Are We Ready for Self-Quantifying and Preventive Health Behavior at Work? Exploring Employees' Types and Engagement

Silke Weißenfels
University of Hagen
silke.weissenfels@fernuni-hagen.de

Karolin Kappler
Catholic University of Applied Science
k.kappler@katho-nrw.de

Dario Duffner
University of Hagen
dario.duffner@studium.fernuni-hagen.de

Stefan Smolnik
University of Hagen
stefan.smolnik@fernuni-hagen.de

Abstract

The boundaries between life and work become blurred, and new work patterns are very demanding for employees. Future work environments should consider employees' health and pay more attention to digital interventions for preventive health behavior and well-being at work. Accordingly, this study focuses on identifying employees' needs and triggers to engage in self-quantifying at work. To assess this objective, we develop employees' types based on survey data and cluster analysis. Our empirical results emphasize that the open-minded improvers are willing to engage and that they are not susceptible at all, while the conscious pragmatists value the perceived usefulness and autonomy of self-quantifying at work. The vigilant hesitaters might be triggered by social comparison. Our research provides a new perspective on engagement in self-quantifying, and insights for preventive health behavior, healthy employees, and well-being in future work environments. These results offer starting points for meaningful work to stay employable and productive.

Keywords: self-quantifying at work, preventive health behavior, types of employees, occupational health, technology use

1. Introduction

Transforming work patterns and changing employment arrangements pose challenges to organizations and their employees (Baptista et al., 2020). The boundaries between life and work become blurred (Richter, 2020), with COVID-19 as a facilitator of digital work and virtual teams. Specifically, employees' work-life balance is more demanding due to remote work (Charalampous et al., 2019) and the lack of spatial separation (Herath & Herath, 2020). Remote working leads to employees suffering technostress, dissatisfaction, exhaustion due to virtual meetings, and triggers additional mental strain (Richter, 2020; Waizenegger et al., 2020). Although video conferences are held more frequently, employees feel lonely and isolated, leading to depressions (Alam, 2020). Likewise, longer working hours increase the risks of burn out (Kudyba, 2020). Organizations need to care for their employees to keep them employable and productive (Wessels et al., 2019) and to support their well-being at work to ensure healthy work environments. Employee well-being is multidimensional, linked to the subjective perception and physical and mental constitution (Keeman et al., 2017). Keeping this in mind, there is a substantial need to find solutions to establish work environments that prevent employees suffering from health-related issues at and due to their work.

According to the World Health Organization (WHO), employees should have access to (digital) interventions providing health prevention and healthy workplaces (World Health Organization & Burton, 2010). Occupational health is a discipline that promotes physical and mental health, as well as employees' well-being (World Health Organization & Burton, 2010). Similarly, the objective to promote and improve health and working conditions is also known as workplace health promotion (Rongen et al., 2013). Organizations transform the health promotion in prevention toward employees' empowerment and involvement. Accordingly, employees are invited to take over responsibility for self-care using voluntary, autonomous digital devices and platforms (Lupton, 2016; Swan, 2013). A shift to self-motivated preventive health behavior can lead to a mindful work-life balance (DeJoy & Wilson, 2003; Lupton, 2016). In fact, the underlying paradigm to adopt preventive health behavior at workplaces is that employees first become aware of their risks, acknowledge unhealthy behavior, and at the same time develop the motivation for a behavior change (Cheung et al., 2021).

The documentation of physical and mental conditions, environmental factors, as well as biometric data improves self-knowledge and well-being (Ajana,

URI: https://hdl.handle.net/10125/103024
978-0-9981331-6-4

2017), and triggers users to improve their fitness and health (Swan, 2012). Self-quantifying therefore offers a great potential to achieve a better health condition and outcome and for health prevention (Swan, 2012). With this in mind, a behavior change is demanding (Becker, 1974). Particularly, health behavior is mostly affected by attitudes, intentions, and social influences (Noar et al., 2008). Information and communication technologies (ICTs), including mobile and wearable technologies support self-tracking and self-quantifying (used here as an umbrella term) (Lupton, 2014; Swan, 2013). ICTs motivate toward behavior changes (Giddens et al., 2017) and create persuasive interaction (Oinas-Kukkonen & Harjumaa, 2009) by forming attitudes and, consequently, behavior. However, the decision-making process to use technologies for health-related reasons differs from other contexts (Sun et al., 2013). Since third parties can promote self-quantifying, for example, to enhance employees' health and well-being, it appears challenging to understand the individual's basic motivation and triggers for self-quantifying (Lupton, 2014, 2016)—particularly in occupational settings.

In our study, we concentrate on demystifying these triggers by categorizing employees' types. Do employees really strive for improved self-knowledge through the evaluation of personalized data (Ajana, 2017; Lupton, 2014; Oinas-Kukkonen & Harjumaa, 2009) to prevent themselves from unhealthy working patterns? By focusing on extending the discourses on occupational health, health promotion and prevention at work using digital means, and by also observing how new work environments impact employees' health and well-being, we pursue the following research questions:

What employees' types engage in self-quantifying? What determinants influence employees toward preventive health behavior at work?

By using survey data and by applying a cluster analysis, our objective is threefold: First, we find value in understanding employees' willingness and engagement in self-quantifying at work. Second, we develop employees' types to offer new perspectives for self-quantifying and its acceptance. Third, we strive to explore the determinants influencing occupational self-quantifying and preventive health behavior.

2. Theoretical background

2.1. Self-quantifying in occupational settings

Occupational health protects employees against, for example, hazards, risk, and issues associated with unhealthy workplace conditions (Schulte et al., 2012); engenders awareness in occupational settings; and can empower employees' preventive health behavior. Accordingly, digital means assist to measure and intervene in employees' behavior by offering automatic feedback (Roossien et al., 2021), monitoring productivity, identifying health risks, and providing instructions. Furthermore, this empowerment through recording health data (Lupton, 2016; Swan, 2012) offers possibilities to identify health-related issues and to promote awareness and autonomy (Ajana, 2017). In fact, the collection of personal information support self-reflection, visualize performance (Lupton, 2014), and foster self-knowledge (Choe et al., 2014). Employees are sensitized to unhealthy patterns and to circumstances that they are unaware of while, for example, observing body functions on a regular basis (Lupton, 2016). Besides this, the analytical functions have the power to maintain a targeted behavior (Lupton, 2014; Swan, 2012). Digital technologies reveal hidden patterns, lead to the comparison of results and behavior in groups, and modify them (Lupton, 2014). Particularly, wearables have shown the potential to draw attention to health-related issues (Gonzalez & Mitra, 2019), to encourage self-quantifying, and to exhibit alternative behavior (Mercer et al., 2016). The user's self-quantifying motivation is often twofold: (1) improving the individual's health by monitoring real-time data and (2) reaching a peer group's competitive goal (Gonzalez & Mitra, 2019). Alternatively, engaging in self-tracking triggers positive emotions and feelings (Naci & Ioannidis, 2015) and creates well-being. For an organization, promoting health and well-being improves commitment (Rongen et al., 2013), leading to positive outcomes (Diener & Seligman, 2004), and a better performance (Bevan & Cooper, 2022).

2.2. Understanding determinants for self-quantifying and preventive health behavior at work

The objective of our study is to explore employees' types and motivation to engage in self-quantifying for preventive health behavior at work by using technologies. Preventive health behavior builds on health-promoting activities to avoid health conditions (Harrison et al., 1992) since individuals are sometimes unaware of their actual behavior and behavior changes are challenging. Behavior develops over time and the motivation to engage should last for a considerable period of time for any benefit to be perceived (Bettiga et al., 2020). For this reason, regularly reinforcing employees' motivation (Bettiga et al., 2020), for example, through self-monitoring techniques, is crucial to disrupt habits. Intention embraces the motivation to exhibit a specific behavior and appears to be the key indicator for achieving a certain outcome (Sheeran, 2002). Likewise, motivation is needed for valuing an intention and to change behavior in a particular manner (Sheeran, 2002). Persuasive technological interventions support and motivate individuals to adopt healthy behavior and avoid harmful ones (Orji & Moffatt, 2016). Moreover, integrating the social dimension into an information system takes into account individuals' willingness to evaluate their ability and their competitive behavior (Oinas-Kukkonen & Harjumaa, 2009). This can be done by setting goals and by competing with others (Oinas-Kukkonen & Harjumaa, 2009), thus changing behavior via motivation (Abraham & Michie, 2008). A competitive situation is also a major force to exhibit a particular behavior. Individuals strive for attention, coalition and peer formation, as well as stimulation from outside and the connection with others (Lu et al., 2004). Demonstrating well-being, a health-promoting behavior at work, and the belonging to a peer-group can influence the willingness to disclose and share personal information (Buchwald et al., 2017; Lu et al., 2004). Consequently, we focus on social comparison, referring to the extent to which individuals are willing to evaluate, compete with regard to, and share their health performance and data with others (Zhang & Lowry, 2016).

Similarly, to maintain employees' ability to work (Wessels et al., 2019), they should be empowered to conserve their health and well-being and to adopt healthier working behavior. Accordingly, perceived autonomy emerges as referring to the extent to which individuals are enabled in personalized manners, using technologies freely and willingly (Zhang & Lowry, 2016). If technologies foster employees' sense of autonomy as a basic need and they feel enabled to regulate and interact autonomously, the employees are willing to use digital health devices at work (Roossien et al., 2021). Moreover, willingness to stay well and commitment to engage in being healthy at work (Roossien et al., 2021) is triggered by personalized digital health settings (Zhang & Lowry, 2016) that support employees' perceived autonomy. Above all, employees aim to decide not only which personal information to voluntarily disclose or share but also how to reach their desired preventive health behavior (Roossien et al., 2021).

Likewise, to increase awareness for an intended behavior change (Burke et al., 2009), self-monitoring as used in clinical contexts (Cohen et al., 2013) lends support to learn about the conditions, health behavior, and well-being, and helps understand and change habits (Abraham & Michie, 2008). Individuals can perceive their body and its signals more consciously. Particularly, to initiate behavior changes result from an individual's digital documentation, the visualized performance, and the analytical functions through metrics (Burke et al., 2009; Lupton, 2014; Zhang & Lowry, 2016). Self-monitoring is the perceived degree of being able to observe and keep records of a certain health behavior. Furthermore, self-monitoring helps achieve stability in performing a routine, discloses the personal progress (Burke et al., 2009), and therefore has the disruptive power to change an unpopular behavior. Moreover, self-monitoring fosters awareness about the physical and mental condition, followed by the goal to keep up with a certain behavior (Barratt, 2017).

At the same time, we integrate technology acceptance variables into our research. Technology acceptance evolves from attitude and positive willingness influenced by external factors (Davis, 1989; Venkatesh et al., 2003). The technology acceptance model (TAM) analyzes these effects by using the two variables perceived usefulness and perceived ease of use (Davis, 1989; Venkatesh et al., 2003). While perceived usefulness describes the degree to which a person believes in the benefits of and in using a technology, the perceived ease of use is the degree to which a technology can be used with little effort and expense (Davis, 1989; Venkatesh et al., 2003). These variables relate to individuals' attitude toward use and affect their behavior intention (Davis, 1989). System attributes and characteristics cannot, however, solely reveal attitudes toward and intention to use (Davis, 1989; Fishbein & Ajzen, 1975).

3. Research design and method

We developed a questionnaire based on our literature review following Straub's guidelines (Straub, 1989) to derive relevant factors for our categorization. Since high consistency and reliability are desirable, we adapted proven constructs, indicators, and their items from previously validated studies. During the development process set out in our study, we created item pools for each construct. We adjusted and redefined the item pools according to the following procedures: First, we asked experts to check the questionnaire, providing clarity about the target constructs' relevance (MacKenzie et al., 2011). Second, we undertook a card-sorting and item-ranking exercise to ensure the measurement model's quality. The constructs' convergence and divergence were therefore to be assessed (Moore & Benbasat, 1991). Next, to perform our cluster analysis with R, we conducted a confirmatory factor analysis using SPSS AMOS 28. The model parameters were determined using the maximum likelihood method. The computed factor scores were applied for our cluster analysis to reveal heterogeneous employees' groups (Ketchen & Shook, 1996) and to derive meaningful and interpretable clusters. Except for a few, for example, demographic data, all our items were evaluated using five-point Likert-type scales. Our constructs included attitudes and opinions operationalized by means of reflective measures.

The survey instrument was field tested under real conditions via an online-based survey in early March 2022 in Germany. In spring 2022, the data collection took place for five weeks and resulted in a convenience sample of n=316 respondents, with fully completed online surveys. We assessed a completion rate of 78%. Sixty-two percent of the respondents are female, 37% are male, 1% are diverse. We noted an average age of 44 years. The sample used for this study affirmed a high educational level, with 61% having attained a university degree. We could not find significant differences between early and late respondents when it came to the respondents' answers to the questionnaire, suggesting that the nonresponse bias's threat could be excluded. Since not all the questions were mandatory, we ran a data imputation using 5,000 iterations (McKnight, 2007) to handle the missing data. However, we had to exclude two data sets during the data cleaning, as the response time was less than five minutes. After the data cleaning, n=314 records remained. With this data set, we conducted our factor and cluster analysis. To estimate the number of clusters, we used the R package NbClust (Charrad et al., 2014). The results indicated four clusters including six constructs which were then used in k-means to evaluate our data (Kuncheva et al., 2006).

4. Data analysis and results

4.1. Factor analysis

By examining the factor loadings, the results demonstrated that all loadings exceed the threshold of 0.6 (Bagozzi & Yi, 1988). Furthermore, we analyzed the constructs' reliability, convergent validity, as well as discriminant validity, and undertook several measures to assure a valid measurement model (Hair et al., 2017). All our constructs exceed the recommended threshold for the composite reliability of 0.7 (Nunnally, 1979) and for the maximal reliability (MaxR(H)). We assessed the minimum for the average variance extracted (AVE) of 0.5. Finally, the discriminant validity, measured by the maximum shared variance (MSV) (Hair, 2010), was successfully approved by AVE values of each latent construct higher than the corresponding MSV. Considering these results, it is evident that all our indicators exceed the required thresholds. Table 1 demonstrates these results.

Table 1. Results factor analysis.

Factors	CR	AVE	MaxR(H)
Social comparison	.940	.888	.944
Perceived autonomy	.908	.711	.910
Self-monitoring	.848	.651	.856
Perceived usefulness	.903	.703	.930
Perceived ease of use	.756	.509	.760
Behavior intention	.942	.802	.956

Note: CR = composite reliability, AVE = average variance extracted, MaxR(H) = maximal reliability

Finally, all of our constructs exceed the recommended threshold for the Cronbach's alpha of 0.70 (Nunnally & Bernstein, 2008), indicating high internal consistency of the constructs.

4.2. Cluster analysis

With the cluster analysis, we intended to obtain insights on the applicability of our variables to derive meaningful and interpretable clusters. The determination of the data basis, the data cleaning, as well as the measurement model's validation improved the results' value and quality (Fayyad et al., 1996). Furthermore, we passed several rounds for the algorithm's selection, the data mining, and the interpretation of our results (Fayyad et al., 1996) to discover the most relevant categorization. In total, we used six clustering methods (HAC Ward, DIANA, k-means, PAM, mclust, fuzzy c-means) and compared them when it came to our research endeavor's added value. We decided to continue with k-means and determined an overall average silhouette coefficient of 0.29. As a result of this process, we were able to derive four different employees' clusters shown in Table 2.

Cluster 1 includes 86 employees with a slightly averse tendency to engage in self-quantifying in occupational settings. This group neither develops a behavior intention nor perceives any usefulness and autonomy of or while self-quantifying at work. However, in general, these employees do not entirely question self-monitoring. Although it appears that they are undecided, they are not so strongly opposed to social comparison. Consequently, we name these employees vigilant hesitaters.

Table 2. Results cluster analysis.

k-means	Cluster 1	Cluster 2	Cluster 3	Cluster 4	F value (ANOVA)
Social comparison	-0.047	1.039	-0.790	-0.868	124.465
Perceived autonomy	-0.731	0.581	-1.894	0.434	230.918
Self-monitoring	-0.310	0.489	-1.815	0.152	134.440
Perceived usefulness	-0.741	0.554	-2.043	0.501	171.389
Perceived ease of use	-0.365	0.255	-1.079	0.281	59.232
Behavior intention	-1.083	0.718	-2.157	0.645	282.810

Cluster 2 includes 105 employees, and all factor scores are above the average zero mean. These employees have a distinct motivation to engage in self-quantifying, and they also perceive its usefulness. Similarly, they develop a positive behavior intention. This group also has an affinity toward observing and monitoring their health behavior and aim to engage with little effort and expense. Above all, these employees appreciate social comparison. We name them open-minded improvers, as they are interested in improving their preventive health behavior and well-being at work.

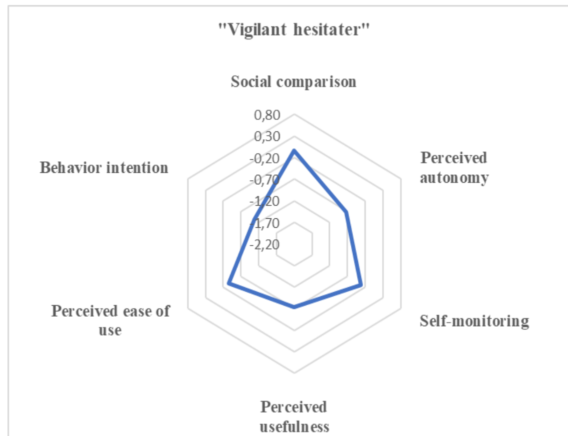
Cluster 3 includes only 22 employees who have the opposite preferences and share no similarities with Cluster 2. This group, i.e. Cluster 3, has the lowest factor scores. Consequently, these employees do not perceive any usefulness of occupational self-quantifying. This is also reflected in the negative results of behavior intention. Moreover, their interest in monitoring their health behavior is vague. They do not intend to compare their results and compete within their team at work. Consequently, we call them skeptic independents.

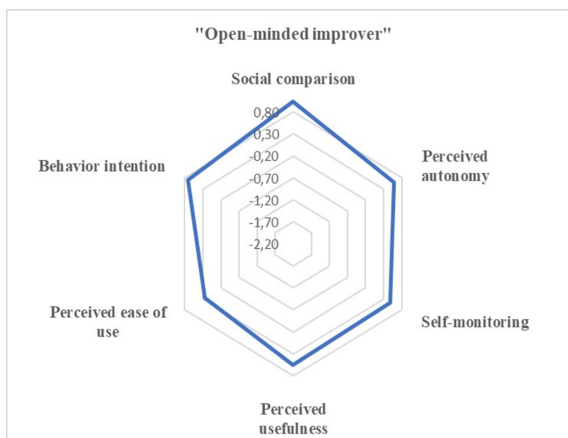
Cluster 4 includes 101 employees. This group, the conscious pragmatists, represents a rather neutral stand. It appears that these employees perceive self-quantifying as useful. They will very likely engage, and perceive self-quantifying easy to use. Perceived autonomy plays an essential role to them. This group indicates that the digital documentation and monitoring of health behavior is conceivable for them. Interestingly, these employees are not willing to compare their health performance with others. Our employees' types including a short description is shown in Table 3.

Table 3. Employees' types.

Types	Definition
Vigilant hesitater (n=86)	Susceptible to usefulness and engagement, not so strongly averse to social comparison
Open-minded improver (n=105)	Not susceptible at all, strive for social comparison
Skeptic independent (n=22)	Susceptible to everything, cannot associate any benefits
Conscious pragmatist (n=101)	Susceptible to social comparison, need autonomy, value usefulness, intend to engage

The different characteristics including the measures' results are shown in Figure 1.





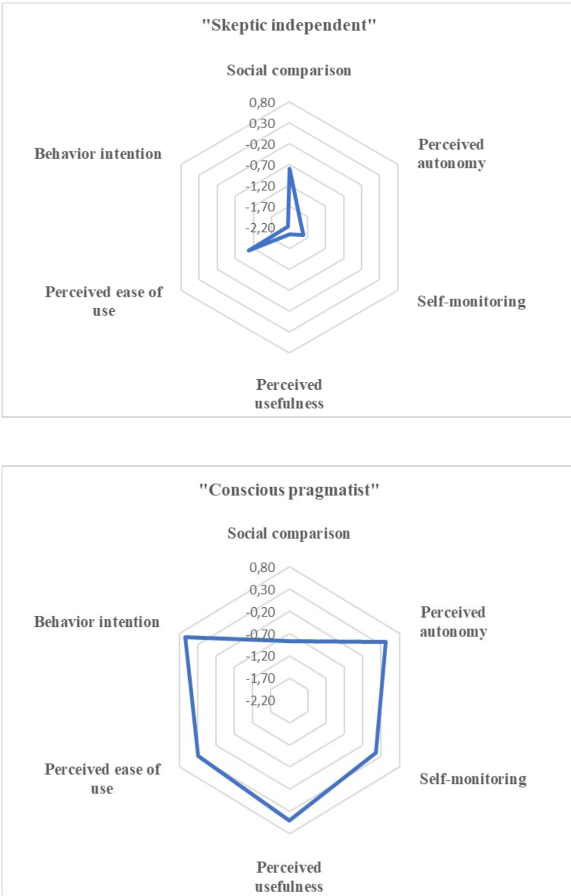


Figure 1. Radar charts of clustering results.

We iteratively process and highlight the differences in our clusters. The difference between the open-minded improvers and the conscious pragmatists is that the latter is susceptible to compete and to compare self-quantified results in a team. The vigilant hesitaters, on the other hand, are less averse to competition and comparing and could be persuaded to disclose their personal information and progresses in a team. We found that the vigilant hesitaters (with 65% in full-time jobs) have an explicit tendency to balance working from home and working in the office; most of them assess their state of physical and mental health as very good to quite good. At the same time, the skeptic independents relate to the generation consisting of persons who are 50–65 years old. While most of the open-minded improvers are younger than 45, the conscious pragmatists are predominantly older than 40. The skeptic independents assess their physical and mental health as very good to quite good. Interestingly, an above-average number of employees in this cluster works regularly, switching between working from home and working at the office. Fifty-five percent of these employees work full time. The group of open-minded improvers includes predominantly women. On average, manifested by contract, they work fewer hours per week (47% work 30–39 hours per week; 28% work over 40 hours per week) than the other groups. These employees assess their physical and mental health as quite good to very good. Sixty-nine percent of the conscious pragmatists work full time, with predominantly men within this cluster. This group assesses their state of health as follows: physically very good to quite good, mentally quite good to very good, and 14%, surprisingly, as excellent.

6. Findings and conclusion

In our study, we proposed to explore employees' types and motivation to engage in occupational self-quantifying for preventive health behavior. Keeping in mind how new work environments impacted employees, our analysis offer a solid, promising starting point, as not much is known about digital occupational health including self-quantifying in occupational settings (Hall et al., 2022; Yassaee & Mettler, 2019). Our findings present a unique perspective on employees' needs, determinants, and behavior intentions. The results, based on survey data and cluster analysis, demonstrate that the open-minded improvers and the conscious pragmatists are interested in self-care and preventive health behavior at workplaces. Nonetheless, they value the ease of use and usefulness of technologies that reveal hidden (unhealthy) patterns (Lupton, 2014) and improve their well-being. We found that, on the one hand, social comparison and the achievement of a competitive health goal play a vital role. Moreover, by triggering social comparison through, for example, setting goals, the willingness to engage in self-quantifying could be achieved for vigilant hesitaters. Interestingly, on the other hand, we discover that social comparison can influence employees and their behavior intention negatively (conscious pragmatists). The skeptic independents appear out of reach or unconvinced of self-quantifying in occupational settings. Consequently, they are not motivated to engage in preventive health behavior and well-being at work. These employees are not willing to disclose or share health data in a group to reach a outcome (Roossien et al., 2021). The conscious pragmatists perceive autonomy as important while evaluating personal progress, achieving routine, and disrupting unhealthy behavior at work (Burke et al., 2009). After all, these employees do not pursue for a stimulation from outside.

Surprisingly, we observe that the balance between working from home and the office could positively affect employees' assessment of their physical and mental health (for the vigilant hesitaters and the skeptic independents). Furthermore, employees who do not always work full time, like the open-minded improvers, embrace self-quantifying at work.

Our research emphasizes that self-quantifying is an opportunity to improve preventive health behavior at work in a particular manner (Sheeran, 2002), even if one can speak here of a mix of pushed self-tracking using persuasive computing for a behavior change (Purpura et al., 2011). Awareness of employees' preventive health behavior should not be lacking in organizations' new work environments. We recognize that there is an existing need to increase our attention on digital interventions for the care of employees, particularly through prevention that applies self-quantifying in modern organizations. Moreover, as our study concentrates on employees' health, in further research, this field should be widened towards managers or self-employed individuals. Our theoretical contribution lies in the development of an employees' typology as an instrument with which to face the different determinants for preventive health behavior in future healthy work settings. Our practical contributions lie in helping organizations that deal with impacts of digital work on their employees and transforming work patterns. These organizations are enabled to understand the triggers of employees' engagement and overcome obstacles so as to promote preventive health behavior and well-being, which, in turn, can develop into a supportive addition to the meaningfulness and quality of work (Rongen et al., 2013). Besides this, employees' voluntary self-quantifying at work is a chance to create awareness of prevention (Kim et al., 2016), reveal health-related issues, and in the long term encourage employees to exhibit alternative health behavior (Oinas-Kukkonen & Harjumaa, 2009). Furthermore, we complement the domains of occupational health and workplace health promotion, ICT (including mobile and wearable technologies), as well as the health behavior domain, by demonstrating a new and empirically-based categorization, using clustering technique. Conversely, from a critical perspective, employees' dataveillance and tracking are, however, ethically and culturally questionable (Roossien et al., 2021).

7. Limitations and further research

We propose that self-quantifying in occupational settings is a key factor for preventive health behavior in new work environments. Therefore, we intend to clarify the employees' motivation and determinants for this voluntary endeavor. We face several limitations and identify departure points for further research: We are aware that our research could not explain how behavior evolves. Furthermore, we are also acknowledge that our research could not demonstrate if self-quantifying at work exhibits a specific preventive health behavior and results in behavior changes. We could not rule out that unconscious cultural bias influence the responses and our findings. At the same time, for the k-means clustering, we had to specify the number of clusters in the beginning and only handle numerical data. We are aware of the sensitivity to clusters' outliers due to the use of mean values (Grabusts, 2011). Since we only collected data online, our results' generalization and application in other settings and contexts may be questioned (Lee & Baskerville, 2003). Our study's scope is limited due to the design, the data collection, and variables referring to a single point in time. Moreover, despite our accurate items' testing by card sorting, it appears possible that by applying items in a different cultural area, the same associations are not always made. Nevertheless, our study's design allows research endeavors to replicate, for example, in the occupational health domain.

Making use of our findings, we suggest employing personality traits, guiding perception and behavior (McCrae & John, 1992) for future research approaches. Employing personality traits could be relevant, as they can be vital components not only to design self-quantifying at workplaces but also to influence the technology's use (Barnett et al., 2015). Furthermore, we encourage to assess the effects of gamified information systems, following the gamified tasks triggering motivation and employees' engagement (Barratt, 2017) for self-quantifying. Summing up, we expect that there should be more conceptual models and insights on employees' preventive health behavior and well-being at work to handle the demands and the nature of future work environments. Consequently, within our next research project, we analyze and integrate health beliefs, based on the assumption that individuals strive to stay well and attempt to avoid perceived health threats (Becker, 1974; Rosenstock, 1974). From this project, we expect to predict the likelihood of adopting preventive health behavior at work (Rosenstock, 1974). Furthermore, scoping a longitudinal study, we claim that any behavior change might occur over a period of time to create a foundation for healthier working in demanding work environments for all those in professional settings.

8. References

Abraham, C., & Michie, S. (2008). A taxonomy of behavior change techniques used in interventions. *Health Psychology : Official Journal of the Division of Health Psychology, American Psychological Association*, *27*(3), 379–387. https://doi.org/10.1037/0278-6133.27.3.379

Ajana, B. (2017). Digital health and the biopolitics of the Quantified Self. *Digital Health*, *3*, 1-18. https://doi.org/10.1177/2055207616689509

Alam, M. (2020). Organisational processes and COVID-19 pandemic: implications for job design. *Journal of Accounting & Organizational Change*, *16*(4), 599–606. https://doi.org/10.1108/JAOC-08-2020-0121

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74–94. https://doi.org/10.1007/BF02723327

Baptista, J., Stein, M.-K., Klein, S., Watson-Manheim, M. B., & Lee, J. (2020). Digital work and organisational transformation: Emergent Digital/Human work configurations in modern organisations. *The Journal of Strategic Information Systems*, *29*(2), 101618. https://doi.org/10.1016/j.jsis.2020.101618

Barnett, T., Pearson, A. W., Pearson, R., & Kellermanns, F. W. (2015). Five-factor model personality traits as predictors of perceived and actual usage of technology. *European Journal of Information Systems*, *24*(4), 374–390. https://doi.org/10.1057/ejis.2014.10

Barratt, P. (2017). Healthy competition: A qualitative study investigating persuasive technologies and the gamification of cycling. *Health & Place*, *46*, 328–336. https://doi.org/10.1016/j.healthplace.2016.09.009

Becker, M. H. (1974). The Health Belief Model and Sick Role Behavior. *Health Education Monographs*, *2*(4), 409–419. https://doi.org/10.1177/109019817400200407

Bettiga, D., Lamberti, L., & Lettieri, E. (2020). Individuals' adoption of smart technologies for preventive health care: A structural equation modeling approach. *Health Care Management Science*, *23*(2), 203–214. https://doi.org/10.1007/s10729-019-09468-2

Bevan, S., & Cooper, C. L. (2022). *The Healthy Workforce: Enhancing Wellbeing and Productivity in the Workers of the Future*. Emerald Publishing.

Buchwald, A., Letner, A., Nils Urbach, & Matthias von Entreß-Fürsteneck (2017). Towards explaining the willingness to disclose personal self-tracking data to service providers. *Proceedings of the 25th European Conference on Information Systems*, 3071–3081. https://aisel.aisnet.org/ecis2017_rip/55

Burke, L. E., Swigart, V., Warziski Turk, M., Derro, N., & Ewing, L. J. (2009). Experiences of self-monitoring: Successes and struggles during treatment for weight loss. *Qualitative Health Research*, *19*(6), 815–828. https://doi.org/10.1177/1049732309335395

Charalampous, M., Grant, C. A., Tramontano, C., & Michailidis, E. (2019). Systematically reviewing remote e-workers' well-being at work: a multidimensional approach. *European Journal of Work and Organizational Psychology*, *28*(1), 51–73. https://doi.org/10.1080/1359432X.2018.1541886

Charrad, M., Ghazzali, N., Boiteau, V., & Niknafs, A. (2014). NbClust: An R Package for Determining the Relevant Number of Clusters in a Data Set. *Journal of Statistical Software*, *61*(6), 1–36. https://doi.org/10.18637/jss.v061.i06

Cheung, K. L., Hors-Fraile, S., & Vries, H. de (2021). How to use the Integrated-Change Model to design digital health programs. *Digital Health*, *8*, 143–157. https://doi.org/10.1016/B978-0-12-820077-3.00008-0

Choe, E. K., Lee, N. B., Lee, B., Pratt, W., & Kientz, J. A. (2014). Understanding quantified-selfers' practices in collecting and exploring personal data. In M. Jones, P. Palanque, A. Schmidt, & T. Grossman (Eds.), *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1143–1152). ACM. https://doi.org/10.1145/2556288.2557372

Cohen, J. S., Edmunds, J. M., Brodman, D. M., Benjamin, C. L., & Kendall, P. C. (2013). Using Self-Monitoring: Implementation of Collaborative Empiricism in Cognitive-Behavioral Therapy. *Cognitive and Behavioral Practice*, *20*(4), 419–428. https://doi.org/10.1016/j.cbpra.2012.06.002

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

DeJoy, D. M., & Wilson, M. G. (2003). Organizational Health Promotion: Broadening the Horizon of Workplace Health Promotion. *American Journal of Health Promotion*, *17*(5), 337–341. https://doi.org/10.4278/0890-1171-17.5.337

Diener, E., & Seligman, M. E. P. (2004). Beyond Money: Toward an Economy of Well-Being. *Psychological Science in the Public Interest : A Journal of the American Psychological Society*, *5*(1), 1–31. https://doi.org/10.1111/j.0963-7214.2004.00501001.x

Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). From Data Mining to Knowledge Discovery in Databases. *AI Magazine*, *17*(3), 37. https://doi.org/10.1609/aimag.v17i3.1230

Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research*. *Addison-Wesley series in social psychology*. Addison-Wesley.

Giddens, L., Leidner, D., & Gonzalez, E [E.] (2017). The Role of Fitbits in Corporate Wellness Programs: Does Step Count Matter? *Proceedings of the 50th Hawaii International Conference on System Sciences*, 3627–3635. 10.24251/HICSS.2017.438

Gonzalez, E [Ester], & Mitra, S. (2019). Wearable Technologies: The Motivational Impacts on Individual Well-Being. *Proceedings of 25th Americas Conference on Information Systems*. https://aisel.aisnet.org/amcis2019/healthcare_it/healthcare_it/18

Grabusts, P. (2011). Distance Metrics Selection Validity in Cluster Analysis. *Scientific Journal of Riga Technical*

University Computer Sciences, *45*(1). https://doi.org/10.2478/v10143-011-0045-y

Hair, J. F. (2010). *Multivariate data analysis*. Prentice Hall.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). SAGE.

Hall, K., Oesterle, S., Watkowski, L., & and Liebel, S. (2022). A Literature Review on the Risks and Potentials of Tracking and Monitoring eHealth Technologies in the Context of Occupational Health Management. In *Wirtschaftsinformatik*. https://aisel.aisnet.org/wi2022/digital_health/digital_health/9

Harrison, J. A., Mullen, P. D., & Green, L. W. (1992). A meta-analysis of studies of the Health Belief Model with adults. *Health Education Research*, *7*(1), 107–116. https://doi.org/10.1093/her/7.1.107

Herath, T., & Herath, H. S. B. (2020). Coping with the New Normal Imposed by the COVID-19 Pandemic: Lessons for Technology Management and Governance. *Information Systems Management*, *37*(4), 277–283. https://doi.org/10.1080/10580530.2020.1818902

Keeman, A., Näswall, K., Malinen, S., & Kuntz, J. (2017). Employee Wellbeing: Evaluating a Wellbeing Intervention in Two Settings. *Frontiers in Psychology*, *8:505*. https://www.frontiersin.org/article/10.3389/fpsyg.2017.00505

Ketchen, D. J., & Shook, C. L. (1996). The Application of Cluster Analysis in Strategic Management Research: An Analysis and Critique. *Strategic Management Journal*, *17*(6), 441–458. http://www.jstor.org/stable/2486927

Kim, Y., Park, J., & Park, M. (2016). Creating a Culture of Prevention in Occupational Safety and Health Practice. *Safety and Health at Work*, *7*(2), 89–96. https://doi.org/10.1016/j.shaw.2016.02.002

Kudyba, S. (2020). COVID-19 and the Acceleration of Digital Transformation and the Future of Work. *Information Systems Management*, *37*(4), 284–287. https://doi.org/10.1080/10580530.2020.1818903

Kuncheva, L. I., Vetrov, & D. P. (2006). Evaluation of Stability of k-Means Cluster Ensembles with Respect to Random Initialization. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *28*(11), 1798–1808. https://doi.org/10.1109/TPAMI.2006.226

Lee, A. S., & Baskerville, R. (2003). Generalizing Generalizability in Information Systems Research. *Information Systems Research*, *14*(3). 10.1287/isre.14.3.221.16560

Lu, Y., Tan, B. C. Y., & Hui, K. L. (2004). Inducing Customers to Disclose Personal Information to Internet Businesses with Social Adjustment Benefits. *ICIS 2004 Proceedings*, *45*, 571–582. https://aisel.aisnet.org/icis2004/45

Lupton, D. (2014). Self-tracking cultures: towards a sociology of personal informatics. *Proceedings of the 26th Australian Computer-Human Interaction Conference on Designing Futures: The Future of Design*, 77–86. https://doi.org/10.1145/2686612.2686623

Lupton, D. (2016). The diverse domains of quantified selves: self-tracking modes and dataveillance. *Economy and Society*, *45*(1), 101–122. https://doi.org/10.1080/03085147.2016.1143726

MacKenzie, S., Podsakoff, P., & Podsakoff, N. (2011). Construct Measurement and Validation Procedures in MIS and Behavioral Research: Integrating New and Existing Techniques. *MIS Quarterly*, *35*(2), 293–334. https://doi.org/10.2307/23044045

McCrae, R. R., & John, O. P. (1992). An introduction to the five-factor model and its applications. *Journal of Personality*, *60*(2), 175–215. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

McKnight, P. E. (2007). *Missing data a gentle introduction*. Guilford Press.

Mercer, K., Li, M., Giangregorio, L., Burns, C., & Grindrod, K. (2016). Behavior Change Techniques Present in Wearable Activity Trackers: A Critical Analysis. *JMIR MHealth and UHealth*, *4*(2), e40. https://doi.org/10.2196/mhealth.4461

Moore, G. C., & Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research*, *2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

Naci, H., & Ioannidis, J. P. A. (2015). Evaluation of Wellness Determinants and Interventions by Citizen Scientists. *JAMA*, *314*(2), 121–122. https://doi.org/10.1001/jama.2015.6160

Noar, S. M., Chabot, M., & Zimmerman, R. S. (2008). Applying health behavior theory to multiple behavior change: Considerations and approaches. *Preventive Medicine*, *46*(3), 275–280. https://doi.org/10.1016/j.ypmed.2007.08.001

Nunnally, J. C. (1979). An Overview of Psychological Measurement. In B. B. Wolman (Ed.), *Clinical Diagnosis of Mental Disorders: A Handbook* (pp. 97–146). Springer US. https://doi.org/10.1007/978-1-4684-2490-4_4

Nunnally, J. C., & Bernstein, I. H. (2008). *Psychometric theory* (3rd ed.) *McGraw-Hill series in psychology*. McGraw-Hill.

Oinas-Kukkonen, H., & Harjumaa, M. (2009). Persuasive Systems Design: Key Issues, Process Model, and System Features. *Communications of the Association for Information Systems*, *24*(1). https://doi.org/10.17705/1CAIS.02428

Orji, R., & Moffatt, K. (2016). Persuasive technology for health and wellness: State-of-the-art and emerging trends. *Health Informatics Journal*, *24*(1), 66–91. https://doi.org/10.1177/1460458216650979

Purpura, S., Schwanda Sosik, V., Williams, K., Stubler, W., & Sengers, P. (2011). Fit4Life: The design of a persuasive technology promoting healthy behavior and ideal weight. *Proceedings of the SIGCHI Conference*, 423–432. https://doi.org/10.1145/1978942.1979003

Richter, A. (2020). Locked-down digital work. *International Journal of Information Management*, *55*, 102157. https://doi.org/10.1016/j.ijinfomgt.2020.102157

Rongen, A., Robroek, S. J., van Lenthe, F. J., & Burdorf, A. (2013). Workplace Health Promotion: A Meta-Analysis of Effectiveness. *American Journal of Preventive Medicine*, *44*(4), 406–415. https://doi.org/10.1016/j.amepre.2012.12.007

Roossien, C. C., Jong, M. de, Bonvanie, A. M., & Maeckelberghe, E. L. M. (2021). Ethics in Design and Implementation of Technologies for Workplace Health Promotion: A Call for Discussion. *Frontiers in Digital Health*, *3*, 106. https://doi.org/10.3389/fdgth.2021.644539

Rosenstock, I. M. (1974). The Health Belief Model and Preventive Health Behavior. *Health Education Monographs*, *2*(4), 354–386. https://doi.org/10.1177/109019817400200405

Schulte, P. A., Pandalai, S., Wulsin, V., & Chun, H. (2012). Interaction of occupational and personal risk factors in workforce health and safety. *American Journal of Public Health*, *102*(3), 434–448. https://doi.org/10.2105/AJPH.2011.300249

Sheeran, P. (2002). Intention—Behavior Relations: A Conceptual and Empirical Review. *European Review of Social Psychology*, *12*(1), 1–36. https://doi.org/10.1080/14792772143000003

Straub, D. (1989). Validating Instruments in MIS Research. *MIS Quarterly*, *13*(2), 147–169. https://doi.org/10.2307/248922

Sun, Y., Wang, N., Guo, X., & Peng, Z. (2013). Understanding the acceptance of mobile health services: A comparison and integration of alternative models. *Journal of Electronic Commerce Research*, *14*(2), 183–200. https://www.researchgate.net/publication/287867125_Understanding_the_acceptance_of_mobile_health_services_A_comparison_and_integration_of_alternative_models/citation/download

Swan, M. (2012). Sensor Mania! The Internet of Things, Wearable Computing, Objective Metrics, and the Quantified Self 2.0. *Journal of Sensor and Actuator Networks*, *1*(3), 217–253. https://doi.org/10.3390/jsan1030217

Swan, M. (2013). The Quantified Self: Fundamental Disruption in Big Data Science and Biological Discovery. *Big Data*, *1*(2), 85–99. https://doi.org/10.1089/big.2012.0002

Venkatesh, Morris, & Davis (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Waizenegger, L., McKenna, B., Cai, W., & Bendz, T. (2020). An affordance perspective of team collaboration and enforced working from home during COVID-19. *European Journal of Information Systems*, *29*(4), 429–442. https://doi.org/10.1080/0960085X.2020.1800417

Wessels, C., Schippers, M. C., Stegmann, S., Bakker, A. B., van Baalen, P. J., & Proper, K. I. (2019). Fostering Flexibility in the New World of Work: A Model of Time-Spatial Job Crafting. *Frontiers in Psychology*, *10:505*. https://doi.org/10.3389/fpsyg.2019.00505

World Health Organization, & Burton, J. (2010). *Who healthy workplace framework and model: Background and supporting literature and practices*. World Health Organization. https://apps.who.int/iris/handle/10665/113144

Yassaee, M., & Mettler, T. (2019). Digital Occupational Health Systems: What Do Employees Think about it? *Information Systems Frontiers*, *21*(4), 909–924. https://doi.org/10.1007/s10796-017-9795-6

Zhang, J., & Lowry, P. B. (2016). Designing Quantified-Self 2.0 Running Platform To Ensure Physical Activity Maintenance: The Role Of Achievement Goals And Achievement Motivational Affordance. *Proceedings of 20th Pacific Asia Conference on Information Systems*, 1–11. https://www.researchgate.net/publication/307263660_Designing_Quantified-Self_20_Running_Platform_To_Ensure_Physical_Activity_Maintenance_The_Role_Of_Achievement_Goals_And_Achievement_Motivational_Affordance