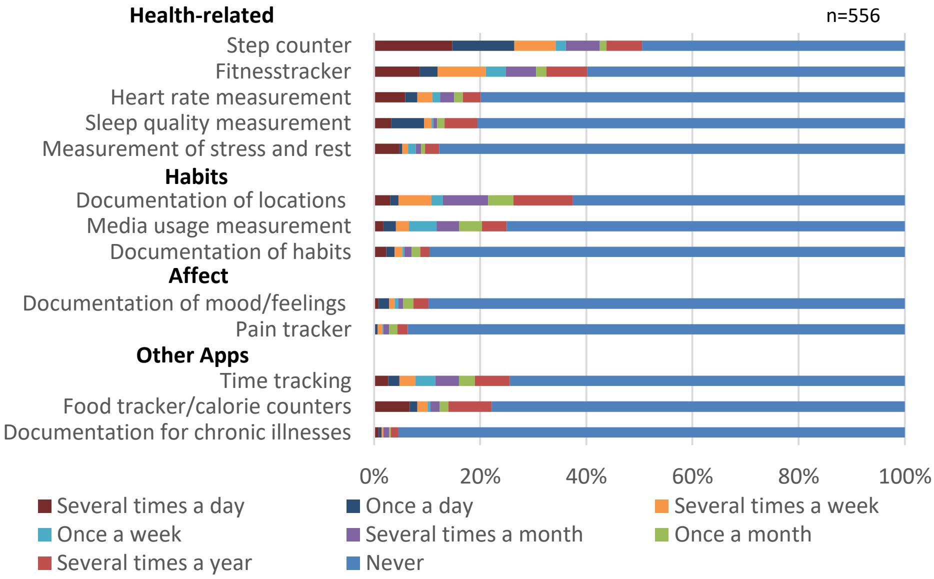

Figure 2. Factors and frequency of use of self-tracking activities

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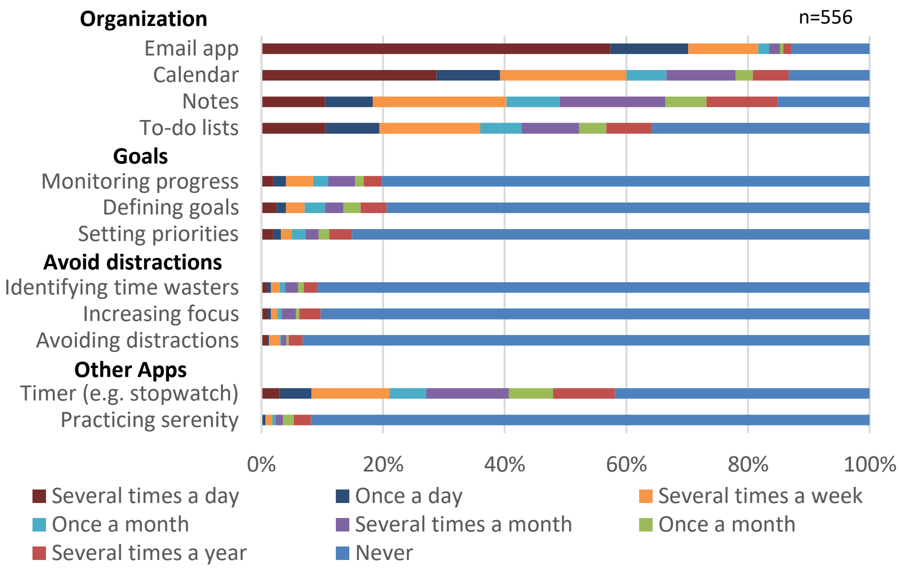

Figure 3. Factors and frequency of use of self-management activities

Table 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.

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 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 und additional limitations however, our survey study may be considered an important first step towards better understanding the use of ICT for self-management.

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