MASTER

Health and comfort in the smart office

Understanding office workers’ preferences for assessment tools

Groß, Marcel L.

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Health and comfort in the smart office: Understanding office workers' preferences for assessment tools

M.L. (Marcel) Groß – 1740180

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First supervisor	Dr.ir. H.A.J.A. (Rianne) Appel-Meulenbroek Real Estate Management and Development Eindhoven University of Technology
Second supervisor	Sophie Schuller Real Estate Management and Development Eindhoven University of Technology
Third supervisor	Dr. Dujuan Yang Information Systems in the Built Environment Eindhoven University of Technology

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Summary

Digital transformation significantly impacts various societal aspects, including the domain of the built environment (Thomas, 2020). Smart technologies promote the “application of data to drive autonomous controls […] to deliver improved health, wellness, human performance, comfort, efficiency, safety and security” (Nelson et al., 2022, p. 326). Smart technologies which involve the acquisition, analysis and application of data (Zhang et al., 2022) are also being integrated into workplaces, transforming them into smart offices. This research focuses on those that assess the health and comfort of office workers which is a scarcely researched subdivision of smart offices (Papagiannidis & Maeikyan, 2020). Thus, this thesis is predominantly an exploratory research trying to contribute to this research gap.

Improving working conditions and office workers’ satisfaction is a growing priority for many employers (Attaran, 2017; Brugmans et al., 2017). Related to that is the health and comfort in the office which are important concerns among office workers and their employers promoting this for them (Borsos et al., 2021). Consequently, it seems especially relevant to investigate assessment tools, which in this study can be defined as instruments and methodologies used to acquire, analyse and apply data to promote the two objectives of health and comfort in the office. Since these assessment tools are mostly implemented for the benefit of the office workers, understanding their preferences towards these tools is critical for a successful office design (De Been & Beijer, 2014; Kim & de Dear, 2012). That said, little research is done regarding the opinions of office workers themselves about these assessment tools.

This research focuses on two main constructs: First, based on the literature review, the types of assessment tools and which characteristic attributes of these tools office workers prefer are analysed. In particular, four assessment tools that are especially representative of tools existing in real offices and are distinguishable by their level of smartness are identified: surveys, smartphone app-based surveys, room-mounted sensors, and wearables. Which specific health and comfort aspects these tools should address from the viewpoint of the office workers are derived from the literature review. The sedentary behaviours, stress levels, as well as lighting, temperature, and noise conditions are concluded to be the five most prominent aspects of office workers’ health and comfort in the office environment. Second, the literature reveals that the perception of the assessment tools is influenced by various personal characteristics of office workers, such as their perceptions of health and comfort regarding their current office environments, their demographic backgrounds (age, gender, origin, education

level) and their previous experiences (with assessment tools and with digital devices, as well as their attitudes towards data privacy). Thus, the main research question is formulated as follows:

> *How do attributes of assessment tools and personal characteristics relate to office workers' preferences for assessment tools assessing their health and comfort in the office?*

An online questionnaire is developed for this exploratory research that is distributed within personal and professional networks. 46 responses from office workers predominantly from the Netherlands and Germany are included in the descriptive and bivariate analysis.

The analysis reveals a generally positive attitude of office workers towards tools providing (very) personalised outputs, measuring environmental and bodily parameters, utilising artificial intelligence, and collecting data via the smartphone. A high accuracy of tools and frequent data measurements are also viewed favourably among office workers. Conversely, a neutral opinion exists towards tools tracing movement patterns, the responsibility of data collection (internal vs. external party), and the method of data collection (self-reported vs. automatic). Office workers express dislike if personal information is collected and if measurements take place directly on the body.

Many of the tools' specific attributes significantly impact their desirability among office workers – if the tool's attributes are perceived positively, it is likely that this assessment tool as a whole is rated positively. Smarter tools, such as wearables, offer substantial benefits but are perceived as more intrusive. The trade-offs between these attributes relate to how tools are ranked and which ones workers prefer to have in their offices. Notably, office workers prefer room-mounted sensors for assessing comfort aspects, while wearables are favoured for measuring health aspects despite the fact this tool collects personal information directly on the body. Thus, a general preference for smarter tools seems to exist. Wearables are an outlier, being preferred for health but not comfort. Surveys are also widely accepted despite their unfavourable ranking, suggesting that non-smart tools are less polarising compared to smart tools. That said, a majority of office workers favour having surveys, smartphone apps, and room sensors present in the office and would like to have all five major health and comfort aspects addressed by these tools.

While attributes of assessment tools majorly relate to office workers' preferences, personal characteristics like demographics also play a role. Interestingly, relatively older office workers (the mean age of the sample being 32.7 years) show greater favour towards advanced tools, and women tend to be more supportive of wearables and prefer their own organisation to be in charge of data collection. If office workers are already pleased with the health and comfort in their office, they are less inclined to favour tools that address their health and comfort. While these insights contribute new findings to existing literature, other variables like the origin and education level of office workers, contrary to prior findings in the literature, do not seem to have a relationship with office workers' perceptions within this sample. Similarly surprising is that previous experiences with tools as well as office workers' technology savviness and attitude towards data privacy do not consistently predict preferences, which challenges the initial expectations.

The findings are intended to help workplace managers and assessment tool manufacturers in creating more favourably received assessment tools providing a higher utility to office workers. When introducing assessment tools in the office, a gradual implementation to get office workers acquainted with the tools while paying attention to their different personal needs and concerns can enhance the usage of the assessment tools. While there is no one-size-fits-all solution, tool manufacturers should minimise intrusiveness while maximising the personal insights of tools. Making tools more customisable for the individual while prioritising data privacy is a possible design strategy.

The study has several limitations. The sample is relatively small and biased towards highly educated, relatively young office workers from the Netherlands and Germany. The risk of confounding variables and underlying biases because of the chosen methodology moreover limits the validity of the insights, resulting in, amongst other aspects these key takeaways for future research efforts: a larger, more diverse sample, incorporating qualitative or mixed methods, and exploring additional variables.

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1. Introduction

Digitalization has a major influence on almost every aspect of society (Thomas, 2020). The built environment is no exception to that. An often-cited concept within this context is the term ‘smartness’. This attribute is often associated with the city or the building (Froufe et al., 2020) but is also used on a smaller spatial scale level. A prominent example is the smart home which is subject to extensive research efforts (Mozer, 2005; Marikyan et al., 2019). Despite the steadily rising number of related scientific publications on this topic, comparatively little research can be found about smartness in relation to the workplace (Marikyan et al., 2019). Where research exists, office buildings are typically researched the most (Remes et al., 2022), but other workplaces, such as construction sites (Huo, 2020; Patel et al., 2022; Zhang et al., 2023) are also considered.

Smart offices are becoming increasingly popular (Nanayakkara et al., 2020). As part of the smart building domain, they promote the “application of data to drive autonomous controls […] to deliver improved health, wellness, human performance, comfort, efficiency, safety and security” (Nelson et al., 2022, p. 326). The application of data refers to a multi-layered concept that includes the acquisition, analysis and finally the application of data (Zhang et al., 2022). Moreover, this definition includes different beneficiaries of smart office technologies which cannot just be the building owner or the environment but also the users of the spaces (Froufe et al., 2020). The group of users can be split into the employers and their employees as their interests are not necessarily the same. Of course, companies expect a return on their investment either through direct benefits such as a reduction of costs for the building operation (Brugmans et al., 2017) or by boosting office workers’ productivity (Papagiannidis & Marikyan, 2020; Remes et al., 2022; Van der Valk et al., 2015). However, many studies reveal that employers tend to introduce such technologies with the primary purpose of improving the working conditions and satisfaction of the office workers which in turn could of course boost their productivity (Attaran, 2017; Brugmans et al., 2017; Papagiannidis & Marikyan, 2020).

It, therefore, seems especially relevant to further evaluate office workers as a subgroup of beneficiaries of smart technologies in the office. Recent developments such as the Covid-19 pandemic reveal feasible alternatives to the office as a workplace for office workers such as teleworking, leaving many office spaces vacant to this day (Barnes & Ferris, 2023). As office workers often do not view working in the office as a necessity anymore (Gibson et al., 2023), the resulting lack of attendance may cause concerns for companies. Vital elements of working in the office such as collaboration, informal meetings and spontaneous social interactions between office workers are limited if interactions only occur online (Smite et al., 2023). Thus, it comes as no surprise that companies put an increasing effort into improving the experience office workers have in their office spaces as one component of persuading them to come back into the office more regularly (Appel-Meulenbroek et al., 2022). Offering a lot of potential benefits to office workers, smart technologies can become a part of this strategy. As user preferences, perceptions and adoption are central to the success of any office design (De Been & Beijer, 2014; Kim & de Dear, 2012; Tuzcuoğlu et al., 2023), examining office workers' preferences about smart technologies is crucial.

These technologies address a wide range of purposes such as enhancing social behaviour and collaboration (Kim et al., 2012; Mićić et al., 2022), increasing happiness (Yano et al., 2015), safety (Moshawrab et al., 2022), productivity (Papagiannidis & Marikyan, 2020; Remes et al., 2022; Van der Valk et al., 2015), improving space utilization (Clark et al., 2018; Valks et al., 2021), and health and comfort (He & Agu, 2014; Koldijk, 2012; Mateevitsi et al., 2014; Muaremi et al., 2013).

The office environment is responsible for a whole range of health and comfort-related concerns for its occupants (Zhang et al., 2022). In line with the generally rising public awareness of those issues (Borsos et al., 2021), experts believe that it is important to incorporate health as a major quality within the office environment in the future (Nanayakkara et al., 2021).

Consequently, this study specifically focuses on instruments and methodologies that acquire, analyse and apply data (a three-layered architecture introduced by Zhang et al., 2022) to improve the health and comfort of office workers. While smart technologies can fulfil these objectives, other comparable methodologies such as surveys that may not satisfy the above introduced standards of smartness by Nelson et al. (2022) try to achieve those results too. The goal of this research is to find out about office workers' preferences towards the instruments and methodologies that can be considered relatively smart but also those that would not necessarily be labelled smart. This allows for a comparison between the preferences towards these very different configurations. Whether being smart or not, these instruments and methodologies are combined under the term assessment tools in this study.

Health and comfort-related assessment tools focus on a quite diverse set of aspects (why these in particular are chosen is described in the literature review). Relevant aspects that they try to tackle, amongst other things, are stress levels, sedentary behaviours, temperature, lighting and noise conditions for workers in the office environment. As different assessment tools often prioritize only a limited number of those health and comfort-related aspects, it is especially interesting to know which of them, not just which health and comfort aspects but also which assessment tools that address those, are actually most preferred. Moreover, it is intriguing to find out in how far these preferences for assessment tools differ depending on which health and comfort aspects are addressed. Amongst other things, such insights could help workplace managers put a higher priority on implementing certain tools (over others) that focus on specific health and comfort aspects. While other studies underline the importance of health and comfort to office workers (e.g., Borsos et al., 2021), to my knowledge research is scarce that takes the next step to derive which of these 5 major health and comfort-related aspects of assessment tools are preferred over the others by the office workers. Schall et al. (2018) compare different health risk factors that health professionals would be most interested in having captured by wearable sensors at their workplaces. However, as this study is restricted to wearables, a lot of health and comfort-related outcomes are not covered and only a specific user group (health professionals) is addressed.

Instead, this thesis compares a broader range of tools, preferences and experiences among office workers in general - a much bigger user group compared to studies such as Schall et al. (2018). As such, this research is not just about wearables, but also room-mounted sensors controlling (among other things) the climate in the rooms, personalized surveys integrated into smartphone apps and more conventional, anonymized surveys are included. These are 4 types of assessment tools derived from the literature review that are (or are becoming) relatively common in offices in relation to measuring the health and comfort of office users.

To gain a deeper understanding of if, and why, certain tools are preferred over others and to potentially improve the setup of particular assessment tools, it is important to investigate the attitude towards the specific attributes of the tools as well. Donkers et al. (2023) for instance choose attributes like the level of automatization of the assessment tools to then investigate for which assessment tools which level of automatization is most preferred. To my knowledge, this has not yet been done for a wider range of tool attributes within a single study. Thus, this study compares office workers' perceptions towards 9 different attributes typical for the chosen assessment tools. The specification of the attributes varies between the different assessment tools and should either be perceived positively by office workers (a high range of outputs (Mani & Chouk, 2017) and a high accuracy) or negatively (measurements in close proximity to the user (Raff & Wentzel, 2023) and a large quantity of collected personal information (Gorn & Shklovski, 2016; Harper et al., 2022; Lai et al., 2003; Teebken & Hess, 2021; Zieglmaier et al., 2022). For some attributes, it is unclear how office workers perceive them at all or whether they perceive them positively or negatively. This concerns whether data is measured or self-reported, the frequency of assessments, which organization is responsible for the assessments, the level of technological intelligence but also the level of automatization (Ahmadi-Karvigh et al., 2017; Day et al., 2019; Donkers et al., 2023; Kwon et al., 2019; Lashina et al., 2019; Tuzcuoğlu et al., 2023).

What becomes clear from existing literature on these different attributes of assessment tools is that a higher level of smartness does not necessarily mean better, from the viewpoint of the office workers. The 'very smart' tools such as smartphone apps or wearables, for instance, can often provide more finely-grained, detailed, personalised and accurate insights (e.g., Martire et al., 2018; Movebite, 2023; Noon, n.d.; Pina et al., 2012; Salamone et al., 2018) but there is a chance that this is being considered as more intrusive by the users. Intrusion here refers to what Raff & Wentzel (2023) frame as technology that breaches the boundary to the private. This multidimensional concept not just refers to the office workers' data privacy which is challenged when implementing such assessment tools causing concerns (Collins & Marassi, 2021). The physical presence of technology adds another dimension to the term intrusion (Raff & Wentzel, 2023). Users of smart home technology describe this feeling for instance as "hosting an invisible guest at home" (Raff & Wentzel, 2023, p. 5). Perceiving technology as intrusive can therefore also be caused by specific placements of the technology and its proximity to the user. Interestingly, these more advanced smart office technologies are generally placed in closer proximity to the user by being installed on the desk (Mateevitsi et al., 2014), chair (Hu et al., 2020), computer (Muaremi et al., 2013) or even on the office worker's body itself through wearables (Martire et al., 2018; Pina et al., 2012; Salamone et al., 2018).

Office workers' personal characteristics are supposedly influential too in how office workers perceive the assessment tools. These include office workers' perception of health and comfort in their current office, their perception of the 5 health and comfort aspects, their demographics (gender (Jacobs et al., 2019); age (Röcker, 2010); education level (Röcker, 2010); and origin (Cvrcek et al., 2006; Röcker, 2010)) and their previous experiences with the assessment tools. Lastly, office workers' attitudes, towards data privacy and their technology savviness (Mani & Chouk, 2017) could also relate to the perception of the assessment tools. As a result of these findings, my research addresses the research questions introduced in chapter 1.1.

1.1 Research questions

Main question

How do attributes of assessment tools and personal characteristics relate to office workers' preferences for assessment tools assessing their health and comfort in the office?

Subquestions

1) *What are relevant aspects of office workers' health and comfort in the office to assess with assessment tools?*
2) *Which types of office-related health and comfort assessment tools can be distinguished?*
3) *Which attributes of assessment tools might determine office workers' preferences?*
4) *Which personal characteristics might determine office workers' preferences?*
5) *Which types of assessment tools are preferred by office workers for measuring their health or comfort in the office?*
6) *How do attributes of assessment tools relate to office workers' preferences for health and comfort assessment tools?*
7) *How do personal characteristics relate to office workers' preferences for health and comfort assessment tools?*

1.2 Methodology

As smart offices are a scarcely researched domain (Papagiannidis & Maeikyan, 2020), this research contains many exploratory elements to try to fill existing research gaps. A questionnaire is designed for this research that is analysed with descriptive and bivariate statistics to find out more about office workers' perception of the health and comfort assessment tools and to gain information about their personal characteristics. This methodology is commonly used in workplace-related research to gain relatively large amounts of quantitative information in an effective way and to collect the preferences and opinions of workplace occupants (Appel-Meulenbroek et al., 2018). This approach aligns well with the research objectives and allows to identify patterns, trends and correlations, which are crucial to answering the research questions comprehensively. The questionnaire is distributed to office workers within the personal and professional networks of the researcher.

1.3 Outline

This thesis is structured into seven chapters. Following this introduction, chapter 2 starts with a short introduction to smart offices by exploring the concept of "smartness" within the built environment (chapter 2.1). In chapter 2.2, common assessment tools of different levels of smartness that address the five key health and comfort aspects in office environments are reviewed. Chapter 3 investigates factors influencing how office workers perceive the assessment tools introduced in chapter 2. These perceptions are influenced by both the specific characteristics of the assessment tools (chapter 3.2) and the personal characteristics of the office workers (chapter 3.3). The chapter concludes with the conceptual model (chapter 3.4) that is the basis of the research design explained in chapter 4. This methodology chapter explains the rationale behind the chosen approach (chapter 4.1). The data collection process is described in chapter 4.2, including a detailed description of the variables and questions used in the questionnaire (chapter 4.3). Additionally, the chapter covers the assessment of reliability and validity, as well as steps taken to ensure internal consistency (chapter 4.4), the data cleaning and preparation (chapter 4.5), and how the subsequent data analysis is done (chapter 4.6). One part of the data analysis is the descriptive analysis (chapter 5). It includes two subchapters. One addresses the personal characteristics of respondents (chapter 5.1) and the other focuses on their perceptions of health and comfort assessment tools (chapter 5.2). Chapter 6 is about the bivariate analysis that identifies relationships between the various variables. It explores connections between assessment tool characteristics and office workers' perceptions of the tools (chapter 6.1), between office workers' personal characteristics and their perception (chapter 6.2), and between personal characteristic variables (chapter 6.3). The final chapter 7 provides a comprehensive conclusion and discussion of the thesis findings. It addresses the research questions (chapter 7.1), discusses the study's limitations, and offers recommendations for future research (chapter 7.2) and practical applications (chapter 7.3).

2. The smart office

2.1 Defining smartness in the context of the built environment

The built environment is majorly impacted by digitalization (Thomas, 2020). Many different technologies are being developed for diverse purposes within this domain. Such technologies are often labelled 'smart'. This term is commonly used in relation to various scales within the built environment with concepts such as the smart city, smart building and smart office becoming more common since at least 20 years ago (Bordel Sánchez et al., 2015; Froufe et al., 2020). These concepts are closely interrelated and therefore often evolve similarly driven by technological advancements (Froufe et al., 2020).

While there are seemingly no definitions that are dominating the discourse, this thesis is oriented towards the understanding of 'smartness' within the built environment introduced by Batov (2015), Froufe et al. (2020), Mozer (2005) and Nelson et al. (2022). According to them, smart should not be mistaken for the sole automation of technologies (Batov, 2015). Instead, what makes such technologies distinctively smart is that they are 'intelligent' (Batov, 2015). "Instead of being programmed to perform certain actions, the house essentially programs itself by monitoring the environment and sensing actions performed by the inhabitants […] and learning to predict future states of the house" (Mozer, 2005, p. 3). A smart system therefore typically requires hardware that senses the state of the environment (sensors) and software that processes specific parts of the collected information to make decisions or predict a future state (Batov, 2015). Moreover, a network connects all of the different hardware devices and software systems to create an intelligent building (Batov, 2015).

As the ultimate goal of every smart technology is to create a benefit for certain beneficiaries, Froufe et al. (2020) specifically focus on those so-called drivers to analyse what defines a smart building. Drivers are aspects like building performance, sustainability, user security and health and eventually determine which technological systems are implemented (rather than the other way around)(Froufe et al., 2020).

The 'Smart Building Collectives' definition combines the mentioned key aspects of smartness. They define smartness within buildings as the "application of data to drive autonomous controls or building automation (that brings the intelligence) to deliver improved health, wellness, human performance, comfort, efficiency, safety and security" (Nelson et al., 2022, p. 326). Application of data in this definition should be understood as a multi-layered concept as it includes the acquisition, analysis and subsequent application of data (Zhang et al., 2022). For delivering a certain output, the two layers beforehand therefore also need to be included in a smart system.

When taking a closer look at those drivers and benefits, certain main beneficiaries of smart technologies within the built environment can be derived: the environment, owners and users (Froufe et al., 2020). This research concentrates on the users and office workers in particular to contribute to the growing number of scientific articles researching user needs in smart environments.

2.2 Assessment tools

Technology plays a key part in shaping the future office experience (Nanayakkara et al., 2021). Within companies, this for instance shows itself in transformation strategies to create a digital workplace design typically supporting other goals such as collaborative and flexible work or a new work culture (Mićić et al., 2022). This trend is supported by the introduction of "smart workplace solutions" (Remes et al., 2022, p. 59). To clarify, this concept does not include the technologies (such as computer programs) that office workers are using to fulfil their main tasks at work. Our introduced definition of smartness within the built environment (see chapter 2.1) put into the context of the office rather relates to assessment tools that collect and process information about the building, the floor spaces, rooms, and workstations as well as the occupants themselves to create outputs and benefits for the environment, the building owner or the users respectively. As mentioned in the introduction (see chapter 1), this study however not only includes such relatively smart assessment tools but also comparable non-smarts counterparts that try to achieve the same objective which is why the more general term of assessment tools is utilized.

While a lot of research focuses on the assessment tools designed to benefit the building operations (Remes et al., 2022), which favours the environment and building owners, it becomes apparent that less focus is put on the tools with the user as the beneficiary (Remes et al., 2022). Different terms are introduced for that such as "user-centred" (Remes et al., 2022, p. 42) or "occupant-centric" (Djenouri et al., 2019, p. 7) but they refer to the same type of tool. The group of users can be split into the companies that occupy these spaces on the one hand and the individual office workers on the other hand. As mentioned in the introduction, office workers are the main beneficiaries of smart office technology due to the importance of improving their office experience (De Been & Beijer, 2014; Kim & de Dear, 2012;

Tuzcuoğlu et al., 2023). Thus, this thesis dives deeper into this subgroup. Within the wide variety of assessment tools, those that improve office workers' health and comfort can be derived as some of, if not the most relevant tools. When being asked about the main trends for future offices, some workplace strategists of big corporations answer that they would be "technology-driven, community-oriented, sustainability, health and wellbeing focused" (Nanayakkara et al., 2021, p. 1). Assessment tools that promote office workers' health and comfort seem to be an obvious outcome of these trends. This goes hand in hand with the increasing awareness of employers and office workers for health- and comfort related matters in their workplace (Borsos et al., 2021) which is why observing this aspect of smart offices appears to be especially relevant.

2.2.1 Overview of tools assessing aspects of office workers' health & comfort

In the previous chapters, the research focus is narrowed down to employee-centric smart office assessment tools with positive health and comfort-related outcomes for office workers. Smart office assessment tools can, in general, provide those benefits by discovering relationships between the individuals' health and various office-related features (Zhang et al., 2022). Delivering "adaptive and targeted health promotion measures for each office worker and supporting the design and optimization of organizational health-oriented measures" (Zhang et al., 2022, p. 1) is another use-case of smart tools. Because this study investigates office workers' perception towards different kinds of assessment tools with different levels of smartness, it is also interesting to include related assessment tools that are not smart following the definition of chapter 2.1 to see whether smartness itself, is a preference. Thus, the tools are referred to as health and comfort assessment tools as a more general term for the remainder of this thesis.

The architecture of such assessment tools can be broken down into the three layers of collecting, processing and using information (Batov, 2015). A similar three-layered architecture is formulated by Zhang et al. (2022) specifically for (smart) assessment tools promoting office workers' health and comfort. The acquisition layer includes the collection of all kinds of heterogeneous data from various sources such as sensors. Next, the analysis layer describes how these data inputs are evaluated by a model that can filter out the important information. Based on that the model decides if actions are necessary. Finally, the application layer is the output of this evaluation. This can for instance be in the form of advice given to initiate behavioural changes or an automatic adjustment of the work environment parameters. Assessment tools cover all three layers of data acquisition, analysis and application.

An especially important characteristic of the assessment tools that should be influential for how office workers perceive those tools is their degree of intrusiveness (see chapter 4.3.2). This characteristic consequently differs between the different tools and requires to be briefly defined here as it is used in the descriptions of the various tools in the following sub-chapters. Intrusion refers to what Raff & Wentzel (2023) frame as technology that breaches the boundary to the private. This, on the one hand, expresses itself in employees feeling insecure about their data privacy. Assessment tools can on the one side objectively cross the boundaries of employees' privacy. It can be questioned if many assessment tools are even legally allowed in the EU under the General Data Privacy Regulations (GDPR) due to the inevitable, substantial collection of private data (Collins & Marassi, 2021). However, even if every legal requirement should be fulfilled, employees could still have more subjective fears like that their organizations could essentially spy on them or unintended data leaks appear (Harper et al., 2022; Neff & Nafus, 2016; Teebken & Hess, 2021). Moreover, having tools physically present in the office in sometimes close proximity to the users is another dimension of intrusiveness (Raff & Wentzel, 2023). In the context of smart home technologies, this creates a feeling described as "hosting an invisible guest at home" (Raff & Wentzel, 2023, p. 5). Users can therefore also perceive tools as intrusive due to the specific placements of the tools and how much they are physically bothered by the tools. More advanced and smarter tools could tend to be perceived as more intrusive.

In the context of smart environments, Kubicki et al. (2022) differentiate between comfort and health. Comfort is the result of "indoor environment conditions that facilitate a state of satisfaction of bodily wants in occupants, based on their individual preferences and their given activity (…)" (Kubicki et al., 2022, p. 2). Indoor environment conditions can also be healthy by promoting "physical resilience and restitution of occupants, and limit physical stressors causing infirmity, disease and years of potential life lost" (Kubicki et al., 2022, p. 2). However, it is also noted that the distinctions between the two concepts can be blurry as different experts define them differently (Kubicki et al., 2022). The literature reveals important aspects of the indoor environment that determine office workers' health and comfort. Stress (Ganster & Rosen, 2013) and sedentary behaviour (Genin et al., 2018) are seen as being majorly important regarding office workers' health. Next to that, Rasheed et al. (2021) and Sakellaris et al. (2016) identify lighting, temperature noise conditions and air quality as predictors of the comfort level. Given that the concepts of health and comfort are somewhat blurry (Kubicki et al. 2022), it needs to be noted that these 6 introduced aspects can both impact office workers' health and comfort. This classification is done on the basis that stress and sedentary behaviours are directly concerned with the body of the individual and lighting, noise, temperature and air quality conditions are more related to the indoor environmental conditions. A closer look is taken at the existing assessment tools aiming to provide benefits for these health and comfort aspects. Conclusions can be drawn on which common features characterize the assessment tools.

Stress levels

Stress is a widespread and growing problem among knowledge workers working in offices (Koldijk et al., 2016). This can express itself in the perception of stressors in case the given amount of work exceeds the own capacity or in the experience of stress which manifests itself in actual reactions of the body such as neck pains or headaches (Koldijk et al., 2016). Following Ganster & Rosen (2013) stress can be most associated to the health of office workers. In a conventional way, detecting and reducing stress often relies on conducting surveys (Koldijk et al., 2016). However, this method alone is often not able to deliver the wanted success (Koldijk et al., 2016). Other, smarter tools can potentially improve this by detecting stress and stressors more reliably with sensor data. Moreover, self-reporting stress in surveys only allows to detect psychological stress, while the detection of physiological stress requires measurements with sensors (Wettstein et al., 2020)

Still, most of the analysed tools are additionally using questionnaire-style data collection methods which directly engage the users of the tool (Bakker et al., 2012; Muaremi et al., 2013; Schavemaker et al., 2014). The surveys reveal the user's perception of stress which can vary between individuals (Muaremi et al., 2013). This data can then be used in combination with other indicators for the stress level measured by sensors (Muaremi et al., 2013). Surveys are for instance done through interfaces that pop-up on the user's devices asking them about their perceived energy (Schavemaker et al., 2014) or stress level (Muaremi et al., 2013). Tailor-made smartphone apps for this purpose integrate chatbots that are based on artificial intelligence algorithms (Noon, n.d.). This could improve personalised insights that can be gained from the surveys while reducing the number of times users need to answer questions (Noon, n.d.). Another tool requires users to tag their events in their electronic calendar and report in how far they feel stressed out about them (e.g., a meeting felt tense) (Bakker et al., 2012). In all cases, surveys can give insights into the user's individual perceived stress level either in continuous periods or specifically linked to events. However, the validity of the outputs depends of course on the accuracy of the user's subjective inputs.

Another commonly used technology for stress-related assessment tools is capturing the usage patterns of the own computer or smartphone (Koldijk, 2012; Muaremi et al., 2013; Schavemaker et al., 2014). All sorts of data such as the time spent working with each computer program or app as well as the mouse clicks and keyboard inputs can be collected. Moreover, phone calls, GPS positions and movements can especially be tracked through the smartphone (Muaremi et al., 2013). This information is collected to derive the further context the user is embedded in that could cause stress or relaxation (Koldijk, 2012). In one case, this data is used to measure the working speed of the user a possible indicator for how stressed the user is (Schavemaker et al., 2014).

Wearables such as wristbands or belts are also in use to collect data about heart rate (Koldijk, 2012; Muaremi et al., 2013), blood volume (Koldijk, 2012) and skin responses (Bakker et al., 2012, Koldijk, 2012). These can detect stress for example during the night when the user cannot answer surveys (Muaremi et al., 2013) and are important as the surveys alone have been regarded as being somewhat inaccurate and incomplete when it comes to identifying the different dimensions of stress (Koldijk et al., 2016).

Of course, it can be expected that the more data from different ranges of sources is collected, the more precise the identification and prediction of the stress level can be. Koldijk (2012) points out that context data (collected via the computer and smartphone) especially helps with predicting and potentially preventing future stressful events. It can be possible to give the users warnings about upcoming possibly stressful situations and then for instance adjust the time scheduling to allow for more time for this particular task or hide less important emails within this timeframe. Bakker et al. (2012) are able to create a similar outcome with their tool after the users have been tagging their events in their digital calendar by the degree of perceived stressfulness. A different approach is taken by Schavemaker et al. (2014). Their output consists of an openly accessible monitor in the office that essentially pictures the stress level of all employees to encourage open interaction and to critically assess the issues related to stress at their workplace (Schavemaker et al., 2014).

Through those different configurations, several levels of stress-related assessment tools can be derived. Many tools collect individuals' perceptions of stress through surveys and can additionally analyse related body parameters through sensors. While surveys rely on the subjective input of users, wearables can also objectively measure the physiological stress level (Wettstein et al., 2020). By doing so, it can be accurately detected whether a user feels stressed out and if a change of behaviour is needed. Stress-related patterns can be detected by machine learning algorithms that enable a reduced frequency of collecting data through surveys which require manual user inputs. The outputs of those tools can also be personalized and the context regarding the user's activities can be analysed. Thus, data about the user's context such as usage patterns of the computer and the individual calendar can be added to the pool of information. As the stress level can then be attributed to the individual's habits and schedules, more case-specific recommendations can be made.

Sedentary behaviours

On average, "81.8% of the working process is sedentary" (Zhang et al., 2022, p. 7) in offices. Thus, several physical problems can arise due to prolonged sitting and static body positioning (Zhang et al., 2022; Roossien et al., 2017). This increases the chances of "fatigue, poor mood, as well as cardiovascular diseases and other chronic diseases" (Lindberg et al., 2018, p. 689). Sedentary behaviour can be predominantly categorized as a health concern for office workers (Genin et al., 2018).

To counter those issues, different assessment tools are existing that nudge the users to stand up and walk around more often (He & Agu, 2014; Mateevitsi et al., 2014; Movebite, 2023 Pina et al., 2012). The smartphone application of Movebite (2023) uses artificial intelligence-based chatbots. This works essentially like a survey to gain insights into the behaviour of the user to create personalized recommendations for a healthier lifestyle (Movebite, 2023). Another method to collect the necessary data about whether and how long a user is currently sitting at the desk is by desk-mounted motion sensors (Mateevitsi et al., 2014), the accelerometers inside smartphones (He & Agu, 2014) or through wearable wristbands (Pina et al., 2012). Arguably the most accurate method to detect different behaviours linked to exact locations in the office is the relatively hardware-intensive data collection method of Pollard et al. (2021). For that, accelerometers are installed in badges that can be attached to the user's office access pass (Pollard et al., 2021). Such sensors that measure activity patterns can also be worn as a wristband (Parkka et al., 2007).

The collected information can be used in different ways. Mateevitsi et al. (2014) install a digital bar next to the computer that slowly changes colour the longer the user is remaining seated. Smartphones (He & Agu, 2014) and desktop apps (Pina et al., 2012) are developed that give more detailed advice such as adding detours to the daily walking route or suggesting specific small breaks to the users. Moreover, the users can also insert their own goals which then influence the frequency and duration of the suggested activities by the app (He & Agu, 2014). The time spent sitting down cannot just be reduced by effectively stopping the work and leaving the workstation. By introducing furniture such as height-adjustable workstations (Biddle et al., 2020) work can be continued as usual while the negative effects of sedentary behaviour are also reduced.

Another negative impact of sedentary behaviour is the sitting posture itself which can oftentimes be incorrect and, amongst other things, can cause problems for the users' back (Hu et al., 2020). Common tools to mitigate those associated health risks rely on pressure sensors integrated into office chairs (Hu et al., 2020; Roossien et al., 2017) or within portable cushions which are also usable on wheelchairs or in the car (Ma et al., 2017). Paliyawan et al. (2014) use desk-mounted Microsoft Kinect camera sensors. All of these sensors can detect the sitting postures and the duration of users remaining in a specific position (Hu et al., 2020; Ma et al., 2017; Paliyawan et al., 2014; Roossien et al., 2017). The positioning of the neck is also an important aspect of the sitting posture which can be tracked with a headset-mounted sensor (Markopoulos et al., 2020).

To some degree, all of the tools analysing the sitting posture rely on algorithms that can extract precise information about the sitting posture, duration and how often alternations between postures are made to determine the healthiness of the posture (Markopoulos et al., 2020; Paliyawan et al., 2014; Roossien et al., 2017). Alternatively, such machine learning algorithms can also be used to reduce the number of needed sensors and to increase the robustness of the results (Hu et al., 2020).

Feedback about whether a change of sitting posture is needed, in one instance is provided to the users via vibrations in the chair (Roossien et al., 2017). Because this method does not sufficiently initiate the wanted behaviour changes, other tools rely on a monitor user interface which shows the current posture, its 'healthiness' and what can be improved (Paliyawan et al., 2014; Roossien et al., 2017). Both purposely built screens and apps for the smartphone are established for giving this feedback (Paliyawan et al., 2014; Roossien et al., 2017). The tool of Markopoulos et al. (2020) gives audio advice about neck exercises directly via the user's headset.

Multiple levels regarding assessment tools dealing with sedentary behaviour can be derived from this. Some tools only detect and give advice about sitting behaviour. This either requires deriving the user's activity patterns subjectively through self-reporting or more objectively through motion sensors like cameras, wearables or smartphones. The output to users consists of general or personal feedback for instance about whether a break should be taken at the current moment. More advanced tools can moreover also analyse the sitting posture of the users either by pressure sensors or cameras. This can be used to give feedback through audio messages, monitor-based user interfaces or vibrations that can also suggest what aspects of the posture should be improved. On top of that, some assessment tools then also include height-adjustable desks that promote healthier behaviour and are moreover somewhat tailored towards the user's specific preferences. As such these tools are capable of giving personalized advice depending on the users' individual daily routines (e.g., adjusted walking routes to the home) and in response to the given health and fitness goals of each user.

Lighting conditions

Comfortable lighting conditions are influenced by the amount of daylight, exposure to glare, the colour temperature of the interior, electric lighting and the level of brightness within the office space (Papagiannidis & Marikyancan, 2020). A similar aspect is concerned with the prolonged staring at digital devices (Martire et al., 2018). Inadequate lighting conditions can contribute to headaches and nausea (Papagiannidis & Marikyancan, 2020), insufficient sleep (Boubekri et al., 2020) or even obesity and psychiatric disorders (Vetter et al., 2011). Inappropriate usage of devices can be harmful to the eyes (Martire et al., 2018). Lighting conditions can be defined as an aspect most related to the comfort of office workers (Sakellaris et al., 2016). On the other hand, being comfortable with the lighting positively influences employees' productivity (Papagiannidis & Marikyancan, 2020). Creating optimal lighting conditions is challenging as 'optimal' depends on the specific work tasks, the time of the day and the season (Papagiannidis & Marikyancan, 2020). Moreover, the individual's preferences and sleep cycle also influence whether the lighting is perceived as comfortable or not (Vetter et al., 2011). Assessment tools for lighting are developed to address multiple aspects such as controlling the exterior light entering the office, the artificial lighting within the building and monitoring the lighting emitted from computer screens.

Day et al. (2019) deal with the first aspect by reviewing different systems of regulating exterior light. The intensity of the light and how far it penetrates into the building can be estimated based on the building's location and which geographic direction the façade is facing (Day et al., 2019). A more accurate method actually measuring these two factors is a façade-mounted photometer (Day et al., 2019). Predefined thresholds for the light intensity and penetration are set which define whether the windows should let more or less light into the building (Day et al., 2019). This is either controlled by window blinds, windows that can be tinted through electrochromic glazing or fabric-shade screens (Day et al., 2019). What makes those distinctions relevant is the level of control the users have over each technology. Although all of them operate to some degree automatically, the level of control changes. The tinted windows do not allow for any individual control, while the other two systems can be overridden by the user for a set amount of time (Day et al., 2019). Moreover, the window blinds are divided into two sections and one of them is completely controlled manually (Day et al., 2019). While the possibility of control is the highest here, this also requires the users to alter the position of the blinds based on their own impulses. This may lead to inappropriate lighting conditions if the adjustment is done too late or not at all and if a lot of users are involved in the process.

Other assessment tools are concerned with controlling the artificial interior lighting. By establishing more small-scaled measurements that distinguish between the light levels of different workspaces, a first step towards considering the individual's different preferences towards the lighting is done. Van Duijnhoven et al. (2018) develop an estimation model that relies on the placement of only a few lighting sensors at fixed spots within the office space. These reference locations and their measurements can be used to derive the lighting exposure of other places in the office. If this information is then combined with the data from a location detection sensor (like the smartphone), the light exposure cannot only be estimated for each workplace but also for each user. It is then possible to adapt the lighting accordingly for each user.

As sleep cycles differ (e.g., some persons are more active in the morning etc.) this should ideally also be suited to the individual body rhythm (Papatsimpa et al, 2020). For that, a model is introduced which can suggest an individual lighting profile consisting of different colours and levels of brightness to match the individual character and lifestyle (Papatsimpa et al, 2020). This would of course require that these parameters are measured or are known prior for each user. By combining multiple previously mentioned features, the tool by Nagy et al. (2015) is perhaps the most comprehensive when it comes to dealing with interior lighting. In this case, the lighting sensors are attached to each user's desk while the occupancy of the desk is monitored with room-mounted motion sensors (Nagy et al., 2015). Through dynamic, statistical analysis the system learns the behaviour and lighting preferences of each occupant (e.g., different activity patterns throughout a typical workday) and at which level of brightness the lights are switched on manually (Nagy et al., 2015). The system then adapts to the user's preferred level of brightness throughout the day and adjusts the threshold of when to switch on or off the light automatically (Nagy et al., 2015).

Lastly, Martire et al. (2018) are specifically targeting the adverse effects of screen time and the emitted artificial light of those devices. Wearables (head-mounted sensors) are used to detect the colour of the light and the digital screen time for each user (Martire et al., 2018). The data is analysed with a machine learning algorithm making the results more robust to different individual behaviours such as different head positions and movements in relation to the screen which previously has made the sensor data inaccurate.

While there are essentially three different niches targeted by the different assessment tools, several levels of smartness for the different tools assessing lighting can be derived. Simpler systems cannot detect lighting levels for individual spaces or users and can therefore only adjust the lighting for a larger space or for a larger number of users. More advanced systems are able to sensor the environment on a more finely-grained spatial scale level but often require intrusive sensors like wearables or other sensors that are somewhat monitoring the behaviour of users. Moreover, the building's systems may only have limited possibilities in how far the lighting can be adjusted to the individual user's needs. Lastly, models have been developed that can either make it possible to accurately estimate the lighting level despite only limited usage of sensor technology or are able to improve the accuracy of the raw sensor data. Very sophisticated tools are also able to learn the preferences of each user and can adjust the lighting system accordingly.

Temperature conditions

"Thermal Comfort is defined as the psychophysical satisfaction of an individual immersed in a thermal environment (...). Thermal comfort is influenced by (…) air temperature, relative humidity, air velocity, and mean radiant temperature (…), metabolic activity and clothing" (Salamone et al., 2018, p. 1). It is another aspect that is mostly related to the comfort of office workers (Sakellaris et al., 2016). Next to assessing those variables to derive the individual's level of comfort, it is also necessary for assessment tools to consider the personal characteristics of each user (van der Valk et al., 2015) as the preferences towards the 'ideal' indoor environment vary (Papagiannidis & Marikyan, 2020). This is partly due to differing physical characteristics but also because of the individual's clothing situation (Kim et al., 2018). Feeling comfortable positively influences productivity (Papagiannidis & Marikyan, 2020). If thermal comfort is not given "physical stress (thermal stress), illnesses and poor performance of occupants" (van der Valk et al., 2015, p. 2) can occur. Not least because of that Kubicki et al. (2022) identify thermal comfort as one of the overall most dominant topics related to smart buildings.

There are assessment tools in which thermal conditions are measured through a system of room-mounted temperature and humidity sensors (Valinejadshoubi et al., 2021). This data is then linked to a Building Information Model of the building to automatically detect and display in which spaces threshold levels for the temperature and humidity are exceeded (Valinejadshoubi et al., 2021). The results can be used by (facility) managers to adjust the indoor environment accordingly (Valinejadshoubi et al., 2021).

The assessment tool of Zang et al. (2019) also uses temperature and humidity sensors to track the conditions of the indoor environment but additionally implements an air velocity detector and, more significantly, cameras. The cameras are there to derive the different perceptions of thermal comfort for each user. Through a machine learning algorithm, it can be analysed which kind of clothing (e.g., the thickness and fabric) each user is wearing. Gao and Keshav (2013) use a Microsoft Kinect sensor for this purpose which can also detect the movements and subsequently the activity level of the users. In combination with the environmental parameters, those factors greatly influence the individually perceived thermal comfort level (Zang et al., 2019). Then, the parameters of the indoor environment can be adjusted accordingly in a fully automatic way to maximize the average comfort level among all users (Zang et al., 2019).

Another way to track the different perceptions of thermal comfort per user is through self-reporting (Lee et al., 2019). This is either done by giving feedback voluntarily whenever they feel thermally uncomfortable or in scheduled intervals (Lee et al., 2019). Models are implemented that can learn patterns from the individual's reports of how comfortable they feel (Lee et al., 2019). It is then possible for the model to predict when the user is likely to feel uncomfortable in the future without asking the user for as much feedback anymore (Lee et al., 2019). The thermal control can then be adjusted accordingly to prevent the user from feeling uncomfortable (Lee et al., 2019).

Salamone et al. (2018) combine room-mounted sensors that measure the relevant environmental parameters with a survey and even wearables attached to the users. While the survey also asks the users about their perceived comfort level similar to Lee et al. (2019), the wearable wristband can additionally measure the heart rate, the skin temperature and the movement of the user (Salamone et al., 2018). This comprehensive dataset is fed into a machine learning algorithm which essentially helps to fill in gaps created by each data acquisition method (e.g., too little user feedback through the surveys) and to find correlations between measured comfort levels and reported comfort levels (Salamone et al., 2018). Consequently, the accuracy of detecting and predicting the individual's thermal comfort level is further improved (Salamone et al., 2018). Such finely-grained information is ideally used for devices that can individually regulate the thermal environment of a single workstation. Kim et al. (2018) define these as personal comfort systems which can, for instance, be desk-mounted fans or heaters and heated and/or cooled chairs.

Assessment tools dealing with thermal comfort can subsequently also be divided into different levels of smartness. In the most basic configuration, sensors can only detect the environmental parameters of the spaces, but nothing is known about the experience of the respective users. Consequently, adjustments to improve the thermal comfort can only be made on a bigger scale across the office and these are not tailored towards the users. However, these are unintrusive tools for the users and no personal data is needed. Next, the individual's level of comfort is added to the tools through self-reporting. This could, however, be considered as intrusive and can cause concerns about the use of personal data, while the accuracy of the data is somewhat still limited. Adjustments to the environment are still made on a the bigger-scale (e.g., for each room) so that the average comfort level of all individuals is maximized. At last, the accuracy of predicting the personal level of comfort is increased by adding wearables measuring physical body parameters as well as the indoor environment near the body or with cameras that can detect the clothing and activity of users. While these are certainly tools that require the most personal data to be collected, the adjustments to the environment can be made on a very individual level by personalizing the thermal parameters for each workstation (e.g., through heated and cooled chairs).

Noise conditions

A considerable amount of office workers feel exposed to noise and a study found that over half of respondents named noise as the most disturbing aspect of their office environment (Kjellberg & Landström, 1994). This has a negative impact on both overall job satisfaction (Kjellberg & Landström, 1994) and motivation level (Evans & Johnson, 2000; Jahnke et al., 2011). Exposure to noise from the environment can cause all kinds of health and comfort-related issues such as an "increased risk of ischaemic heart disease, sleep disturbance, […] annoyance, stress-related mental health risks" (Aletta et al., 2018, p. 2). Nevertheless, noise is mostly a comfort-related aspect for office workers (Sakellaris et al., 2016).

Noise disturbance can be countered by establishing so-called positive soundscapes (Aletta et al., 2018). This refers to pleasant, calm or vibrant acoustics which can reduce the health-related issues induced by noisy environments and make the noise less disturbing (Aletta et al., 2018). However, what is perceived as pleasant acoustics depends on the type of activity and is also subjective (Medvedev et al., 2015). Sound masking can be an effective strategy to create such positive soundscapes (Softdb, n.d.). Disturbing and unpleasant sounds can be automatically neutralized by a system that generates a masking sound which is a subtle background ambient sound through loudspeakers muffling out the noise disturbances (Softdb, n.d.). Sensors in the ceiling detect the disturbing sounds and the sound masking can be individually adjusted for the specific needs of different office sections (Softdb, n.d.). Sound cannot just be masked but can also be actively reduced. This can either be done with wearables such as noise-cancelling headphones and earplugs (Kari et al., 2017; Shen et al., 2018). However, no significant positive effects on the health and comfort of the users could be detected in a research about these devices (Kari et al., 2017). Another technology relies on sound bubbles which are able to cancel out the sound directly around the users without the need for a wearable (Silentium, n.d.). To my knowledge, it is not discovered though if such a tool is also implemented in offices or if it has any positive effect on comfort and health.

Another coping strategy, instead of changing the acoustics of the environment, is to assign employees to those workstations that suit their preferences regarding the environmental conditions (such as noise level) most in a flexible office space (Berelson et al., 2018). While the specific conditions for each workstation are also measured with sensors distributed in the space, office workers' preferences have to be prerecorded (Berelson et al., 2018). Finally, an algorithm decides which employee to assign to which workstation to maximize the overall utility level (Berelson et al., 2018). Alternatively, noise levels can also be measured with wearables such as a smartwatch (Abboushi et al., 2022).

Air quality

Office workers' awareness of the importance of indoor air quality has increased since the COVID-19 pandemic which also leads to an increased supply of more affordable technologies that can measure the relevant air quality parameters (Kubicki et al., 2022). Apart from the risk of infectious diseases being spread, particulate matter ($PM_{2.5}$) and carbon dioxide (CO_2) emissions are the most relevant components of indoor air that are responsible for causing health problems (Motlagh et al., 2019). Air quality is mostly related to the comfort in office environments (Sakellaris et al., 2016). High CO_2 levels alone can lead to "problems such as fatigue, lethargy, headache, and cardiac arrhythmia as well as difficulty in retaining cognitive performance" (Zhong et al., 2020). It also reduces employees' productivity and can result in Sick Building Syndrome (Aryal et al., 2019). The World Health Organization states that "acute respiratory infections, chronic obstructive pulmonary disease and cataracts" are the main health concerns of high $PM_{2.5}$ concentrations (Patel et. al., 2017, p. 59).

There are assessment tools that try to derive the air quality without actually installing the respective sensors which can measure it. Motlagh et al. (2019) finds that from the data of sensors detecting occupancy and movement in a room, the $PM_{2.5}$ concentration can quite accurately be predicted. However, for estimating the CO_2 in the air, this method does not prove to be successful (Motlagh et al., 2019). According to Wong et al. (2006) and Aryal et al. (2019), CO_2 levels are, however, a better predictor for overall indoor air quality than $PM_{2.5}$.

Consequently, sensing devices are introduced that can measure several parameters of the indoor air (Yang et al., 2017; Zhong et al., 2020). Zhong et al. (2020) develop a box that cannot just measure the concentration of CO_2 and particulate matter but also airflow, humidity, air pressure and noise level. An algorithm can analyse patterns between those parameters to accurately predict the CO_2 level within the upcoming 20 minutes (Zhong et al., 2020). The indoor air quality can of course vary significantly between different rooms as the users' respiration is mainly responsible for the CO_2 concentration indoors (Aryal et al., 2019) which is why multiple locations of measurements are necessary throughout a building.

The collected data from such sensors measuring air quality can be essentially used in two ways. Notifications about the expected CO_2 levels can be transmitted to the users, for instance via the Apple watch, "to motivate the users to develop habits on indoor air quality management" (Zhong et al., 2020, p. 3) (e.g., opening up a window before the concentration becomes too high). Moreover, the sensor data can be linked to devices regulating the indoor air such as air purifiers (Panicker, 2020; Yang et al., 2017). As soon as threshold levels for air pollution are exceeded, these are turned on automatically to regain the desired air quality (Panicker, 2020; Yang et al., 2017). While such devices typically improve the air quality on a room or building level, it is also important to consider the air in the immediate proximity of the users (Aryal et al., 2019). While sitting still, CO_2 tends to build up in this air bubble around a user and therefore a desk fan can greatly help to dissipate the accumulating CO_2 (Aryal et al., 2019).

Compared to assessment tools that deal with other comfort-related issues, no technology concerned with air quality is discovered that includes surveys. This comes as no surprise as humans cannot really sense the state of the air quality as the consequences experienced for their own comfort cannot necessarily be traced back to inadequate air quality. There is also no mention of individual differences in the perception of air quality.

As a result, the different levels of assessment tools dealing with air quality essentially differ in how accurate the measurement and prediction are, for which purpose this information is used and for which spatial scale levels the respective tool is used. In the most basic configuration parameters determining the air quality are only estimated based on other (motion) sensor data. This only yields relatively inadequate results. Other assessment tools are more sophisticated as they are actually able to sense all kinds of relevant parameters which can result in accurate data. Predictions are possible about how the air quality is going to evolve and automatic changes are made to the air regulation within specific rooms. Lastly, tools can use this information to additionally notify and educate the users about the current situation on their personal devices. Moreover, users can choose to use a desk fan to improve the conditions of their personal workspace.

2.2.2 Conclusion - four common assessment tools assessing aspects of office workers' health & comfort

This study focuses on 4 abstracted versions of commonly existing tools based on the broad range of tools introduced in the previous sub-chapter 2.2.1 in particular that assess the 6 health and comfort aspects (sedentary behaviours, stress levels, as well as lighting, temperature, noise conditions and air quality). Narrowing down the number of tools to 4 is necessary given the selected research method (see chapter 4) so that respondents of the questionnaire are not fatigued while answering a range of questions about each of the tools. The selection and definition of the 4 tools are however not exclusively based on actual tools that are already existing as this would not adequately represent the vast amount of features the tools can offer. Instead, the 4 tools should be understood as a highly abstracted version of commonly existing tools. Nevertheless, the choice and definition of these 4 particular tools is an attempt to cover the broad range of tools existing in real life (introduced in the previous subchapter) as comprehensively as possible in the questionnaire.

The 4 tools: surveys, smartphone app-based surveys, room-mounted sensors and wearables are further described in chapter 4.3.2. Note that room-mounted sensors are only addressing comfort-related aspects (lighting conditions, temperature conditions, noise conditions). Also, it becomes apparent that surveys should not really be considered as a smart assessment tool as such, In contrast to the other tools, they lack advanced data collection or processing methods. However, they are often either used in conjunction with other, smarter assessment tools or are used as a non-smart substitute to the other types of assessment tools. It is therefore intriguing to find out how surveys are perceived in comparison to the other, smarter tools. Thus, including surveys in this research as a "baseline tool" allows to evaluate whether the attribute of smartness in tools is really preferred or not.

3. Perception of health and comfort assessment tools

3.1 Role of office workers’ perception

As already stated, the experiences office workers have in their office environment majorly impact their work and health (De Been & Beijer, 2014; Zhang et al., 2022). These experiences, on the other hand, are determined a lot by office workers’ perceptions of and expectations for their office environment (Kim and De Dear, 2012). Finding out more about how they perceive different characteristics of a smart office is thus an essential part of this research.

First, the aim of this research is not just to find out which types of health and comfort assessment tools are most preferred by office workers but also how attributes of these tools are perceived. Any research design is, however, limited in terms of scope. Therefore, how many attributes can be selected and how extensively these attributes can be described in the empirical research is also limited. It is consequently necessary to first break down which attributes of the assessment tools are already proven to have (based on existing research) or are likely to have an influence on how office workers perceive health and comfort assessment tools. As such, the goal of subchapter 3.2 is to derive the most striking positive and negative aspects that are related to the tools from the viewpoint of the office workers.

Second, the personal characteristics of office workers can have an influence on their perception of the tools too next to the attributes of the assessment tools themselves. Subchapter 3.3 therefore reviews the research about which of those characteristics is expected to relate to the perception of health and comfort assessment tools.

The cited research elaborates on these facets. It has to be noted that due to the limitations of each of the research papers mentioned, the derived insights have to be viewed with care. Not only can the research settings and methods be different to this thesis but some of the cited literature is also not exclusively about the perception of very similar assessment tools but instead also about tools and technologies used in other domains such as smart homes. In other instances, the office workers’ perception has been studied in regard to related concepts such as IoT rather than ‘smart’ tools.

3.2 Attributes of assessment tools related to office workers’ perception

User experience and level of automatization

Users want to make sense and be able to experience a smart concept (Tuzcuoğlu et al., 2023). However, user engagement in advanced health and comfort assessment tools is often times lacking (Aral et al., 2019). Such tools should therefore be easy to use and add convenience to the workplace (Boivie, 2005; Remes et al., 2022; Tuzcuoğlu et al., 2023). Suitable interfaces are for instance needed to make the control of data inputs easier (Donkers et al., 2023; Tuzcuoğlu et al., 2023).

That said, it is not clear-cut how much user control and how much automatization during the collection of the data is most desirable. Some scholars mention that a middle ground with some level of user control is ideal (Tuzcuoğlu et al., 2023) which at the same time also means that some level of automatization should be included according to employees (Ahmadi-Karvigh et al., 2017). Donkers et al. (2023) examine that users like to receive suggestions rather than having a fully automated control. Other research reveals that this depends on which purpose the data is used for. Röcker (2009) finds that personal input is not desirable if personal data needs to be entered manually as many are reluctant to give away private information in such a way. That said, employees prefer to be asked for their consent (Teebken & Hess, 2021). Having an element of manual control is the preferred way when assessment tools influence thermal comfort (Kwon et al., 2019). It is said that this is because thermal comfort is perceived very individually and thus users are more satisfied if they have control over it (Kwon et al., 2019). A similar observation has been made for lighting-related technologies for which users wish to have some personal control over them (Ahmadi-Karvigh et al., 2017; Day et al., 2019; Lashina et al., 2019). Interestingly, it shows that employees do not use this functionality very regularly though which leads to the conclusion that the feeling alone of having the possibility to take over the controls is important to the employees rather than actually taking over the controls (Lashina et al., 2019).

Another study finds that the preferred level of automatization furthermore differs depending on education (less educated persons prefer more automatization) and income level (Ahmadi-Karvigh et al., 2017). Moreover, if users are in favour of the technology getting implemented or are open to new experiences they are more likely to opt for a high level of automatization (Ahmadi-Karvigh et al., 2017).

Overall, no clearly favoured level of automatization or level of personal control can be derived. Office workers generally seem to prefer a mixture of some automatization and some personal control at the same time for assessment tools. While the level of automatization can refer to the acquisition and also the application layer of the assessment tool, it is especially interesting to find out more about the perception of the level of automatization in the data acquisition process as it still relatively unclear how office workers perceive the various possible levels of automatization while acquiring data.

Personal data privacy & security

How private data is handled is not just a concern for employees but is also regulated throughout the EU by the General Data Protection Regulation (GDPR)(Collins & Marassi, 2021). Every employer in the EU must demonstrate compliance with the GDPR and breaching it is unlawful (Collins & Marassi, 2021). Regarding assessment tools that deal with employees' health several principles of the GDPR become especially relevant. It is only allowed to collect private data for predefined and explicit purposes which prohibits the use of this data for any other purposes (Collins & Marassi, 2021). Furthermore, as little as possible (especially privacy-invasive) data is to be collected to achieve this sole purpose (Collins & Marassi, 2021). Therefore, the results should be obtained in the least invasive way for the employees (Collins & Marassi, 2021). Lastly, inaccurate data is not supposed to be stored or collected (Collins & Marassi, 2021). While these requirements apply to the collection of personal data, the regulations concerning health data are even more restrictive (Collins & Marassi, 2021). The latter concerns all personal data that reveals the employee's health status. Thus, it could be argued that as soon as it is possible to derive any further conclusions (whether accurate or inaccurate) from the health-related data (e.g., a prolonged period of sedentary behaviour could indicate depression) the assessment tool processes health data (Collins & Marassi, 2021). Consequently, a reasonable amount of features of health and comfort assessment tools that have been covered so far (see chapter 2.2.1) could to some degree breach the GDPR. However, the regulations overall have a lot of unclarified "blind spots" (Harper et al., 2022, p. 488) in this respect and the regulations also allow for exceptions (Collins & Marassi, 2021). Specific assessment tools can thus only be properly evaluated on a case-by-case basis (Collins & Marassi, 2021).

On the one hand, those legal requirements could put clear limits on how privacy-invasive the assessment tools can be for office workers. On the other hand, office workers have also expressed their own views on the matter which is described in this chapter. This should not be underestimated given the possible company-internal resistance if concerns are not addressed appropriately. Moreover, there is the possibility that office workers have perhaps subjective fears about data not being handled correctly and for instance express their concerns about unintended data leaks (Harper et al., 2022; Teebken & Hess, 2021). This perception can of course potentially still persist even if the employer has implemented all conceivable precautions into the system. These fears may also be caused or amplified by office workers oftentimes not knowing about data being collected, not having any access to the data or not knowing about the functionality of specific assessment tools (Harper et al., 2022; Neff &

Nafus, 2016). As the variety of collected information from assessment tools could be used to derive all sorts of conclusions connected to the behaviour, preferences and identity of the user, office workers may be afraid of this “user profiling” (Harper et al., 2022, p. 469).

That said, these concerns differ between the types of data collected (Gorn & Shklovski, 2016). Some office workers express their dislike of sharing data if it impacts their private lives (Gorn & Shklovski, 2016) or if data is used for secondary uses such as performance assessments (Teebken & Hess, 2021). Data anonymity is a particularly important feature that needs to be in place (Harper et al., 2022; Teebken & Hess, 2021). Moreover, employees do not like to share their current location (Lai et al., 2003) and feel uncomfortable when being watched when interacting with those tools (Röcker, 2009). Office workers are more willing to use many of the functionalities of assessment tools in a private setting rather than in a public situation with multiple other users present (Röcker, 2009).

The level of privacy sensitivity also depends on the kind of sensor technology used. Collecting data through “webcam, sound sensor, computer content, and digital communication” (Koldijk et al., 2016, p. 10) or more generally with video and audio recordings (Harper et al., 2022) is considered to be more privacy sensitive. On the other hand, “motion sensors, heart rate, and skin conductance” (Koldijk et al., 2016, p. 10) are seen as less privacy-sensitive data collection methods. Collins & Marassi (2021) argue that especially wearable technology invades employees’ privacy in several aspects. The collected information is potentially more diverse and finely grained than with other technologies allowing to draw profound conclusions about the health status (Collins & Marassi, 2021). As the wearables work best if they are worn 24/7 and therefore also outside of working hours, this technology potentially crosses the boundary between work life and private life and clashes with the autonomy and bodily integrity of office workers (Collins & Marassi, 2021). Jacobs et al. (2019) find out that office workers therefore prefer to only use the wearables during the time spent at work.

The willingness to use wearables and other assessment tools also depends on their intended purpose (Donkers et al., 2023; Gorn & Shklovski, 2016; Koldijk et al., 2016; Schall et al., 2018; Teebken & Hess, 2021). Interestingly, while the GDPR includes even more restrictive requirements for health-related data (Collins & Marassi, 2021), employees actually seem to be more inclined to share private data if the tool can promote their own health (Gorn & Shklovski, 2016). For health professionals capturing their “awkward postures and forceful exertions” (Schall et al., 2018, p. 5) is considered to be the most valuable insight of wearables among all health-related outcomes. Less important aspects are repetition and physical fatigue followed by mental fatigue and vibrations (Schall et al., 2018). Donkers et al. (2023) make a more generalized observation that in case the technology helps employees with their daily lives and tasks they are more willing to share data.

Many scholars mention that making the whole process of data handling as transparent as possible is positive for the acceptance (Khakurel et al., 2018, Koldijk et al., 2016; Harper et al., 2022; Teebken & Hess, 2021). Koldijk et al. (2016) even suggest introducing a very personalized system. Users should then be able to choose which type of sensor information is collected and how it is extracted and stored (Koldijk et al., 2016). However, Zieglmaier et al. (2022) find that this increased awareness actually leads to more conservative data handling as users get to know that a lot of their private data is being processed (Zieglmaier et al., 2022). To improve the willingness to share data, other appeal strategies should be used instead (Zieglmaier et al., 2022). The positives of the assessment tools should be underlined by communicating the added values for the user and concrete incentives should be given for using the tools (Zieglmaier et al., 2022).

In other instances, companies try to legitimate the collection of private data by asking the employees for their consent (Collins & Marassi, 2021). In several cases, this method is not deemed as a legitimate legal basis to justify private data collection as the power imbalance between the organizations and their employees means that consent cannot be freely given (Collins & Marassi, 2021). A way to counter that problem could be to involve and consult the employees early on in the implementation process (Jacobs et al., 2019) for example through their representatives such as trade unions or other collectives (Collins & Marassi, 2021). The possibility for individuals to opt out of being assessed by the assessment tools could also be a conceivable solution to increase the trust of office workers.

Level of technological advancement - proximity to the user, technological intelligence, level of accuracy, range of outputs

What majorly relates to the general usefulness of assessment tools for office workers is of course how advanced they are from a technological perspective – in chapter 2.2.1 it is discovered that this mainly translates into more complex systems for the data acquisition (e.g., through more sensors), data analysis (e.g., machine learning algorithms and artificial intelligence), or data application (e.g., forecasts and advice to act upon tailored towards the individual). Djenouri et al. (2020) suitably sum this up with the term granularity. For instance, translated to tools measuring the occupancy of a room, this could mean that the least granular system can only detect if the room is occupied or not (Djenouri et al., 2020). More advanced systems could then also analyse how many people are in the room or even derive the gender of each of those persons (Djenouri et al., 2020).

A multitude of attributes can be linked to the level of technological advancement. Regarding the data acquisition, how close to the users the measurements are done is a variable that often changes depending on how granular the output is expected to be. However, no study seems to explicitly study the office workers' opinions about this attribute which is surprising given how different the daily usage of the respective devices should feel (e.g., a device worn on the body vs. a sensor attached to the ceiling). Following Raff & Wentzel's (2023) concept of intrusiveness, it can be expected that a close proximity of the device to the user can be seen as intrusive by users.

Moving on to the data analysis, a high level of technological intelligence is necessary to allow for an advanced data analysis. However, to my knowledge, no previous study investigates office workers' opinions of highly intelligent technology (such as artificial intelligence) being introduced to assessment tools. Given the recent rise of popularity and controversy connected to these technologies (Nitiéma, 2023), it is worth examining this aspect though.

At the stage of the data application, more advanced assessment tools can also enable a higher level of accuracy of the results which of course increases the usefulness for the users. While it is obviously sensible to suggest that a higher usefulness is always appreciated by the users, the users also need to recognise the value of the more advanced tools. Some users mistrust the core premise that increasing the usage of data can really help to solve any individual or social issues at work (Harper et al., 2022) or indeed make their daily work more efficient (Röcker, 2009). For office workers to be able to 'make sense' of their experience with the respective assessment tool (Tuzcuoğlu et al., 2023) it should be communicated that there is sufficient evidence about the assessment tool actually being able to fulfil its objectives (Jacobs et al., 2019). All in all, this improves the user experience and creates trust which cannot solely be achieved by providing monetary compensation to office workers using the tools (Jacobs et al., 2019). Therefore, it would be interesting to know in how far office workers actually appreciate a higher level of accuracy.

A broader range of outputs of assessment tools should generally be positively perceived by office workers (Mani & Chouk, 2017). As described in the example above about occupancy sensors, the output can range from vague information about the whole office or room to very personalized information about the individual users. The most advanced tools can thus give very individualized insights for the respective users but also on a very fine spatial scale level.

Other technological attributes - frequency of measurement, responsibility of data collection, data type collected

More technological attributes that could potentially have an influence on office workers' opinions about smart office assessment tools relatively stand out during the analysis of the existing assessment tools (see chapter 2.2.1). Because no research is found that have analysed the perception of these attributes, it is interesting to include these particular attributes in this research. Different types of tools differ majorly on how often data is measured (ranging from infrequent to continuous measurements) which may influence how intrusive a tool is perceived. It is likewise unknown whether it is important if the own organization or an external provider is responsible for the data collection. Lastly, different tools derive their outputs by measuring their data types on different spatial scale levels. Some only measure the environmental conditions for the whole office, others do this for each desk and some measure the bodily parameters of occupants. It is not yet clear how each of these data types are perceived.

Conclusion

Oftentimes, there are difficulties when it comes to implementing smart offices (Nappi & de Campos Ribeiro, 2020) and the respective health and comfort assessment tools are therefore still not widely spread (Oudot, 2019). From the findings of other studies that are described in this chapter, it seems that concerns about data privacy and security are a very important factor in this. Moreover, assessment tools may not adequately fulfil the needs of office workers who do not solely seek tools that are very advanced and useful to them. The experience they have with those tools is also vital and can be steered through user interfaces and manual inputs but also 'selling' the respective tools to office workers seems important. These concerns and needs are often relatively context-dependent. The exact configuration and purpose of the assessment tools seem to have an influence on how likely office workers are to approve of a tool. In other words, the 'ideal' set-up of each assessment tool would need to be considered individually and cannot be generalized. It becomes apparent that certain attributes are likely perceived negatively, and others are likely perceived positively by office workers. Oftentimes, these trade-offs need to be considered when implementing or designing an assessment tool since cherry-picking only positively perceived attributes is not possible. Essentially, a balance is needed between a high intrusiveness (perceived negatively with current literature) and a high benefit (perceived positively with current literature). Melenhorst et al. (2004) detect this relationship as well emphasizing that users of such tools expect a greater benefit in return for a higher intrusiveness. Another apparent aspect of the attributes is that they are connected to each other regarding how office workers perceive them. Rupp et al. (2018) show that the perception of specific attributes of a rather smart tool (i.e., wearables) are highly correlated and can even be grouped into combined variables. Overall, several attributes can be described that are deemed to be influential for office workers' opinions about assessment tools by previous literature: the proximity of measurement to the user, the amount of collected personal information and the level of automatization of the assessment tool.

However, it also becomes clear that there are many potentially important attributes of health and comfort assessment tools that are not explicitly examined yet in regard to how they influence office workers' opinions about the 4 chosen assessment tools. This being an exploratory study, the attributes of whether data is measured or self-reported, the frequency of assessments, the range of outputs, the level of accuracy, the level of technological intelligence and which organization is responsible for the assessments are therefore also incorporated in the research design later on.

3.3 Personal characteristics related to office workers' perception

Technology savviness & data privacy

Self-efficacy about technology describes" an individual's perception of his or her ability to use a technological innovative product" (Mani & Chouk, 2017). The user is generally more open to adopting new technology if there is high confidence about being personally able to understand and use it (Mani & Chouk, 2017) or if a positive prior experience with the technology exists (Jacobs et al., 2019). Röcker (2010) also finds out that computer knowledge strongly (more than any other personal characteristic) impacts the willingness to use advanced assessment tools. In this, computer knowledge is derived from the individuals' daily time of usage and the self-assessed level of computer knowledge (Röcker, 2010). The dependence on and the amount of usage of digital devices also positively impact privacy concerns (Mani & Chouk, 2017). It is said that high usage "increases the risks associated with attempts to keep data private, which in turn increases concerns about privacy" (Mani & Chouk, 2017, p. 11). Since data privacy is such a big concern among employees in regard to technologies in the office in general as well (see chapter 3.2), it is therefore interesting to find out whether a difference in the attitude towards data privacy directly relates to variables of office workers' perception. A previous study concludes that workers being less concerned about their private data relates to them having a stronger intention to adopt wearables in their workplace (Choi et al., 2017).

Age

Belonging to certain age groups and generations can have an impact on the perception of advanced assessment tools (Röcker, 2010). Existing literature suggests that older generations are less inclined to use a newly introduced technology (Röcker, 2010) and have a preference towards manually controlling the tools via user interfaces (Donkers et al., 2023). The causes of this should also interrelate with the previously stated self-efficacy (Röcker, 2010). As younger generations spend a lot of time with digital devices their computer knowledge is more advanced making it easier for them to adapt to new tools (Mani & Chouk, 2017; Röcker, 2010). This could be further amplified by cognitive skills declining with age making the adaption to changes more challenging and therefore the willingness to do so declines (Röcker, 2010). On the other hand, it is also detected that younger employees are less willing to share private data (Donkers et al., 2023).

Gender

It is discovered that gender has a significant impact on the attitude towards the perceived ease of use and usefulness of technology (Röcker, 2010). When considering whether to use a tool the ease of use is very important to women, while the usefulness is of greater importance to men (Röcker, 2010). On the other hand, Jacobs et al. (2019) conclude that men are overall more willing than women to use wearables, a relatively advanced assessment tool, in their workplace. That said, women are also slightly underrepresented in the sample of Jacobs et al. (2019) indicating possible research biases.

Nationality and country of work

At least one study finds a significant difference between the willingness to use smart office tools of American versus German office workers with the former being more inclined to use it (Röcker, 2009). This is likely caused by generally different attitudes towards data protection between those cultures which is also connected to greatly different data protection laws (Röcker, 2010). Cvrcek et al. (2006) find out that these differences even exist between different European countries.

Educational level

Employees with higher education levels are using the smart assessment tools more often than the less educated (Röcker, 2010). This is likely because of reduced anxiety due to better judgements and a greater chance to detect the benefits of and adapt to the technology (Röcker, 2010).

Other characteristics according to previous studies

Zhang et al. (2022) detect that the willingness to share data for smart health assessment tools depends on the medical history of the user: Persons with previous health issues are more likely to share their data in that case. The trust towards the own company, the corporate culture and the relationship with colleagues can influence the willingness to use smart assessment tools (Röcker, 2010). However, both of those aspects are difficult to properly determine when implementing specific questions in a user study (Röcker, 2010).

Characteristics not covered by previous studies

This being an exploratory study, other characteristics that are not covered by previous studies but may have an influence on office workers' perception of the assessment tools are also investigated in this research. First, it is interesting to find out whether office workers having previous experiences with the respective assessment tools have a different opinion about them compared to office workers without that experience. It is reasonable to assume that having used a tool possibly alters common preconceptions about these tools, as it for example reduces prior existing anxiety about the tool. However, the gained experiences do not necessarily need to lead to a more positive perception but could result in the opposite and a more negative perception as well.

In which way the characteristics of the office workers' offices influence office workers' perceptions is also unclear. How the respective offices are perceived by office workers regarding their level of healthiness and comfortability could well have an influence on their perception of health and comfort assessment tools. Those tools may become less or more important to office workers depending on the state of their office. Similarly, which of the 5 major health and comfort aspects office workers value most could potentially impact their perception of the assessment tools as these tools may target some of the health and comfort in particular while disregarding others.

3.4 Conclusion literature review

In this chapter relevant findings of the literature review (chapter 2 and chapter 3) are transformed into a preliminary conceptual model (see Figure 1). The conceptual model gives a first overview which constructs, variables and relationships are important to answer the research questions (see chapter 1.1). These expectations are partly based on the empirical findings of prior studies but also on common sense or the own thought process while reviewing the literature. Furthermore, this model is the basis for the method design (see chapter 4.3) which explains in more detail how all of these aspects are empirically measured.

For the conceptual model, two main constructs and several subconstructs (titled dimensions for the rest of the thesis) can be derived based on the findings of the literature review. On the one hand, personal characteristics include all dimensions and variables that are specific to each office worker (see chapter 3.3). Smart workplace health & comfort entails aspects about the health and comfort in the office workers' office and how health and comfort aspects are perceived. The office workers' demographics and office workers' previous experiences (with different assessment tools and digital devices as well as their attitude towards data privacy) are the two other dimensions of the construct of personal characteristics. These may relate to office workers' perception of health and comfort assessment tools, the second main construct. Chapter 3.2 reveals that the attributes of assessment tools are an important predictor of office workers' perception and are therefore one dimension of this construct. It should be noted that other dimensions, that cannot be found in the literature review, are added to this construct later on in the method design to be able to draw a more refined picture of the office workers' perception of assessment tools.

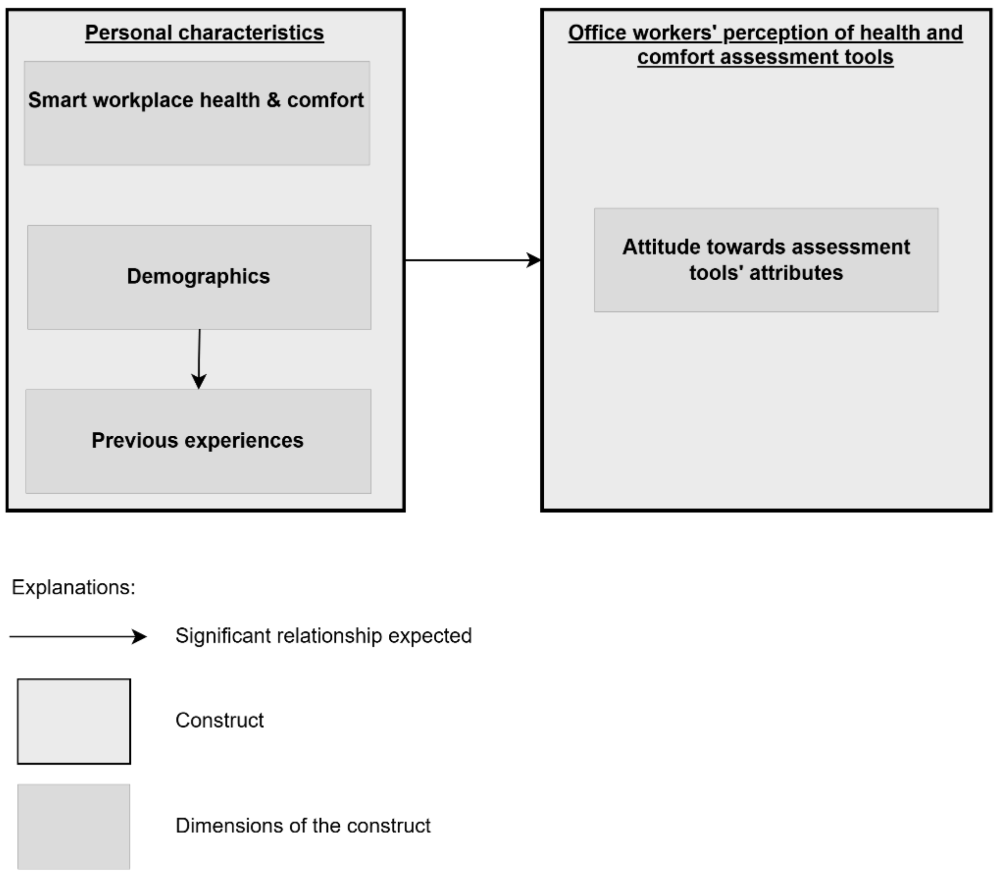


Figure 1: Preliminary conceptual model based on literature review

4. Methodology

4.1 Introduction

Since the literature review of chapter 2 and 3 reveals many research gaps in relation to office workers' perception of health and comfort assessment tools, the chosen research methodology entails many exploratory elements not used in previous studies. Surveys in the form of questionnaires are widely used in research related to the office environment (Appel-Meulenbroek et al., 2018). For studies about employees' experiences, opinions and perceptions (for instance in relation to the indoor environment quality) this methodology is the most used (Appel-Meulenbroek et al., 2018). One of the reasons is that it is a relatively easy methodology to gain large quantities of usually quantitative data (Hua, 2023). But a questionnaire also relies on self-reporting which is a common way to measure people's attitudes and preferences (Gal & Rucker, 2011).

How the sample is assembled, so how the participants are recruited, and which platform is used to host the questionnaire, is described in chapter 4.2. Based on the research design (chapter 3.4), which explains constructs, dimensions and the expected relationships between them, the method design (chapter 4.3) focuses on how constructs and dimensions are further specified into variables and how these are translated into the specific questions of the questionnaire. The quality of the collected data primarily depends on the time and effort needed by participants to complete the questionnaire and how well the participants even understand the questions at hand (Hua, 2023) which is why the design of the questions is so important. Next, in chapter 4.4 it is checked whether items measuring the same subject within a question set are related to each other as intended. Furthermore, this chapter analyses whether the answer patterns of the independent variables are normally distributed. Chapter 4.5 explains how data is processed to remove incomplete data to prepare for analysis. Chapter 4.6 introduces the data analysis methods and statistical tests that are used to analyse the data in chapters 5 and 6. Questionnaires need to fulfil scientific standards to be able to gain valid insights (Hua, 2023) which is accounted for by checking the internal and external consistency in chapter 4.7.

4.2 Data collection

When setting up a questionnaire, a choice needs to be made about who exactly and how many need to participate in it to achieve a satisfactory result (Hua, 2023). The goal of this research is to find out about the preferences and perceptions of office workers in the context of their own office environment. As previous research about this specific research topic is relatively scarce, it is most insightful if inferences over a larger population of office workers can be made. So, because there is no emphasis on any specific subgroups, the population of the research is everyone who regularly works in an office. To filter out anyone who does not comply with this requirement, potential participants are asked upfront to indicate the number of days per week that he or she works in an office of their company or a shared office or coworking space. This filters out employees who solely work from home for instance. If the participant answers "almost never", the results of the questionnaire are not considered for the analysis. These employees that do not regularly work in an office are excluded as they may not have any experience with the working environment in an office or their last experience is somewhat long ago making it harder for them to correctly remember the details of their latest office.

To achieve the research goals, a representative sample of this population needs to be collected. The tests associated with the chosen data analysis methods (see chapter 4.6), require a sample size of at least about n = 20 to n = 25 (Mundry & Fischer, 1998). Therefore, at least 25 participants who fulfil the above-mentioned selection requirement and completely fill out the questionnaire are required. For that, the questionnaire is set up online on LimeSurvey (LimeSurvey, n.d.) which then can easily be distributed and filled out on a computer, laptop or even a smartphone.

To solicit participants, the online questionnaire is distributed among the colleagues working in two offices (Rotterdam in the Netherlands and Düsseldorf in Germany) of the company the student researcher is working for. Furthermore, multiple publicly accessible requests to participate are posted on LinkedIn by the supervisors involved in this thesis. By distributing the questionnaire via a social media platform respondents from various demographic backgrounds and countries can be reached. Lastly, some participants are recruited via the own network of researchers or friends and family members working in an office. Given the predominance of contacts with a high interest in real estate and workplace-related topics, it can be anticipated that these will make up a sizeable proportion of the sample. All respondents filled out the questionnaire in February and March 2024.

4.3 Method Design & Operationalization

Based on the description of constructs, dimensions and the possible relationship between them in subsection 3.4, it is necessary to explain in more detail how these constructs are defined and measured as variables. It is then also depicted how the variables are integrated into the questionnaire through questions and explanations connected to them (see Appendix A for the complete questionnaire). While a few of the included question sets are already used in other studies before (see chapter 4.4.1), others are specifically tailored towards this research.

In any case, the choice, order and phrasing of questions is an especially important consideration in the method design (Hua, 2023). This is so that the questions are relatively easy and straightforward to answer for all participants regardless of their amount of prior knowledge regarding this topic.

A structure with multiple sections and sub-sections (called “steps”) is used in the questionnaire. As a result, participants are guided through the questionnaire one step at a time while continuously gaining more knowledge about the topic. First, without having received any prior information, the participants state the perception towards the health and comfort in their own office. Then, 4 steps are used to give more detailed information about the topic and to ask more specific questions. Each of the 4 steps builds upon the information given in the previous steps. A full overview of the survey is available in Appendix A. An overview of the constructs, dimensions and relationships between are given in Figure 2. All variables used are described in Table 1.

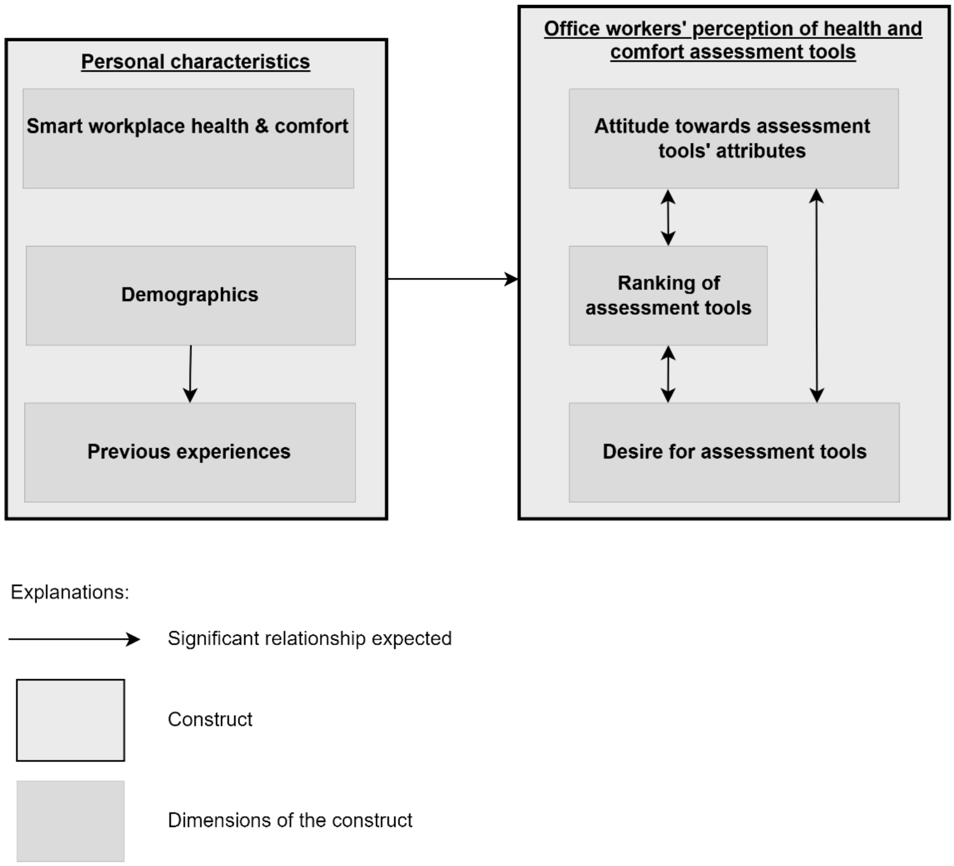


Figure 2: Conceptual model of method design

Table 1: Detailed definition of constructs, dimensions and variables based on the conceptual model

Construct	Dimension	Group of variables	Variables	Description	Measurement scale	References
Personal characteristics	Smart workplace health and comfort	Perception of own office environment	Prior: Perceived health/comfort	Perception of the own, current office regarding the health, comfort level and then individually for the respective aspects	5 point Likert scale	-
			After: Perception of respective health/comfort aspects			-
		Preferences for health and comfort	Ranking of respective health/comfort aspects	Ranking the 5 health and comfort aspects in relation to each other	Ranking 1-5	-

		-	Time spent in the office	Days in a typical week spent working in the office	6 categories	-
	Demographics	-	Gender	Indicating the gender	4 categories	Jacobs et al., 2019
		-	Education	Indicating the highest finished education level	5 categories + open field	Röcker, 2010
		-	Age	Indicating the age	Number field	Mani & Chouk, 2017; Röcker, 2010
		Origin	Country of work	Indicating the current main office location	Selection list	Cvrcek et al., 2006; Röcker, 2009; Röcker, 2010
			Nationality	Indicating the citizenship		
	Previous experiences	Data privacy	Personal attitude towards data privacy	Indicating the attitude	5 point Likert scale	Choi et al., 2017
			Knowledge about data privacy regulations	Indicating the knowledge		Mani & Chouk, 2017
		Technology savviness	Knowledge about and willingness to adapt to digital devices	Indicating the knowledge		Mani & Chouk, 2017; Röcker, 2010
			Time of usage of digital devices	Hours in a typical week spent using digital devices outside of work	4 categories	Mani & Chouk, 2017
		-	Respective tool already present in own office	Existing experience of each tool and in relation to the 5 health and comfort aspects	Yes/No	-

Office workers' perception of health and comfort assessment tools	Attitude towards assessment tools' attributes	-	Amount of collected personal data	Attitude towards different typical attributes associated with each tool	3 point Likert scale	Collins & Marassi, 2021; Gorn & Shklovski, 2016; Harper et al., 2022; Lai et al., 2003; Neff & Nafus, 2016; Teebken & Hess, 2021; Zieglmaier et al., 2022
		-	Level of automatization			Ahmadi-Karvigh et al., 2017; Day et al., 2019; Donkers et al., 2023; Kwon et al., 2019; Lashina et al., 2019; Tuzcuoğlu et al., 2023
		-	Level of accuracy			-
		-	Technological intelligence			-
		-	Data type collected			-
		-	Range of outputs			Mani & Chouk, 2017
		-	Frequency of measurement			-
		-	Proximity to user			-

		-	Responsibility for data collection			-
	Ranking of assessment tools	-	Ranking when health aspects are addressed		Ranking 1-3	-
		-	Ranking when comfort aspects are addressed		Ranking 1-4	-
	Desire for assessment tools	-	Respective tool should be present in the office		Yes/No	-

4.3.1 Variables & questions about personal characteristics

The construct of personal characteristics is distinguished into three dimensions: smart workplace health & comfort, demographics and previous experiences. These are all independent variables that may relate to the dependent variables that constitute the construct of office workers' perception of health and comfort assessment tools (see Figure 2).

Smart workplace health & comfort

One dimension of the construct of personal characteristics is described as smart workplace health & comfort and includes several explanatory variables. In the literature review (see chapter 2.2.1) it is initially discovered that 6 aspects of office workers' health and comfort in the office environment appear to be especially important to workers and simultaneously can be addressed by existing health and comfort assessment tools. Given the length limitations of the questionnaire, it is decided to limit the included health and comfort aspects to 5 in the questionnaire. Out of all the introduced health and comfort aspects, the air quality is deemed to be the least important one and is therefore not further regarded in the research design.

This study therefore focuses on sedentary behaviour and stress as mostly health related aspects as well as the lighting, temperature and noise conditions as mostly comfort related aspects. The research subquestions aim to find out about office workers' preferences for assessment tools specifically in relation to each of these health and comfort aspects. Therefore, how office workers rank these aspects amongst each other and how they already rate the state of them in their current office environments should be impactful for various variables of the office workers' perception of assessment tools. Lastly, it is also reasonable to investigate if the time spent working in the office has any relationship with the dependent variables. Even though it is not specifically mentioned in the literature, it can be anticipated that the actual time spent in the office alters the exposure to tools and the sensitivity to or appreciation of office environment-related matters could change.

The first question of the questionnaire is about the respondents' time spent in the office. This is the opening question so that respondents indicating that they "almost never" work in their company's office or a coworking or shared office space can be filtered out and do not need to answer the rest of the questionnaire. Then, the perception of health and comfort in the own office is derived from two similar sets of questions. The prior question asks about the perceived level of health and comfort in the office without giving any additional information. Step 1 subsequently introduces the 5 relevant health and comfort-related aspects by mentioning some of the most influential issues typically associated with each of the 5 aspects while working in an office setting. As sedentary behaviour is a term that possibly is not known to participants, it is formulated as sitting and moving behaviour in the questionnaire. Moreover, a definition is given of what is meant by health and comfort in the office. Then, participants are asked again to state from their own viewpoint how their office environment scores, but then specifically regarding each of the 5 aspects of health and comfort separately. The question is asked in the same style and on the same scale level as the prior question. This makes it easy to compare how participants perceive their office simply based on their initial gut feelings and how far this matches with the answers given after receiving further information about this specific topic. In step 2, participants are asked to rank the 5 health and comfort aspects in relation to each other. This clarifies which aspect is most (and least) important to the participant. Moreover, later on, it becomes possible to derive how far these experiences and attitudes towards health and comfort in the office relate to how different kinds of assessment tools are perceived.

Demographics

It is revealed that several demographic aspects relate to office workers' perceptions (see chapter 3.4). The nationality of the office worker and the location of their office seems to relate to the attitude towards data privacy and perhaps indirectly also on the perception of assessment tools. Moreover, gender (being male) could relate to the likeliness to rate the more advanced assessment tools positively. A higher education level could indicate a higher willingness to use such smart tools. Meanwhile, higher age could be connected to a smaller likelihood to adapt to new technologies and therefore lower technology savviness That said, younger age groups could also have a more careful attitude towards data privacy. This characteristic perhaps also has indirect relationships with the office workers' perception of assessment tools through the differing technology savviness depending on age.

Demographic questions are presented to respondents as a separate question block at the end of the questionnaire. It is anticipated that these are relatively easy to answer which is why they are best asked at this stage to not unnecessarily fatigue the participants before they move on to the more demanding questions. Questions are asked about the country of origin (revealed by filling in the statement: "I am a citizen of") and the country where the participant works ("I am currently mostly working in"). The gender ("What is your gender?"), age ("What is your age?") and the education level ("What is your highest finished education?") are all straightforward to answer.

Previous experiences

Since data privacy likely is major concern when introducing assessment tools, it is interesting to investigate whether the individuals' attitudes towards data privacy relate to the perception of the tools. Office workers who are less concerned about their private data may prefer the more advanced assessment tools. This aspect can be broken down into the personal attitude towards the collection of private data as well as the knowledge of data privacy regulations. Moreover, office workers' technology savviness is said to also relate to office workers' perception of the assessment tools. A high technology savviness could positively relate to the perception of advanced assessment tools. Technology savviness not only includes the individuals' ease of using and adapting to new technologies but also how often such technologies are used as variables. Having previous experience with a tool could potentially relate to the evaluation of the respective tool.

Following step 2 in the questionnaire which is concerned with the ranking of the health and comfort aspects, step 3 introduces each of the 4 assessment tools. After an introductory text emphasizing the different levels of technological advancement of the assessment tools, respondents are asked whether each of the tools is present in their office and which of the 5 health and comfort aspects are addressed by the tool. Deriving participants' technology savviness is on the one hand done with the help of a previously developed set of items (Areepattamannil & Santos, 2019) that measures the respondents' knowledge about and willingness to adapt to new digital devices. Technology savviness is additionally measured by asking how many hours respondents spend with their digital devices outside of work every day. Lastly, questions about data privacy are asked. Not only does that include a question about respondents' existing knowledge of data privacy regulations. Moreover, an existing set of items is used to measure respondents' attitude towards giving away private data (Harper et al., 2022).

4.3.2 Variables & questions about office workers' perception of health and comfort assessment tools

Various dimensions and variables can be defined of how this construct expresses itself. The perception of assessment tools can be broken down into office workers' attitudes towards assessment tools' attributes – so the attitudes towards the respective tools' characteristic technical features and configurations. These attributes are already introduced in chapter 3.3. To get more comprehensive insights into office workers perception this construct also entails two more dimensions introduced in this subchapter (also see Figure 2). One of them is how office workers rank the different types of tools against each other. It can then be compared how this overall ranking potentially also differs depending on which type of health and comfort aspect is addressed. However, simply comparing if office workers prefer one tool over the other is not sufficient. Whether office workers would like to have each tool present in the office at all is similarly important to investigate.

Defining the health and comfort assessment tools and levels of smartness

First, a detailed overview is given about which health and comfort assessment tools are included and how they are defined in this research (see Table 2). As it is anticipated that the participants of the questionnaire are required to process a considerable amount of information, the information given to participants concerning the assessment tools needs to be as short and precise as possible. This is also because some office workers might not have knowledge about the respective assessment tools requiring them to go through a relatively long thought process before being able to answer questions. Consequently, the amount of assessment tools that can be included in the questionnaire is limited – and so is the information that can be provided to the participants about the tools. Why these specific four assessment tools (surveys, smartphone app-based surveys, room-mounted sensors and wearables) are selected for this research is depicted in chapter 2.2.2.

Furthermore, a main part of this research is also about deriving which kind of tool is most preferred among office workers. The different existing tools consequently need to be summarized into distinct categories. Based on the review of the various assessment tools (see chapter 2.2.1) a suitable scheme is to categorize them into three different levels depending on how smart the respective tools are. How this categorization is set up and how the smartness can be broken down is pictured in Table 2. Obviously, the tools that are already existing in real office environments usually have some unique features to them and thus rarely fit into narrowly predefined levels. The levels can be understood as a generalization and abbreviated version of tools resembling existing health and comfort assessment tools. To be able to compare the three different levels in the analysis, they are defined based on different specifications of the same 9 common attributes which are relevant characterizing features of the tools from the office workers' viewpoint. First, the amount of personal information collected (I) can differ majorly depending on how advanced and finely-grained the range of outputs (II) of the respective tool is (e.g., whether insights are gained about the individual workers or the office/staff as a whole). Similarly, the data type collected (III) refers to the spatial scale level data is measured on (e.g., ranging from very finely-grained measurements on the own body, or the own work desk to more general measurements within the whole room or office). Who is responsible for the data collection (IV) can alter between the own organization office workers are working for or an external provider of the tool. Data processing happens in between the data collection and the output given and differs depending on the technological intelligence of the tool used (V) (e.g., artificial intelligence vs. "conventional" approaches). Different assessment tools collect data in different proximities to the workers (VI). Data can be collected directly from the own body or for instance from the ceilings of rooms. The level of automatization (VII) can range from completely manual, user-operated inputs to fully automatic data collection methods. Highly dependent on other attributes is the level of accuracy of tools (VIII). Last but not least, whether it happens infrequently or constantly, there are vast differences in the frequency of the data measurements of tools (IX). How these attributes are expected to be perceived by office workers is described later in this subchapter.

In the questionnaire, respondents receive explicit information about the health and comfort assessment tools described in the rows "description of tools in the questionnaire" and the rows "statements included in the questionnaire" (for each of the 9 assessment tools' attributes). Unfortunately, it is not possible to include statements for all attributes for all assessment tools as it becomes necessary to limit the amount of details given to respondents. Giving too much complicated information would risk fatigue among respondents which consequently leads to less qualitative responses or respondents quitting the questionnaire. Therefore, the selected statements have been chosen as they provide crucial contextualising background information of the respective assessment tools to the respondents and are expected to generate the most insights for the purposes of this research. However, it can be assumed that respondents are not just basing their opinions and answers on this explicit information that is included in a written form, but it can be expected that certain attributes of the assessment tools are also implicitly inferred by respondents. Therefore, it is for instance not deemed necessary to explicitly mention that wearables are provided and controlled by an external party rather than the own organisation as respondents would likely already infer that anyway. This also reduces the amount of statements that need to be included in the questionnaire.

Table 2: Definition of the health and comfort assessment tools in the questionnaire

Level of smartness	1 (non-smart)	2 (medium)		3 (high)
Name of tool in questionnaire	Survey	Mobile phone apps	Room mounted sensors	Wearables
Description of tool in questionnaire	Yearly, anonymized survey, initiated by your organization	Frequent and personalized app-based surveys on your mobile phone	Room-mounted sensors (with exemplary picture)	Wearable sensors (e.g. a Fitbit)
Addressed health/ comfort aspects	All 5	All 5	Only lighting, temperature and noise conditions	All 5
Amount of collected personal data	No personal information	Personal, self-reported information about behaviour, environmental conditions	No personal information (only movement patterns traceable through measurement of environmental conditions)	Bodily parameters and behaviour patterns
Statement included in questionnaire	“I like that the survey is anonymous and no personal information is collected”	"I like that more personal data is collected"	-	"I like that very personal data is collected”
Level of automatization	Data collection fully manual by users	Data collection fully manual by users	Data collection fully automatized, no manual inputs	Data collection fully automatized, no manual inputs

Statement included in questionnaire	"I like that the data is self-reported in a subjective manner and not measured in a more extensive way"	"I like that the data is self-reported in a subjective manner and not measured in a more extensive way"	"I like that I do not have to give any manual inputs"	"I like that I do not have to give any manual inputs"
Level of accuracy	Low due to low frequency and subjective inputs	Medium due to tailor-made, artificial intelligence-driven questions and outputs, still based on subjective inputs	Medium due to high measurement quality but high distance to users	High due to very detailed input and output information and close proximity to user
Statement included in questionnaire	-	-	-	"I like that the gained insights are very accurate and detailed"
Technological intelligence	Conventional	Data processing with the help of artificial intelligence	Data processing with the help of artificial intelligence	Respondents may infer a high technological intelligence
Statement included in questionnaire	-	"I like that the data is processed with the help of artificial intelligence"	"I like that the data is processed with the help of artificial intelligence"	-
Data type collected	Subjective self-reported data, not measured	Subjective self-reported data, not measured	Objective, measured data (about environment)	Objective, measured data (about environment & body)
Statement included in questionnaire	-	-	"I like that the actual environmental conditions are measured"	"I like that my own bodily parameters are measured" "I like that the actual environmental conditions at my desk are measured"
Range of outputs	Only general, anonymous advice for whole office	Personalized, individual behaviour changes	Advice and adjustments for individual rooms/work areas; movement patterns traceable	Very distinct, personalized advice. Environmental conditions at work desk level can be traced

Statement included in questionnaire	“I like that insights are gained for the office as a whole and not for me specifically"	"I like that personalized, individual behaviour changes can be suggested / gained insights are very personalized"	"I like that such sensor technologies could also enable the tracing of my movement patterns in my room(s)" & "I like that specific adjustments for my individual rooms are possible"	"I like that the actual environmental conditions at my desk are measured" & "I like that personalized, individual behaviour changes can be suggested / gained insights are very personalized"
Frequency of measurement	Only once a year	Frequent	Constantly	Constantly
Statement included in questionnaire	-	-	-	"I like that the measurements are taking place constantly"
Proximity to user	Work laptop, computer	(Personal) smartphone for data collection	Room-mounted (thus still recognizable but not really intrusive)	Immediate vicinity through body contact
Statement included in questionnaire	-	"I like that the surveys can be filled out on my own smartphone"	-	"I like that I have to wear the sensors directly on my body"
Responsibility for data collection	Own organisation	External app provider	Respondents could both infer that the own organisation or an external provider is responsible	Respondent likely infer that the manufacturer of wearable is responsible
Statement included in questionnaire	“I like that my own organisation is responsible for collecting the data”	"I like that an external app provider is responsible for the data collection and not my organisation"	-	-

The chosen 4 assessment tools therefore majorly distinguish themselves by their level of smartness. To allow for a comparison of office workers’ perceptions of assessment tools that are advanced and smart with the perception of tools that are not smart at all, a representative, non-smart assessment tool needs to be defined for level 1. This level is consequently not just set up like this to create clear distinctions to the other levels but also to be able to analyse if participants in the questionnaire rather prefer 'non-smart' or 'smart' tools for addressing the various health and comfort-related aspects. Although the goal of the literature review (see chapter 2.2.1) is not explicitly to find out more about such tools, less advanced instruments are sometimes added to smarter tools to be able to compare subjective data input methods with the often-times more objective smart methods.

Conventional surveys fulfil such a role due to the self-reporting they are based and are an especially often cited assessment tool suitable for this study's definition of level 1. As such, surveys in this context aim to fulfil similar purposes as smart tools but on a less advanced level. This being the least advanced level of assessment tools, it is assumed that in contrast to level 2, these surveys occur infrequently and in an anonymized way. Organizations can initiate these kinds of surveys by themselves (e.g., through in-house departments) to gain insights about the general state of the health and comfort level of their staff and their indoor environments. Additionally, a lack of any advanced data processing ability further infers that limited insights and only abstract and generalized feedback can be given to the whole staff rather than the individuals. The possible advantage of this assessment tool for office workers is that not much or any personal data should be required to derive this level of insights and no actual measurement with potentially intrusive technologies is required.

Level 2 refers to assessment tools of medium technological advancement so in-between the non-smart tools and the very high-end technologies. Two different types of tools are included in level 2 that seem to commonly occur in the previous literature (see chapter 2.2.1) - room-mounted sensors and smartphone-based surveys designed to provide personal insights. Starting with the aspects mostly related to the indoor environment so the lighting, temperature and noise conditions, assessment tools using room-mounted sensor technologies can be considered to be technologically more advanced and smarter than the level 1 surveys (although not as advanced as the level 3 tool. It can be assumed that the data is measured constantly and leads to more objectively viable outputs compared to the self-reporting taking place in surveys. More accurate adjustments can therefore be made to the indoor environment on a room level without using much or any personal information or collecting data in very close proximity to the user.

A more recent development are smartphone-based surveys that are being introduced with a comparable level of advancement and also somewhat similar level of smartness. These surveys are however also able to address stress levels and sedentary behaviours in the office. As the naming suggests and contrary to the surveys of level 1, these surveys can be filled out on smartphone apps provided by external companies. They are also personalized and chatbots driven by artificial intelligence algorithms that improve the possible insights to be gained. It can also assumed that these inputs per user are happening more frequently than in level 1. As more private data is being processed, more personalized insights and a higher, albeit still limited, usefulness of the output of this level of assessment tool are expected. Since data is still being self-reported, this level of assessment tool is therefore subject to the same, previously mentioned subjectivity limitations of surveys.

Level 3 describes current, state-of-the-art and advanced assessment tools. Sensors included in wearables are a very common technology measuring all kinds of bodily parameters, user, or environmental conditions for all included health and comfort aspects in an office setting. Wristbands or smart watches are used noticeably often as hardware. These devices generally come along with a high level of intrusiveness as they are collecting relatively personal data in immediate proximity to office users. On the other hand, it can be expected that this level of assessment tool can deliver the most accurate, detailed and personalized outputs about the individual's behaviour and the environmental conditions at their workstation.

Attitudes towards assessment tools' attributes

After introducing the 4 assessment tools and the levels of smartness included in this study's questionnaire, this section specifically focuses on the 9 common attributes (the tools' characteristic features and specifications) that are used to define the assessment tools. From the questionnaire, it is also possible to derive the attitudes towards these attributes to find out why each of the assessment tools and levels of smartness are liked or disliked by office workers. The literature review reveals many common attributes and specifications of health and comfort assessment tools (see chapter 2.2.1) but also which of those attributes likely relate to office workers' perception of the assessment tools (see chapter 3.2). Other attributes listed here are, however, exploratory and the type of relationship they have with office workers' perceptions can only be assumed for now.

To sum it up, the amount of collected personal data is among the attributes that should overall have a negative impact on office workers' perceptions of such assessment tools. Moreover, some assessment tools such as wearable sensors collect data in very close proximity to the user. It can be expected that closer proximity of a tool to the user is perceived as intrusive possibly resulting in a negative perception.

On the other hand, it can be argued that a higher usefulness and scope of the assessment tools' output (named "range of outputs" in the model) is an attribute that should positively relate to the perception. A higher level of accuracy and therefore more granular outputs is something that the more advanced assessment tools can especially provide which should positively relate to office workers' perception. The output of the assessment tools is potentially more useful in this case.

There is also a range of attributes becoming apparent in existing assessment tools for which it cannot be anticipated or it is unclear whether they have a positive or negative relationship (or no relationship at all) with the office workers' perception: For the level of automatization, so how much manual control users have over the tool, it is unclear whether the impact on the office workers' perceptions are positive or negative. Whether the data is measured in an objective way or provided by the users via self-reports in a subjective manner is another one of those attributes. Moreover, the frequency of the data collection and whether an internal or external party is responsible for that could play a role. Lastly, the level of technological intelligence, with a high level referring to the use of machine learning algorithms, or artificial intelligence respectively, may have an impact on the office workers' perception of assessment tools.

It is not just interesting to investigate how all of these attributes are perceived for each of the assessment tools but also whether these choices are possibly related to the rankings of assessment tools and the desire to have the respective tools present in the office. In Table 2, the rows "statement in the questionnaire" depict the exact statements that need to be evaluated by respondents of the questionnaire. Due to constraints about the length of the survey, opinions cannot be tested towards statements of all attributes and all tools. Statements are included for those tools' attributes that seem to provide the most insights for this research.

Ranking and desire for assessment tools

Next to the evaluation of statements about the assessment tools' attributes, the questionnaire also includes a ranking of the 4 assessment tools. The tools consequently need to be ranked amongst each other indicating the most to the least favoured tool. This ranking is completed 5 times for each health and comfort aspects to derive possibly differing answer patterns if different health and comfort aspects are addressed by the tools. From the rankings, it can be concluded which tools are most preferred by office workers, but it is not clear whether they actually also want to have the respective tools present in their office. Thus, a question is included about whether the respective tool should be present and if so which of the 5 health and comfort aspects should then be addressed by it. Overall, this should yield a relatively precise picture of which kind of assessment tools are most preferred for a specific health and comfort aspect addressed in the office.

4.4 Reliability & Validity

4.4.1 Inter item correlation & Internal consistency

Checking for internal consistency in the dataset is necessary before starting with the data analysis. It is checked whether multiple items that measure the same variable as a scale are sufficiently correlated with each other. If this concerns only two items, an inter-item correlation is run. If the correlation between the two results has a value that is higher than 0.3 (which is considered a medium effect size (Cohen, 2009) and lower than 0.8 (a higher correlation coefficient than this indicates redundancy and can lead to multicollinearity (Midi et al., 2010), the correlation is sufficient to combine the items. If three or more items are compared, the Cronbach's Alpha test is used. Here a value of 0.7 to 0.95 is acceptable to assume that the items are sufficiently correlated (Tavakol & Dennick, 2011). If items are sufficiently correlated, the answers to those items can be combined resulting in an average answer for the respective variable in the data analysis. Consequently, only this combined, average answer is used in the further data analysis in chapters 5 and 6 which allows for a leaner data analysis.

A previous study (Harper et al., 2022) develop a 4 item-question to measure the attitude towards data privacy. The reliability test reveals that the answers for all items are indeed closely correlated with a Cronbach's Alpha of 0.733 (see Appendix B – Figure B1). Similarly, technology savviness is measured by two items (Areepattamannil & Santos, 2019) that are also closely correlated with an inter-item correlation of 0.397 ($p<0.01$) (see Appendix B – Figure B2). Consequently, for both variables, the average answers are used in the data analysis.

4.4.2 Variables with high similarities in their answers

Before the data analysis begins, it is tested whether variables that measure similar aspects in the questionnaire are correlated to each other. In contrast to the relationships explained in chapter 4.4.1, the relationships described in this chapter are unintended relationships between variables that are not explicitly discovered by previous studies. Such similar types of questions are included in the questionnaire to gain a more comprehensive understanding of respondents' preferences and to check whether respondents provide consistent answers. Just like in chapter 4.4.2, if variables are sufficiently correlated (if the correlation coefficient is >0.3 and <0.8 or if Cronbach's Alpha is >0.7), a new variable is created for the data analysis containing the average answers of all input variables. These new variables are not based on already established, purposely developed multi-item scales but are solely created for this research. It is sensible to check for such redundancies to reduce the number of correlations that need to be tested in the bivariate analysis. All variables that fulfil these conditions and therefore have been computed into a new, combined variable are provided in Chapter 5.1.2. Given that these new variables take an average of multiple existing variables, the answers always need to be recoded to a continuous scale for the descriptive and bivariate data analysis.

4.4.3 Normality

Checking whether the answers to variables are normally distributed is necessary so that it can be decided which statistical tests need to be used in the analysis later on. The assumption of normality is checked for all continuous dependent variables that are tested as part of the bivariate analysis. First, the Shapiro Wilk test is utilized. This test is suited for small sample sizes of about $n < 50$ (Habibzadeh, 2024). Only in case the p-value is greater than 0.05, it can be assumed that this variable is normally distributed (Habibzadeh, 2024). However, given the low sample size such tests mostly lead to the conclusion that the variable is not normally distributed. Because of that, an additional visual test is done by looking at the histograms of the variables to determine whether the answers are roughly normally distributed despite the test revealing they are not. All tests are pictured in Appendix C.

Given the low sample size, both the mathematical and the visual tests reveal that the answers to most relevant variables are not normally distributed. There are a few outliers for which the Shapiro-Wilk test indicates a non-normal distribution but the visual test suggests a normal distribution. This is the case for the answers to two statements about the attributes of the assessment tools. More particularly a statement about surveys ("I like that the data is self-reported in a subjective manner and not measured in a more extensive way")(Appendix C – Figure C1) and about smartphone apps ("I like that an external app provider is responsible for the data collection and not my organisation")(Appendix C – Figure C2) can be considered to be about normally distributed. Moreover, the ranking of the smartphone app among the assessment tools of health aspects (Appendix C – Figure C11) and if comfort aspects (Appendix C – Figure C12) are addressed and can be considered to be about normally distributed after the visual inspection. This is also the case for the ranking of surveys if comfort aspects are addressed (Appendix C – Figure C12). The same can be said regarding the knowledge about and willingness to adapt to digital devices (technology savviness) (Appendix C – Figure C3). In one instance, both the mathematical and the visual tests reveal a normal distribution. This concerns the answers to the personal attitude towards data privacy (Appendix C – Figure C4.) Nevertheless, to enable a more consistent inferential data analysis (chapter 6), only non-parametric tests will be used given the overwhelming majority of not normally distributed variables.

4.5 Data preparation

A total of 68 respondents completed the questionnaire. All incomplete responses of respondents not completing the whole questionnaire are excluded from this set for further analysis, except for two cases. One of these two respondents fails to answer the last 12 questions in the questionnaire and therefore data is only missing about the ranking of the different assessment tools and the follow-up questions (see Appendix A). The other person answers one answer less than that and therefore additionally not expresses an opinion about the wearable technology's attributes. However, since both respondents answer the majority of questions and also give valuable insights for answers that are fundamental for answering the research questions, these two responses are included in the final analysis too. This brings the total number of included responses to a sample size of 46 in the final analysis.

The missing data for the unanswered questions of these 2 respondents are not replaced by estimations or averages in the data set. Because of these incomplete responses, the sample size differs between different questions and variables. In the descriptive analysis (chapter 5), the exact sample size for each variable is reported. A few questions are not mandatory to answer which is why the sample size may be lower for those as well. This concerns the questions about which health and comfort aspects each of the 4 introduced assessment tools should address in the office. These questions are only presented to respondents who previously state that they would like to have the respective assessment tool present in the office. Moreover, questions about the respondent's gender, age, citizenship and country of work are not mandatory to answer to avoid respondents quitting the questionnaire because they do not want to provide this personal information.

None of the included responses are characterized by suspiciously consistent answer patterns (e.g., the same answer option like "fully agree" is always selected) which would require the exclusion of these answers. This shows that the respondents not just quickly fill in the survey without spending any thought on it. The shortest answer time of the included responses for the whole questionnaire is 5 minutes with the median time to fill it in being just under 10 minutes. All responses fulfil the check that is performed in the questionnaire to ensure that all of the respondents are working from the office at least once a week. This is a mandatory criterion for participating in the study. As part of the data preparation process, a few custom answers for the question asking about the education level are manually edited and sorted into the existing answer categories for this question.

4.6 Quantitative data analysis & Method description

For the type of data that is collected, two types of data analysis are especially insightful for the purpose of this research - descriptive analysis and bivariate analysis.

4.6.1 Descriptive analyses

At the beginning of the data analysis (see chapter 5), the descriptive data analysis is described. In here, the sample is examined further by analysing a variety of statistical values for all variables included in the questionnaire. A lot of insights to answer the research questions can already be gained by conducting descriptive analysis for all of the variables.

Depending on the variable, specific statistical values are reported. Most variables contain categorical data. In that case, the frequency (so the count of answers given for each of the answer categories) is reported to picture the distribution of the given answers. Some variables are continuous and therefore the mean, median and standard deviation (and optionally also the minimum and maximum) are reported. This concerns the age of respondents but also all variables that consist of combined variables as described in chapters 4.4.1 and 4.4.2. Again, the distribution of the answers for the respective variables can be derived by analysing those values. Since this research includes a lot of explorative elements which (to my knowledge) are not examined by any previous studies, the descriptive analysis is not just relevant to get an overview of the sample. In addition, possibly interesting answer patterns can be detected and first insights to answer some of the research questions can be gained. In particular, the descriptive analysis provides the answer to subquestion 4: "Which types of health and comfort assessment tools are preferred by office workers for measuring different aspects of their health or comfort in the office?"

4.6.2 Bivariate analyses

Following this first step in the data analysis, inferential statistics are used to answer more research subquestions by detecting possible relationships between numerous independent and dependent variables (see chapter 6). More precisely, the research subquestions 6: "How do attributes of assessment tools relate to office workers' preferences for health and comfort assessment tools?" and 7 "How do personal characteristics relate to office workers' preferences for health and comfort assessment tools?" are answered with the bivariate analysis.

Bivariate analysis – a relatively simplistic methodology of quantitative data analysis that nevertheless enables a comprehensive coverage of the measured variables (Erenstein & Farooq, 2009) - involves the analysis of the relationship between two variables, one independent and one dependent variable. If a relationship turns out to be significant, conclusions can be derived for the whole population of office workers (although limitations in terms of the result's validity remain as described in chapter 7.2). The significance level is set at 5% (p-value < 0.05) which is commonly utilized in social science-related research (e.g., Pramitha Dewi & Ganing, 2021). To statistically analyse the relationships, different tests are used for the bivariate analysis. The selection of the test depends on the level of measurement of the dependent and independent variables. This research includes variables that are measured on nominal as well as ordinal and continuous scales. The various Likert scales and the combined variables involved in the research are considered to be approximately continuous (Norman, 2010) which determines the tests used to analyse those variables.

Independent Variable	Dependent Variable			
	Nominal 2 categories	Nominal >2 categories	Ordinal	Interval/Ratio
Nominal 2 categories	Chi- square test		Mann–Whitney U test	Independent sample t-test
Nominal >2 categories			Kruskal-Wallis H test	Analysis of Variance (ANOVA)
Ordinal	Mann–Whitney U test	Kruskal-Wallis H test	Wilcoxon T-test Spearman correlation	Wilcoxon T-test Spearman correlation
Ratio	Independent sample t-test	Analysis of Variance (ANOVA)	Wilcoxon T-test Spearman correlation	Paired sample t-test Pearson correlation

Figure 3: Statistical tests for variables with different levels of measurement

The Figure 3 also includes non-parametric tests. As concluded in chapter 4.4.3, only non-parametric tests are used to analyse the data in this research. In the following, all of the utilized tests in this research are described which includes the combinations of variables for which the test is applicable. The utilized tests are further described in Appendix E.

4.7 Internal & external validity

Ensuring internal and external validity is crucial to the reliability and generalizability of the findings of this study. Given the limited scale and scope of this thesis, it however needs to be mentioned that several limitations due to the limited internal and external validity of this research naturally remain and are further described in chapter 7.2.

Internal validity

Internal validity refers to the extent to which the research design accurately measures the intended variables and no other, unaccounted factors relate to the results (Barry, 2005). The extent to which cause-effect-conclusions are allowed to be drawn is determined by whether internal validity is accounted for (Schonfeld & Chang, 2016). Several potential threats to internal validity are considered and addressed by this research design.

First, an opening question is included to make sure that only respondents who are regularly working in an office are filling out the questionnaire. Thus, respondents who do not fulfil this criteria are filtered out. Even though the remaining sample (n = 46) is not particularly big, it meets the 25 respondent requirement to run the statistical tests. Recruiting participants with various backgrounds (more information on the recruitment is given later on when considering the external validity) is an attempt to nevertheless ensure a high internal validity.

Questions about the respondents' diverse personal characteristics are included in the questionnaire to minimize risking a situation in which changes in a dependent variable are the result of some type of confounding variable of respondents not measured in the questionnaire.

If descriptions or questions in the questionnaire are unclear, or if it takes too long to be completed, misinterpretations or fatigue of respondents could occur negatively affecting the results (Hess et al., 2012). To counter this, the online questionnaire is thoroughly tested with the supervisors, friends and family members before being published. Multiple rounds of feedback ensure that the questions are clear and understandable. By ensuring the survey is concise and user-friendly, participant drop-out rates can be reduced. Feedback from initial testers confirms that the survey can be completed in a reasonable amount of time. However, participants' familiarity with the questionnaire can of course influence their responses. While repeated testing with supervisors, friends and family members helps to refine the questions, it is ensured that the respondents being part of the final sample are not exposed to the questionnaire beforehand. Questions that are very personal, such as about respondents' citizenship, country of work, gender, and age, are optional to answer to respect participants' privacy. This approach encourages honest and complete responses without making participants uncomfortable or even quitting the questionnaire. Lastly, even though this is an exploratory study with many unique questions included in the questionnaire, some of the questions (regarding the attitude towards data privacy and technology savviness) are already used and tested in other studies and can therefore be trusted to yield reliable results in this study as well.

External Validity

External validity refers to the extent to which the findings can be generalized to other settings, populations, and times (Skinner, 1981). Potential threats lowering the external validity and strategies to mitigate those threats are included in the design of this research.

Even though sufficient to run the statistical tests, the small sample size can cause challenges during the analysis. To ensure that the sample is still somewhat representative of the whole population of office workers, several different recruitment channels are used. Respondents are not just recruited via the supervisors' and my own LinkedIn networks but are also working in two offices of my organization that are each situated in a different country (Rotterdam in the Netherlands and Düsseldorf in Germany). Moreover, friends and family members working in offices are also asked to participate in the questionnaire. To analyse how diverse the sample actually is, and in how far it represents the broader population of office workers, questions about diverse personal characteristics are included in the questionnaire. Of course, having a sample that primarily originates from two neighbouring countries may limit the generalizability of the findings to a global context. However, the provided insights are at least not restricted to a single national context.

The study's findings should be applicable to real-world office settings. This is why the chosen tools and descriptions in the questionnaire are designed to reflect actual health and comfort assessment tools as closely and comprehensively as possible. In conclusion, multiple strategies to ensure both internal and external validity are taken to improve the robustness of this study.

5. Descriptive analyses

5.1 Personal characteristics

The personal characteristics contain all variables of the respondents included in the questionnaire that could potentially be related to their perception of health and comfort assessment tools. However, the following chapters solely describe the answer patterns of those variables which nevertheless also provides insights for further data analysis. The personal characteristics can be distinguished into the dimensions of demographics, smart workplace health & comfort and previous experiences.

5.1.1 Demographics

In the study, various characteristics of respondents are taken into account, providing insights into the demographic background of the sample. More specifically, the gender, education level, origin (nationality and the country of work) as well as the age of respondents are included.

Personal characteristics	Frequency Count
Gender	
**n = 44*	
Female	27
Male	16
Other	-
Rather not say	1
Level of education	
**n = 44*	
Secondary education	4
Applied science university degree	4
University bachelor's degree	8
Post-graduate degree	28
Nationality	
**n = 42*	
China	1
Finland	1
Germany	13
Ghana	2
Ireland	1
Netherlands	13
Portugal	2
Russia	1
Turkey	1
United Kingdom	5
United States	2
Country of work	
**n = 41*	
Belgium	1
Germany	13
Hungary	1
Ireland	1
Netherlands	15
Portugal	1
Spain	1
Switzerland	1
United Kingdom	4
United States	3

*refers to the number of respondents that answered the question(s) about this item

Figure 4: Descriptive statistics of demographic variables

Gender

The gender distribution within the study population reveals a predominance of female participants, constituting 27 of the 44 individuals who answer this question. 16 males, on the other hand, answer the questionnaire with one participant not willing to disclose their gender. For the total population of office workers' one would expect both genders to roughly have a 50% share, but this likely also depends on the business sector.

Education level

Moving on to the educational level of participants, it becomes clear that a majority (28 of 44 individuals who give an answer) possess a post-graduate degree. Additionally, 12 participants either hold a University Bachelor's degree or a University of Applied Science degree. Individuals that have no degree in higher education are very underrepresented in the sample with only 4 of them participating in the questionnaire. This may indicate that the sample is somewhat biased towards the highly educated, but populations of office workers generally can be considered to be somewhat more highly educated than the average general population.

Origin

The origin of the participants is split into two questions. First, it is asked which citizenship the individual holds. Germany (13) and the Netherlands (13) make up a slight majority of the sample of 42 respondents. The United Kingdom (5) is the only other nationality that is represented with more than 2 respondents.

Second, the distributions of countries in which the respondents are currently working are very similar. 15 of 41 work in the Netherlands, 13 of them in Germany and 4 in the United Kingdom. The other countries are less represented (with 9 respondents in total).

Age

The mean age of respondents is 32.7 years (SD = 8.207) ranging from 22 to 58. In Appendix D – Figure 1 it can be seen that the sample does not follow a typical normal distribution and is skewed to the right. This reveals a predominance of young starters and young professionals over older age groups in the sample.

5.1.2 Variables with high similarities in their answers

Some variables connected to smart workplace health and comfort and office workers' preferences towards assessment tools are answered significantly similar to variables measuring similar aspects (see Table 3). Based on the requirements and methodology formulated in chapter 4.4.2, new, merged variables are created which are then exclusively used for the following data analysis containing the average answers of all input variables. As only the new variables are reported, this allows for leaner descriptive and bivariate data analyses avoiding the analysis of variables that are very similar to each other without missing any insights.

In regard to smart workplace health and comfort, there is a very high similarity between the answers given to the question about whether the own office is a healthy and whether it is a comfortable place to work. The same can be said regarding some variables regarding office workers' preferences towards assessment tools. This, on the one hand, concerns answers to statements about attributes of assessment tools. For the level of automatization, the statement "I like that the data is self-reported in a subjective manner and not measured in a more extensive way" is presented twice, both in regard to surveys as a means to gather health or comfort information and in regard to smartphone apps as tools that are measuring data this way. Unsurprisingly, the attitudes towards these statements are very similar regardless of which tool is gathering the information (#1 in Table 3). Moreover, another statement about the level of automatization "I like that I do not have to give any manual inputs" shows this high correlation between the answers of the two different assessment tools this statement has been connected to (#2). Lastly, the statement about artificial intelligence ("I like that the data is processed with the help of artificial intelligence") is also included in regard to the two tools and the answers are highly correlated as well (#3). On the other hand, the desire for and ranking of assessment tools also shows similar answer patterns. In case participants indicate that surveys or smartphone apps should be present in the office, they indicate that the surveys (#4) and smartphone apps (#5) should then also address all of the possible health and comfort aspects. The rankings of the 3 assessment tools addressing health-related aspects are very similar between the two different health-related aspects for which this question is filled in separately. This means that the evaluation of the assessment tools seemingly does not depend on which specific health aspect is addressed (#6, #7, #8). The same can be discovered for the rankings of the 4 assessment tools when addressing the individual comfort aspects. Because of the close correlations, it can be said that the ranking of the assessment tools remains the same regardless of which comfort aspect is addressed (#9, #10, #11, #12). Lastly, the perception of the healthiness of the office is correlated with the perceived comfortability (#13).

Table 3: Variables with high similarities in their answers

#	Variables					Statistical test	Statistics
1	Surveys require data to be self-reported	Apps require data to be self-reported				Spearman correlation	r(44) = -.772
2	Room sensors measure data automatically	Wearables measure data automatically				Spearman correlation	r(44) = .399
3	Apps data processed by AI	Room sensor data processed by AI				Spearman correlation	r(44) = .487
4	Surveys to assess sedentary beh.	Surveys to assess stress	Surveys to assess lighting	Surveys to assess temperature	Surveys to assess noise	Cronbach's Alpha	.844
5	Apps to assess sedentary beh.	Apps to assess stress	Apps to assess lighting	Apps to assess temperature	Apps to assess noise	Cronbach's Alpha	.854
6	Rank surveys assessing sedentary beh.	Rank surveys assessing stress				Spearman correlation	r(42) = .546
7	Rank apps assessing sedentary beh.	Rank apps assessing stress				Spearman correlation	r(42) = .380
8	Rank wearables assessing sedentary beh.	Rank wearables assessing stress				Spearman correlation	r(42) = .390
9	Rank surveys assessing lighting	Rank surveys assessing temperature	Rank surveys assessing noise			Cronbach's Alpha	.796
10	Rank apps assessing lighting	Rank apps assessing temperature	Rank apps assessing noise			Cronbach's Alpha	.794
11	Rank room sensors assessing lighting	Rank room sensors assessing temperature	Rank room sensors assessing noise			Cronbach's Alpha	.793
12	Rank wearables assessing lighting	Rank wearables assessing temperature	Rank wearables assessing noise			Cronbach's Alpha	.702
13	Office is healthy	Office is comfortable				Spearman correlation	r(44) = .737

5.1.3 Smart workplace health & comfort

This sub-section dives deeper into office workers' perception of their current office regarding health and comfort and their preferences regarding the 5 main health and comfort aspects in the office.

Perception of the own office environment regarding the health & comfort

Without having received any additional explanations, respondents need to evaluate their office environment in how far it is healthy and comfortable (new variable #13 in Table 3) (on a scale from completely disagree (-2) to completely agree (+2)). On average, the 46 respondents agree (Mean = 0.63; SD = 0.90) that their office is comfortable and healthy (see Appendix D – Figure 2 for more information on how the answers are distributed).

After an introduction to what health and comfort in the office entails, respondents are asked to evaluate how their current office scores on each of the selected 5 health and comfort aspects (see Figure 6 and Appendix D – Figure 3). This gives a more granular picture than the first opening question.

Respondents relatively frequently think that their office is characterized by good lighting conditions (31 out of 46 think that their office has good or very good lighting conditions) and low stress levels (21 (completely) agree with this while only 13 (completely) disagree). On the other hand, 20 respondents disagree (or completely disagree) that their office is characterized by good noise conditions. Besides these aspects that seem to be pretty positive or negative in the respondents' offices, for the two remaining aspects, it cannot be determined as clearly whether they are perceived positively or negatively. As such, the perception of the temperature conditions is relatively evenly spread with roughly an equal number of respondents (completely) agreeing and (completely) disagreeing with the statement. Lastly, a relatively dichotomous distribution can be discovered concerning the perception of the sitting and moving behaviour. Many respondents either agree or disagree that their office promotes good sitting and moving behaviours with only a few (5) respondents having a neutral stance regarding this.

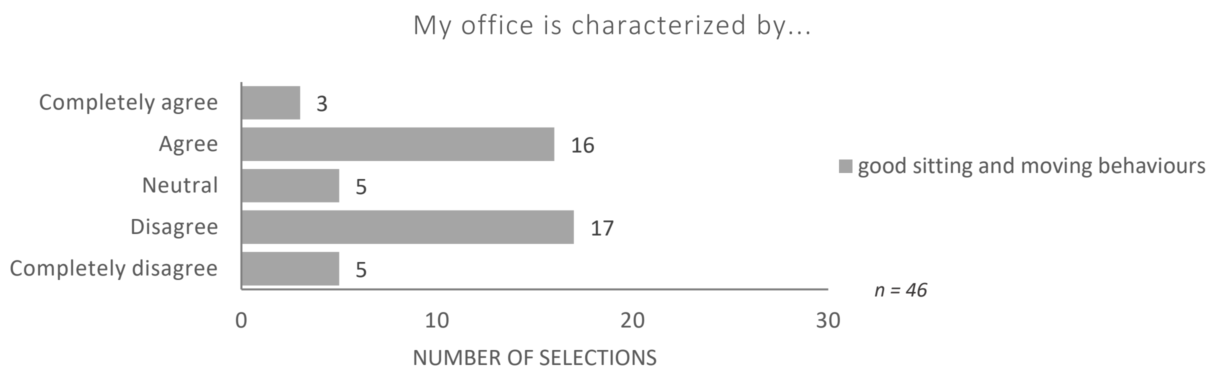
It however becomes apparent that the answer patterns slightly shifted between the first and second questions which may depend on the definition of the 5 health and comfort aspects given to respondents in between the questions. On average, respondents view their office more favourable in regard to health and comfort without the extra information. After receiving the extra information, they change their opinion to some degree when deciding on how their office scores in regard to individual health and comfort aspects. In Figure 7, these individual scores are aggregated to make the answers comparable to the first question. As it is nevertheless difficult to directly compare these two questions with each other due to their different wording and answer options, this insight has to be considered with care if being used for further analysis. Moreover, in the bivariate analysis (see chapter 6.3) it becomes clear that, despite the above-described variations, the first question is not significantly different to the set of second questions.

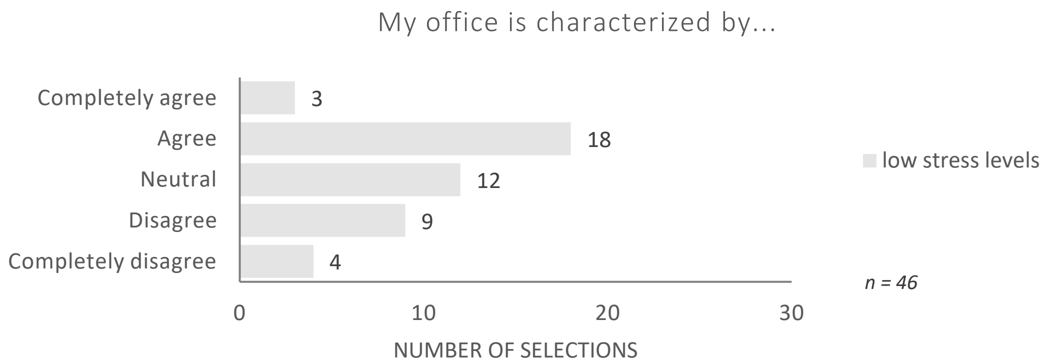
Perception of own office	Statistics		
	Mean	Median	Std. Deviation
*n = 46 Is the own office healthy & comfortable?	0.63	1.00	0.90

*refers to the number of respondents that answered the question(s) about this item

Explanation: -2 = Completely disagree; -1 = Disagree; 0 = Neutral; 1 = Agree; 2 = Completely agree

Figure 5: Respondents' perceptions of own office regarding health & comfort in general





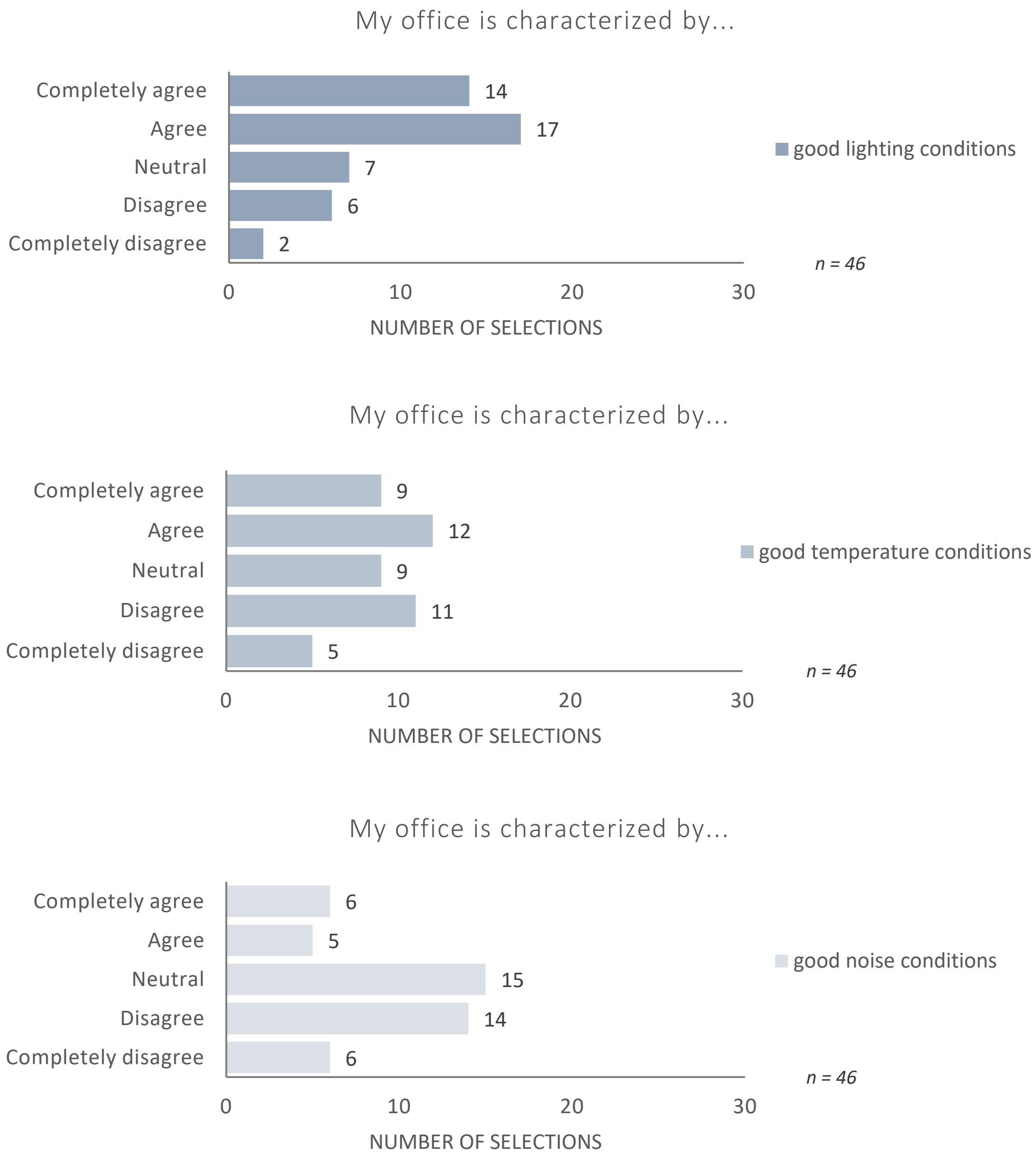
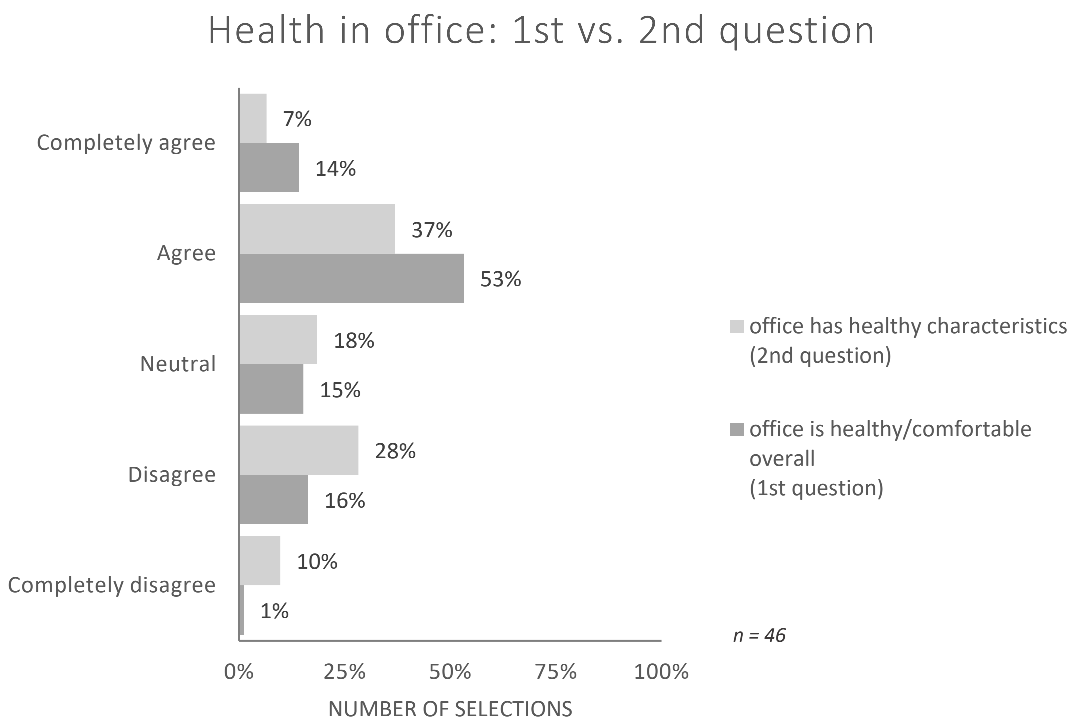


Figure 6: Respondents' perceptions of own office regarding individual health & comfort aspects



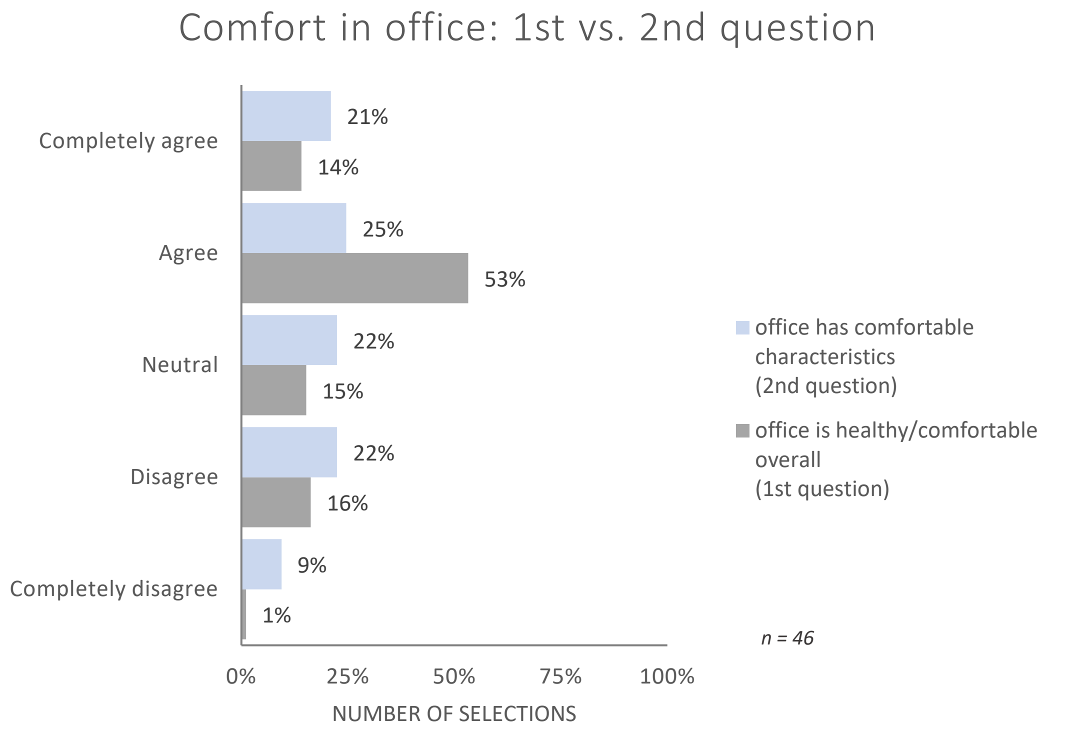


Figure 7: Comparison between answers to the initial question about health & comfort in general and answers to the subsequent question about the individual health & comfort aspects.

Preference towards health and comfort aspects

The rankings of the health and comfort aspects can be analysed in two ways. First, it can be counted which health and comfort aspects are selected in which positions like in the Figure 8. This allows us to see how each of the aspects is distributed across the ranking scale from one to 5. Here it can be seen that the stress level is generally either deemed to be the number one priority to respondents or not important at all. Rarely does this aspect rank in positions 2 to 4. Conversely, the lighting conditions for instance are more often selected in those mid positions (rank 3 or 4). The other three health and comfort aspects seem to be more equally divided across all ranks. So in general, the two health-related aspects seem to rather follow this extreme distribution while comfort aspects have a more normal distribution and are more often selected in the middle ranks.

Another way to analyse the data is by looking at the average rank in which each health and comfort aspect is placed (see Appendix D – Figure 3). It is revealed that the differences between the average rankings are not high. The sitting and moving behaviour is ranked as the most important of the 5 health and comfort aspects (1 being the most important and 5 being the least important rank) (Mean ranking = 2.80; SD = 1.50). The second highest position is occupied by the noise conditions (Mean = 2.87; SD = 1.34) followed by the stress level (Mean = 2.93; SD = 1.72), the temperature conditions (Mean = 3.11; SD = 1.27) and the lighting conditions seem to be the least important (Mean = 3.28; SD = 1.20).

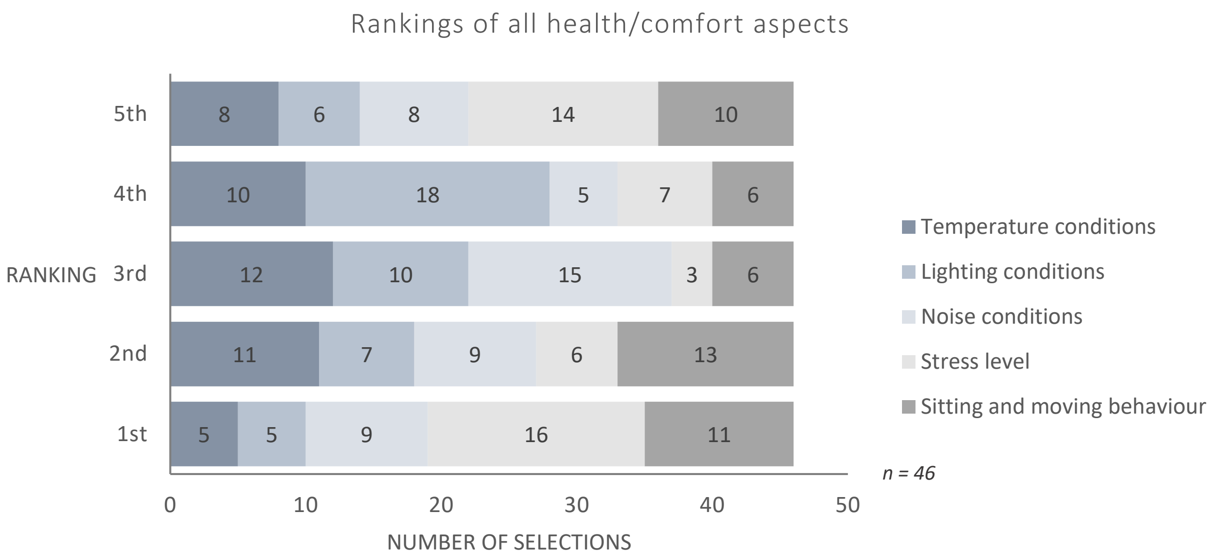


Figure 8: Amount of times each health and comfort aspect is selected for each rank

Time spent working in the office

As intended, none of the respondents select that they almost never work in the office which would automatically end the questionnaire for them. Most of the 46 participants work three (13 selections), four (11) or five days per week in the office (11). Only a few are working one (3) or two days (8) per week in the office.

5.1.4 Previous experience

This chapter describes respondents' previous experiences and attitudes regarding technology savviness, data privacy and whether the 4 health and comfort assessment tools are already present in their office.

Data privacy

With a mean of 0.94 (SD = 0.66) on a scale from -2 (no protective attitude at all) to +2 (very protective attitude) the respondents on average agree with having a protective attitude towards data privacy (see Appendix D – Figure 4 for more information on how the answers are distributed).

While respondents often seem to be concerned about data privacy, their knowledge of data privacy regulations is not quite as advanced. About one-third of the respondents (14 out of 44) indicate that they (completely) agree with having a high knowledge of the regulations, versus 11 neutral responses and more respondents saying that they lack this knowledge (19 out of 44)(see Appendix D – Figure 5 for all responses).

Technology savviness

On average, respondents report that they agree (Mean = 0.59; SD = 0.76) (again on a scale from -2 to +2) with having high knowledge about and feeling comfortable adapting to new digital devices (see Appendix D – Figure 6 for more information on how the answers are distributed). The time of usage indicates that respondents have a high usage time and exposure to digital devices outside of work (see Figure 9).

Digital device usage	Frequency			
	< 1 hour	1-3 hours	3-5 hours	5 or more hours
**n = 44*				
Time spent with digital devices outside of work per day	1	19	15	9

*refers to the number of respondents that answered the question(s) about this item

Figure 9: Respondents' digital device usage

Prior experience with assessment tools

The respondents indicate that room-mounted sensors are the assessment tools that are most often already in use in their office (27 out of 46 respondents)(see Figure 10). The second most used are wearables (14 times) (note that it is not mentioned whether those are personally owned or professionally provided devices), followed by surveys (11) and only 3 respondents report that they have been using smartphone apps for health or comfort at work issues. A few respondents do not know if the respective assessment tool is present in their office. This is most often (6 times) selected for room-mounted sensors which certainly makes sense given their sometimes relatively invisible and unintrusive presence. Opposite to that, no one selects this option in regard to wearables.

When considering which specific health and comfort aspects are already being addressed by the respective assessment tools, more granular insights can be gained (see Figure 10). Respondents report that the normal surveys address all of the 5 aspects pretty equally often. The smartphone apps already try to tackle the sitting and moving behaviour and stress levels according to a couple of respondents. Only one respondent reports the same regarding each of the comfort aspects. Room-mounted sensors are said to measure lighting and temperature conditions but much less often the noise conditions. Lastly, wearables mostly deal with the sitting and moving behaviour and slightly less often also with the stress levels. Very rarely or not at all do wearables address comfort aspects.

Application is present in office?	Frequency			
	Smart application			
	Surveys (*n = 46)	Smart phone apps (*n = 46)	Room sensors (*n = 46)	Wearables (*n =46)
Don't know if application is present	3	2	6	0
Application is not present	32	41	13	32
Application is present	11	3	27	14
If present: Addressed health & comfort aspects				
Sitting and moving behaviour	4	3	-	11
Stress level	4	2	-	7
Lighting conditions	5	1	19	0
Temperature conditions	4	1	16	1
Noise conditions	5	1	4	2

*refers to the number of respondents that answered the question(s) about this item. Note = for each smart application it is asked whether it is present or not and if so which health/comfort aspect is addressed.

Figure 10: Respondents' prior experience with assessment tools

5.2 Office workers' perception of health and comfort assessment tools

Perhaps the most insightful insights during the descriptive analysis are gained by investigating the items of the questionnaire about office workers' perception of assessment tools. The participants' answers to the respective questions help to answer the research subquestion 5 "Which types of assessment tools are preferred by office workers for measuring their health or comfort in the office?". The chapter is split into the attitude towards assessment tools' attributes, the ranking of assessment tools and the desire for assessment tools.

5.2.1 Attitude towards assessment tools' attributes

Attribute: Amount of collected personal information

The complete statistical data about respondents' attitudes towards all of the attributes is pictured in Appendix D – Figure 7. While the answer patterns between the different assessment tools differ a bit and no high correlation can be found here, a main tendency becomes clear nevertheless. Respondents apparently mostly dislike (or are neutral about) personal data being collected by assessment tools with only a few of them liking this attribute of the tools (see Figure 11).

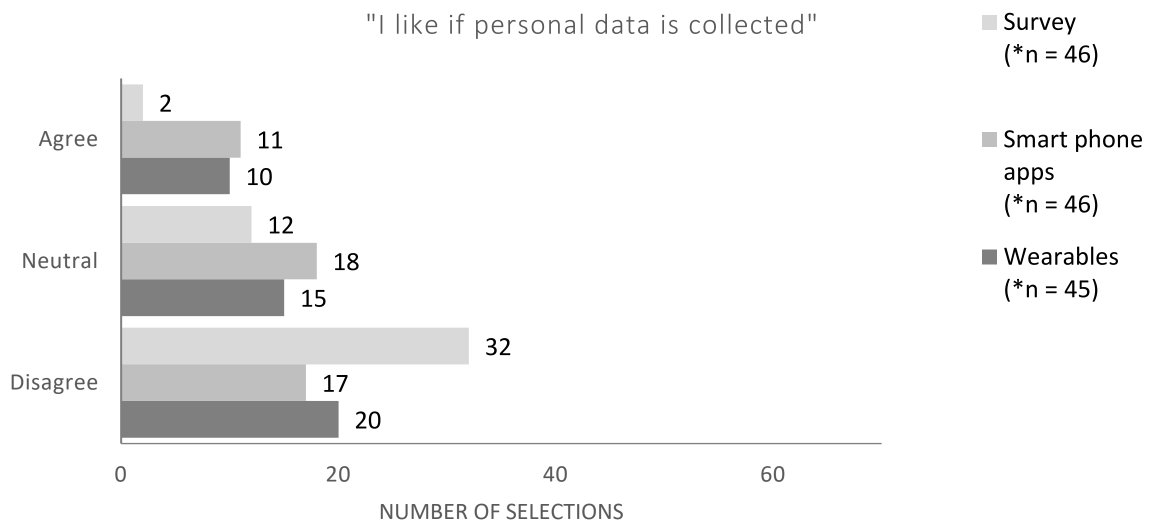
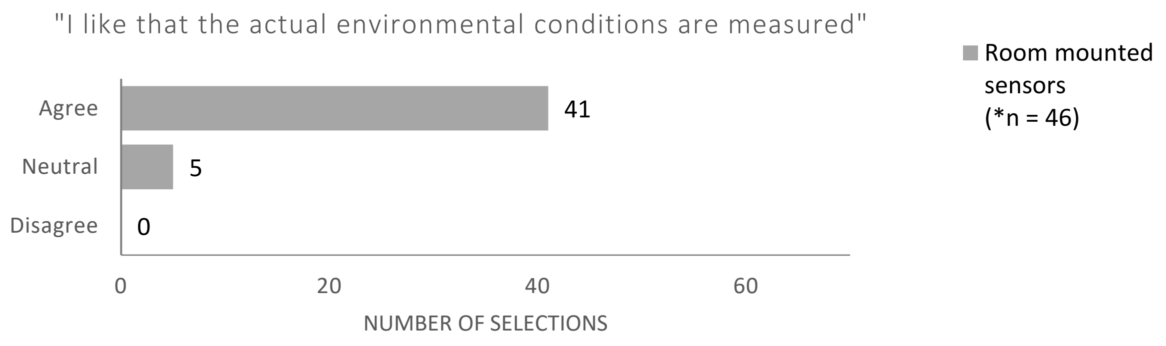
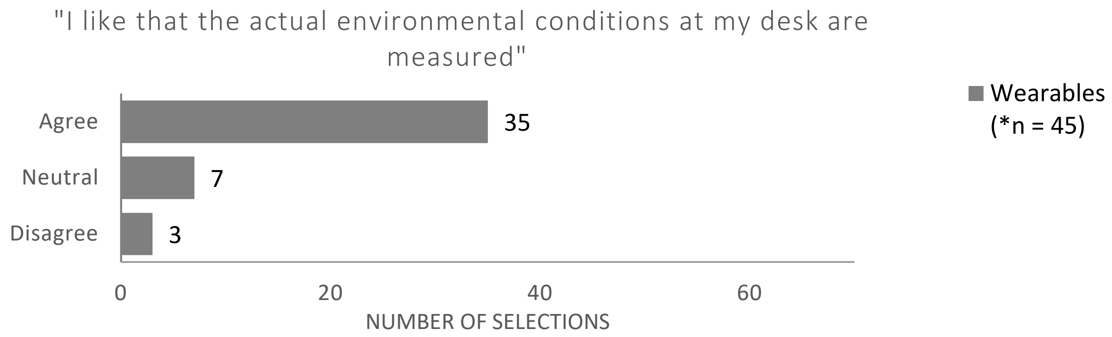


Figure 11: Respondents' attitudes towards the collection of personal data

Attribute: Data type collected

Out of all of the included assessment tools, only room-mounted sensors and wearables are actually measuring data with sensors rather than relying on manual inputs. The former only collects environmental conditions, the latter also collects bodily parameters and moreover measures the environmental conditions more finely grained (at the own desk). An overwhelming majority likes that environmental conditions are collected. 41 respondents indicated this for the room-mounted sensors and 35 for the wearables (see Figure 12). These two statements are not significantly correlated which may be because the wearables are said to measure environmental conditions for each desk rather than the whole room or office. Fewer respondents favour wearables measuring bodily parameters. Only 23 indicate that they like that, while 10 do not like it.





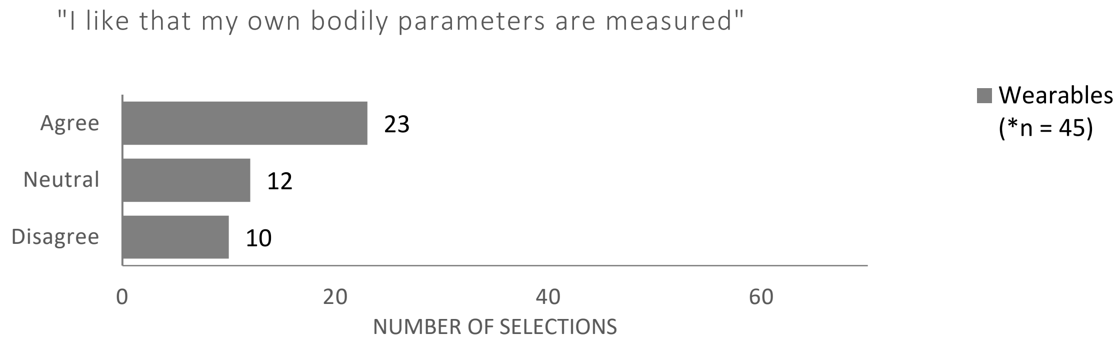


Figure 12: Respondents' attitudes towards the collected data type

Attribute: Range of outputs

This attribute concerns all of the 4 assessment tools (see Figure 13). Normal surveys only result in insights that can be gained for the whole office rather than a specific person. 28 respondents support this type of output, while only 5 state that they dislike it. Collecting personal data also leads to personalized outputs and suggested behaviour changes for the individual which only the smartphone apps and the wearables can offer. However, the answer patterns between the two assessment tools seem to differ as they are not significantly correlated. Generally, respondents like the personalized outputs especially regarding smartphone apps (35 agreements) and a bit less so regarding wearables (27 agreements). Room-mounted sensors, on the other hand, cannot give such personalized insights but adjustments to the indoor environment can be made on a smaller spatial scale than what the normal survey has on offer – not just for the whole office but also for individual rooms. This might be why nearly all (44 out of 46) respondents like this attribute of the sensors. That said, room-mounted sensors also can include other functionalities such as the tracing of the users' movement patterns. Such a relatively intrusive functionality is equally liked (17 times) and disliked (16 times) by the respondents.

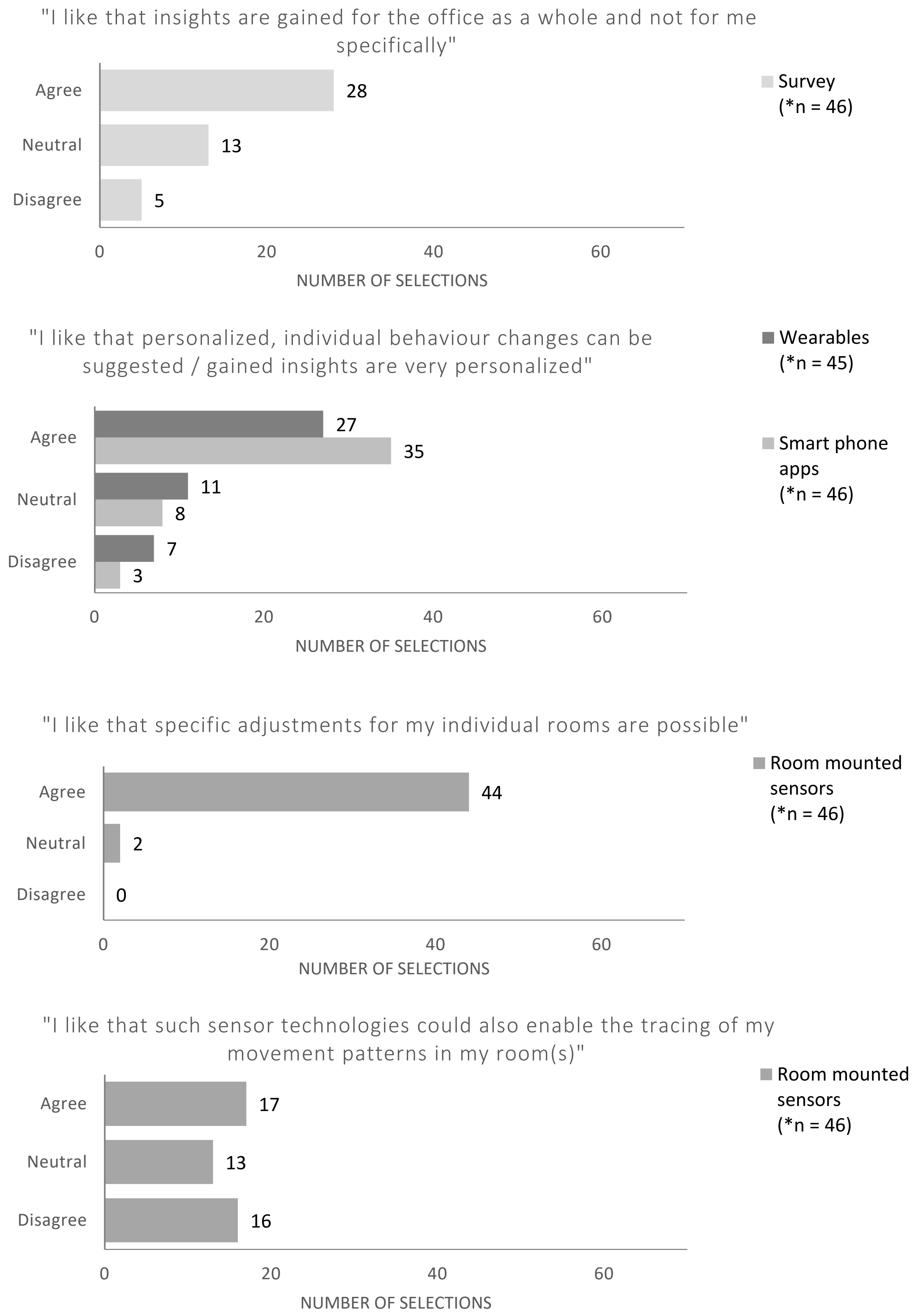


Figure 13: Respondents' attitudes towards the range of outputs

Attribute: Responsibility for data collection

Normal surveys are typically initiated by the own organization of the employee. Almost half of the respondents (22 out of 46) are neutral about this and 18 like it (see Figure 14). On the other hand, smartphone-based apps are typically operated by an external provider. Respondents are relatively neutral (equal amount of agreements and disagreements) about whether their own organization or an external provider should be operating the smartphone-based apps.

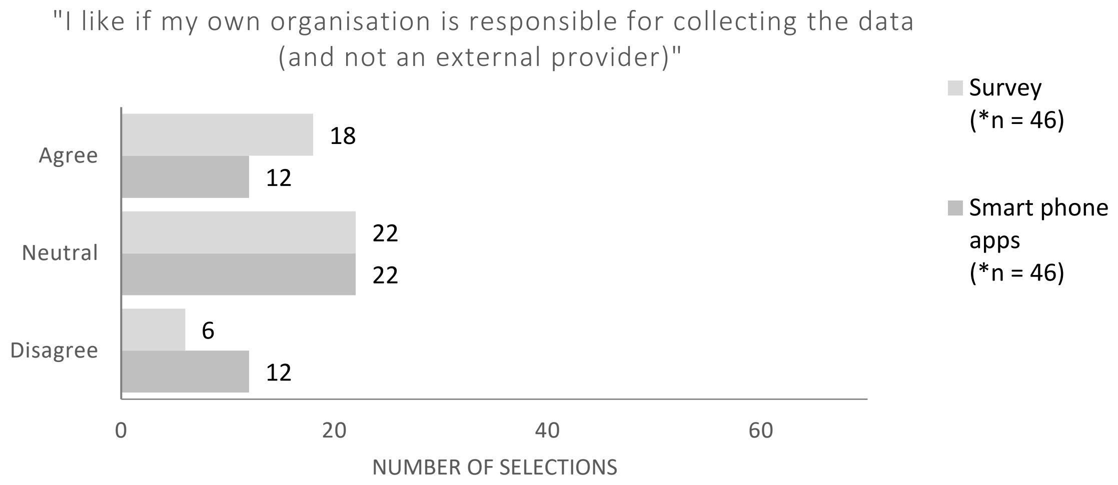


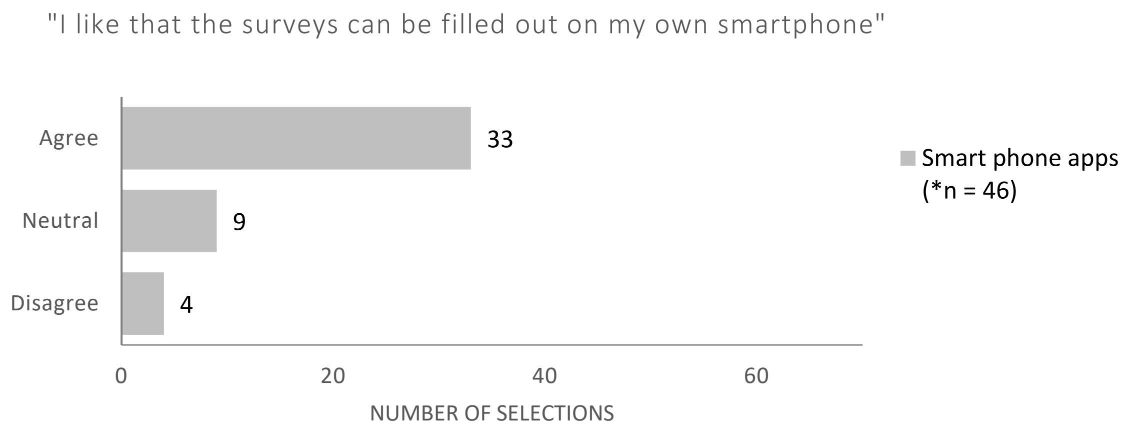
Figure 14: Respondents' attitudes towards the responsibility of data collection

Attribute: Technological intelligence

As stated in the questionnaire, smartphone apps and room-mounted sensors process their collected data with the help of artificial intelligence (combined variable #3 in Table 3). On average, respondents agree (Mean = 0.45; SD = 0.53) (on a scale from disagree (-1) to agree (+1)) with the statement: "I like that data is processed with the help of artificial intelligence."

Attribute: Proximity to user

Smartphone apps and wearables are the two tools that are relatively intrusive and closely positioned to the users. They either require frequent inputs on their own smartphone or actually need to be worn on the body to collect data. Inputting data on the smartphone is liked by 33 out of 46 respondents with only 4 of them disliking it (see Figure 15). In contrast, having sensors attached to the body is disliked by 22 out of 45 respondents – only 4 like it.



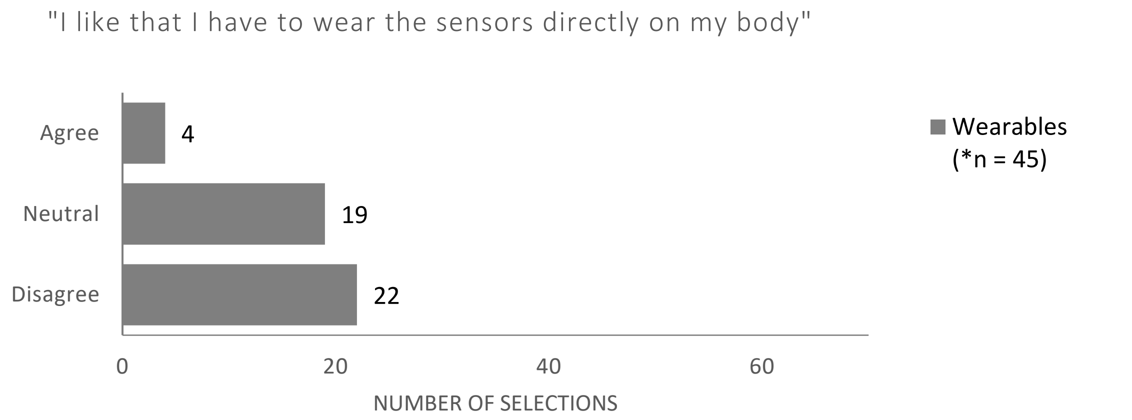


Figure 15: Respondents' attitudes towards the tools' proximity to users

Attribute: Level of automatization

Surveys as well as smartphone apps completely rely on the users' own, subjective inputs to function rather than using measurements (combined variable #1 in Table 3). With a mean of 0.15 (SD = 0.74) (on a scale from disagree (-1) to agree (+1)) respondents are on average neutral about the information being self-reported rather than measured otherwise.

Room-mounted sensors and wearables, on the other hand, measure their data autonomously which makes manual inputs redundant (combined variable #2 in Table 3). On average, respondents like (Mean = 0.66; SD = 0.49) that no manual inputs are necessary for these tools. So, when comparing this to the previous statement, it can be concluded that respondents slightly favour the automatized data collection method over the manual inputs.

Attribute: Level of accuracy

This attribute solely applies to wearables as only this tool can provide the maximum amount of details and insights. Naturally, 32 out of 45 respondents like this high level of accuracy. Only 3 of them dislike this (see Figure 16).

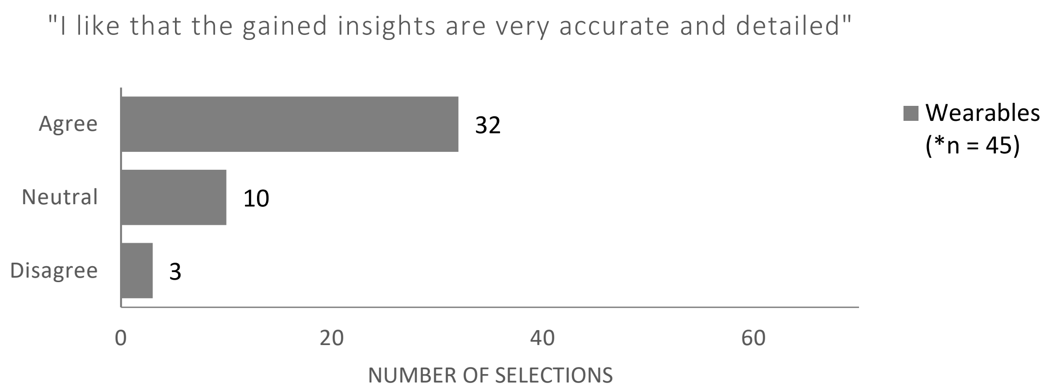


Figure 16: Respondents' attitudes towards the level of accuracy

Attribute: Frequency of measurement

This last attribute also only reflects on the wearables that need to be worn constantly to enable accurate measurements. Interestingly, respondents do not seem to be bothered by this and 31 of 45 even like the constant measurements. Just 3 dislike it (see Figure 17).

Overall, it can be seen that respondents relatively agree with most statements and therefore like these specific attributes of the respective assessment tools. The exceptions to that are respondents having a neutral opinion (the average answer is neutral) about room-mounted sensors being able to also tack movement patterns and about external organizations being responsible for the smartphone apps. Negative opinions (more respondents disagree than agree with the statement) exist about smartphone apps and wearables collecting personal data and about the fact that wearables need to be worn on the body.

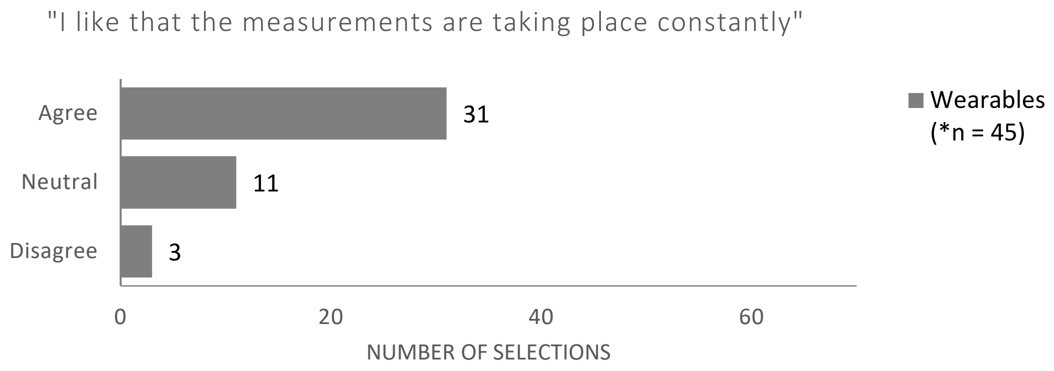


Figure 17: Respondents' attitudes towards the frequency of measurement

5.2.2 Ranking of assessment tools

Participants of the questionnaire are asked to rank the various types and levels of assessment tools indicating their most through to their least preferred options. Because room-mounted sensors are only part of the selection for the three comfort-related aspects but not for the two health aspects, the rankings have to be analysed separately for the health and comfort aspects. Insights from a direct comparison between these individual rankings therefore have to be treated with care. The complete statistics are included in Appendix D – Figure 8. The rankings range from 1 (the most favoured tool) to 3 (regarding health aspects) or 4 (regarding comfort aspects) as the least favoured tool.

Rankings if health aspects are addressed

The average ranking positions of the tools by respondents reveal that wearables are the most favoured tool addressing health aspects (Mean = 1.8; SD = 0.74) (combined variable #8 in Table 3). Smartphone apps follow in second place on average (Mean = 1.99; SD = 0.59) (#7 in Table 3) with surveys being the least favoured tool for addressing health-related aspects (Mean = 2.20; SD = 0.71) (#6 in Table 3). That said, the difference in the average rankings does not seem particularly high and is lower than the standard deviation.

Rankings if comfort aspects are addressed

Room-mounted sensors are, on average and by quite a margin, the most favoured tool to address comfort-related aspects in the office (Mean = 1.27; SD = 0.56) (combined variable #11 in Table 3). Second are smartphone apps (Mean = 2.67; SD = 0.72) (#10 in Table 3) followed by surveys (Mean = 2.92; SD = 0.77) (#9 in Table 3). The least preferred tool to deal with comfort aspects in the office are the wearables (Mean = 3.14; SD = 0.74) (#12 in Table 3).

What becomes clear is that the rankings in regard to comfort-related aspects differ quite a bit when compared with the rankings in regard to health-related aspects. Of course, room-mounted sensors cannot be selected for health aspects so this tool needs to be left out when making this comparison. When comparing rank 2-4 regarding comfort-related aspects with rank 1-3 for health-related aspects a striking difference is that wearables are the least favoured choice for comfort-related aspects while these tools are highest ranked in regard to health aspects.

5.2.3 Desire for assessment tools

Participants are asked whether they would like to have each of the 4 health and comfort assessment tools present in their office and afterwards also which of the health and comfort aspects the respective tool should address. Room-mounted sensors are most desired in the office as 45 out of 46 respondents answer they would like to have them present in their office. These sensors can only address comfort aspects and respondents mostly indicate that they would like to have all three aspects measured (33 votes for noise, 36 votes for lighting and 40 votes for temperature conditions). A majority (34 out of 46 respondents) would also appreciate to have surveys. Again, no big differences can be seen in regard to which health and comfort aspects should be addressed by the surveys (combined variable #4 in Table 3). About half of the respondents (24 individuals) would like to use the smartphone apps and, once again, all of the health and comfort aspects should be equally addressed by them which is underlined by the high inter-item correlations (combined variable #5 in Table 3). Lastly, wearables are only selected by less than half of the respondents (21). Here, it becomes clear that the health aspects (sitting and moving behaviour & stress levels) should be addressed much more often by the wearables than the comfort-related aspects. Apparently, the participants view wearables as devices that should measure bodily parameters (which are more closely related to health aspects) rather than environmental parameters.

A clear picture is presented when just focusing on how many respondents indicate that a respective health or comfort aspect should be addressed by at least one of the three (or 4) assessment tools (see Figure 19). A big majority of respondents indeed selected each of the health and comfort aspects at least once. This underlines that there seems to be a general wish to have all of the health and comfort aspects addressed by some sort of assessment tool.

Should application be present in office?	Frequency			
	Smart application			
	Surveys (*n = 46)	Smart phone apps (*n = 46)	Room sensors (*n = 46)	Wearables (*n =46)
Application should be present	34	24	45	21
Application should not be present	12	22	1	25
Health & comfort aspects to be addressed				
Sitting and moving behaviour	28	15	-	23
Stress level	24	16	-	23
Lighting conditions	21	15	36	6
Temperature conditions	24	17	40	9
Noise conditions	28	16	33	12

*refers to the number of respondents that answered the question(s) about this item. Note = for each smart application it is asked whether it should be present or not and if so which health/comfort aspect should be addressed.

Figure 18: Respondents' desire for assessment tools and which health & comfort aspects should be addressed

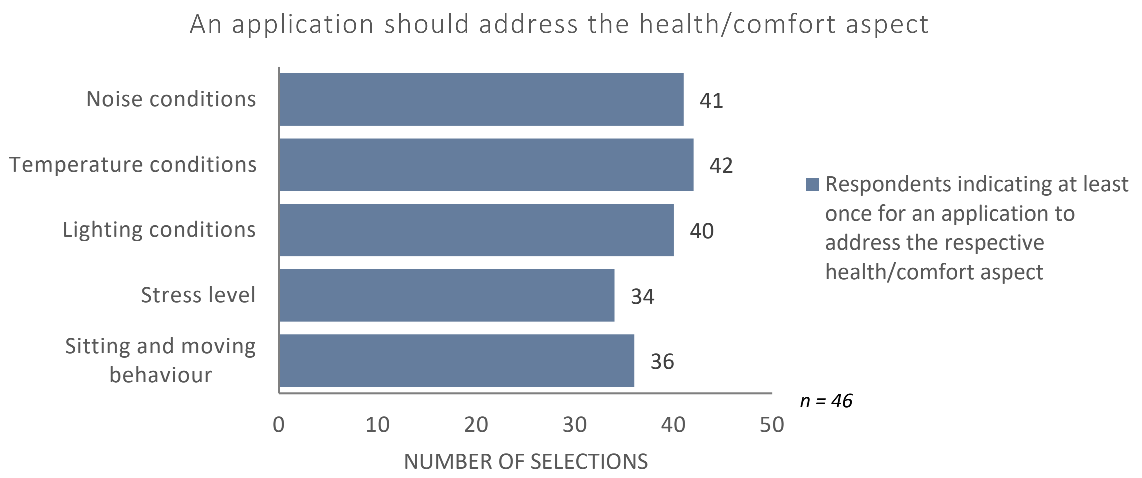


Figure 19: Respondents' desire for which health & comfort aspects should be addressed

5.3 Conclusion descriptive analyses

The sample is characterized by a high percentage of highly educated office workers. This comes as no surprise given that many respondents are recruited from personal and the supervisors' professional networks. About two-thirds of them are female and a slight majority is originating from the Netherlands or Germany – again not a surprise due to the recruitment method. It is interesting that the respondents mainly agree that their own office environment is healthy and comfortable. Even though the general tendencies for the given answers are the same, the distributions of the answer patterns somewhat differ between the different health and comfort aspects. Most noticeably, the perceptions about the sedentary behaviours show a relatively dichotomous answer pattern (respondents either like or dislike it in their office with few opting for the neutral, “middle” option). Similarly, when it comes to ranking the 5 health and comfort aspects amongst each other, the ranking of stress and sedentary behaviour have a relatively dichotomous distribution as well. Respondents either think these aspects are pretty important to them or not important at all. Overall, sedentary behaviour is ranked as most important by respondents on average followed by noise conditions, stress levels, temperature conditions and lighting conditions being the least important.

Respondents have a relatively favourable attitude towards the majority of health and comfort assessment tools’ attributes (see Table 4). Especially interesting is the slightly positive attitude towards the collection of bodily parameters, which is contrary to the expectations. Moreover, a positive attitude exists towards the usage of artificial intelligence for smartphone apps and room sensors. Due to the relative novelty of this technology, this is not necessarily expected. Another interesting positive perception can be reported towards tools giving very personalized outputs, something that is expected to be perceived as intrusive as well. Respondents have a neutral stance on room sensors tracing their movement patterns (which would not necessarily be expected due to the invasion of privacy), on whether the organisation or an external provider is responsible for the data collection and on surveys and apps using self-reported data. Respondents do not like the fact that wearables need to be worn on the body and that they collect personal data. These are both relatively intrusive attributes which is why the negative perception is not a surprise. A contradiction becomes clear that respondents perceive the measurement of bodily parameters positively but at the same time do not want to have them attached to the body. Similarly, a majority of respondents would like to receive personalized outputs by the tools but at the same time only a minority likes that personal information is collected by the tools.

The ranking and desire for assessment tools are perhaps the most interesting insights of the descriptive analysis as these in particular answer the sub question 5: “Which types of assessment tools are preferred by office workers for measuring their health or comfort in the office?”. For the purpose of assessing health aspects, wearables (highest level of smartness) are ranked in the most favoured position, followed by smartphone apps (medium level of smartness) and surveys (non-smart tool) being the least favoured tool. Comfort aspects can moreover be addressed by room-mounted sensors which are by far the most favoured tool for this purpose followed by smartphone apps, surveys and wearables. Regarding health as well as comfort aspects, it becomes clear that one of the tools with a higher level of smartness is preferred over tools with a lower level of smartness (wearables being level 3 and room sensors being level 2). Within that general pattern, the wearables are however a big outlier as they are ranked as the favourite for assessing health aspects and the least favourite regarding comfort aspects. Respondents much more often indicate that wearables should measure health aspects and relatively few want comfort aspects measured by this tool. Maybe respondents think that this tool is not as suited to measure environmental conditions and/or they do not necessarily want to have a measurement directly on their body for such a purpose. As a result, respondents are also in two minds about whether they want to have wearables in use in their office or not. The same can be said regarding smartphone apps. Much higher is the desire for room-mounted sensors but also normal surveys are often selected by respondents as a desired assessment tool. Even though normal surveys are not necessarily ranked favourably, the acceptance of them in the office still seems reasonably high. This indicates that this non-smart tool seems to be less polarizing among respondents, especially compared to wearables – the tool with the highest level of smartness in the questionnaire. In contrast to wearables, if any of the other tools are desired in the office, they then should also address all of the health and comfort aspects. This could also be because the presence of the tools can be seen as a bit of a burden for the office workers who then in return are expecting a lot of insights into various aspects of their office.

Table 4: Expected vs. revealed perception of variables of office workers' perception of assessment tools

Construct	Dimension	Variable	Initial expectations about perception	Based on literature?	Revealed perception
Office workers' perception of health and comfort assessment tools	Attitudes towards assessment tools' attributes	Attitude towards collection of personal information	Negative	Collins & Marassi, 2021; Gorn & Shklovski, 2016; Harper et al., 2022; Lai et al., 2003; Neff & Nafus, 2016; Teebken & Hess, 2021; Zieglmaier et al., 2022	Slightly negative
		Attitude towards personalized outputs	Positive	Mani & Chouk, 2017	Very positive
		Attitude towards outputs for whole office	Unknown	-	Very positive
		Attitude towards measurement of bodily parameters	Negative	Raff & Wentzel, 2023	Slightly positive
		Attitude towards measurement of environmental conditions	Unknown	-	Very positive
		Attitude towards measurement of movement patterns	Negative	-	Neutral
		Attitude towards own organization collecting data rather than external provider	Unknown	-	Neutral
		Attitude towards AI being used	Unknown		Slightly positive
		Attitude towards collecting data via smartphone	Unknown	-	Very positive
		Attitude towards measurement on own body	Negative	Raff & Wentzel, 2023	Slightly negative
		Attitude towards automized collection of data	Not clear	Ahmadi-Karvigh et al., 2017; Day et al., 2019; Donkers et al., 2023; Kwon et al., 2019; Lashina et al., 2019; Tuzcuoğlu et al., 2023	Neutral
		Attitude towards high accuracy	Positive	-	Very positive

	Attitude towards very frequent measurement of data	Unknown	-	Very positive
Ranking of assessment tools (addressing health)	Ranking of surveys	Unknown	-	Rank 3 (of 3)
	Ranking of smartphone apps	Unknown	-	Rank 2 (of 3)
	Ranking of wearables	Unknown	-	Rank 1 (of 3)
Ranking of assessment tools (addressing comfort)	Ranking of surveys	Unknown	-	Rank 3 (of 4)
	Ranking of smartphone apps	Unknown	-	Rank 2 (of 4)
	Ranking of room mounted sensors	Unknown	-	Rank 1 (of 4)
	Ranking of wearables	Unknown	-	Rank 4 (of 4)
Desire for assessment tools	Desire for surveys	Unknown	-	34 of 46
	Desire for smartphone apps	Unknown	-	24 of 46
	Desire for room mounted sensors	Unknown	-	45 of 46
	Desire for wearables	Unknown	-	21 of 46

6 Bivariate analyses & interpretation of results

As this is an exploratory study, nearly all possible relationships between variables are tested for the bivariate analysis. The only exceptions to that are variables for which the descriptive analysis reveals relatively one-sided answer patterns that are skewed to one side (e.g., most of the participants choose only one of the available answer options) and relationships which are completely irrelevant to answering the research questions. The latter is about the relationships between variables of the dimensions "demographics" and "previous experience" on the one hand and variables of the dimension "smart workplace health and comfort" on the other hand. In these cases, the respective relationships are not tested.

Only significant relationships between variables are reported in the tables and visualisations of this chapter. The significant relationships are numbered (#1 to #50) to enable an easy cross-reference to the respective tables containing more information about the relationships at the end of each subchapter. The tables also show whether the relationships are positive (green font) or negative (red font). Even though this can be considered as a mostly explorative study, some relationships are expected based on revealed explicit relationships by earlier studies (compare with chapter 4.3). Therefore, all of the expected relationships based on literature (regardless of whether they actually prove to be significant or not) are shown in Table 5.

The detected significant (and unexpectedly insignificant relationships whenever a significant relationship has been expected) are not just described but also further analysed, interpreted and discussed in the following subchapters of chapter 6. This being an exploratory study, it is not always possible to base the interpretation of results on existing literature which is why further research is necessary to investigate those new hypotheses.

This chapter is subdivided into three parts. First, the relationships in-between different dimensions that constitute the construct "office workers' perception of health and comfort assessment tools" are analysed (chapter 6.1). Then, it is examined how the construct of "personal characteristics" relates to the office workers' perception (chapter 6.2). Lastly, significant and expected relationships in between the construct of "personal characteristics" are analysed (chapter 6.3). The subchapters include small conclusions. The main findings of chapter 6 are the basis to answer the research questions in chapter 7 and lead to the associated limitations and recommendations for future research and practice.

Table 5: Expected bivariate relationships based on literature

Variable I	Variable II	Type of relationship	Source
Technology savviness	Protective attitude towards data privacy	positive	Mani & Chouk, 2017
Protective attitude towards data privacy	Desire to have wearables	negative	Choi et al., 2017
Age	Perception of very smart tools	negative	Röcker, 2010
Age	Technology savviness	negative	Röcker, 2010
Education level	Perception of very smart tools	positive	Röcker, 2010
Being male	Perception of very smart tools	positive	Jacobs et al., 2019
Origin from country with stricter data privacy regulations	Protective attitude towards data privacy	positive	Cvrcek et al., 2006; Röcker, 2009; Röcker, 2010
Level of control over data	Willingness to share private data	positive	Princi & Krämer, 2020

6.1 Attributes of assessment tools related to office workers' perceptions

In this chapter, significant relationships in-between the different dimensions that constitute office workers' perception of health and comfort assessment tools are analysed. These dimensions are the attitude towards attributes of the assessment tools, the ranking of assessment tools and the desire for assessment tools.

6.1.1 Relationships between variables of respondents' attitude towards attributes of assessment tools

First, relationships in-between the variables of respondents' attitudes towards attributes of assessment tools are tested. The attributes "frequency of measurement" and "level of accuracy" are excluded from the analysis as they do not promise to have any significant relationships with other variables because their answer patterns are skewed to one side. Respondents both really like the frequent measurement of data and the high accuracy of tools (see chapter 5.2.1).

While respondents generally dislike if a lot of personal data is collected by the health and comfort assessment tools (see chapter 5.2.1), several other attributes relate to this perception. In this subchapter, Spearman correlations are used to evaluate whether significant relationships exist in-between two variables at a time. There is a significant relationship between liking that surveys collect respondents' personal information and disliking that surveys and smartphone apps require self-reporting rather than data being measured automatically (see relationship #1 in Table 6 and Figure 20). This result is somewhat unexpected because other research finds that a higher level of perceived control (which the self-reported collection of data should rather provide than the automated collection) is related to a higher willingness to share private data (Princi & Krämer, 2020). This difference in the results could perhaps be because office workers would like to have control of their data during the analysis and application of the data but at the same time are fine with an automated approach for the acquisition of the data. While automated data collection could be more convenient because of considerable time savings, respondents could then have a preference to have control over how their data is processed and used subsequently. This could also more generally mean that perceptions towards a characteristic of a tool (here the level of automatization) could change depending on which layer of the tool (the acquisition, analysis or application stage) this characteristic is connected to. It has to be mentioned that a favourable attitude towards the automated collection of personal information is relatively exceptional within the sample though (see chapter 5.2.1) which could suggest that this minority of respondents in general has a preference for advanced data collection methods while having less of a problem with the intrusive nature of the tools typically associated with that. This could lead to the interpretation that general trust in such advanced tools is linked to the office workers' personality traits rather than specific attributes of the tools. Note that these personal characteristics are analysed in a later chapter.

An aversion towards the self-reporting of data also relates to having a preference towards an external provider collecting the data rather than the own organisation (#2). This could simply mean that an automated rather than a self-reported collection of data could perhaps be more associated with external providers. In that case, respondents might infer that these two attributes are linked to each other in reality and therefore their attitudes towards both attributes are also related to each other. In general, it is no surprise that respondents make such implicit inferences that some attributes are naturally connected to each other. A comparable finding is made by Rupp et al. (2018) who also find respondents having a similar perception towards two attributes that are typically related to each other for a specific assessment tool. There are other possible explanations for the relationship between favouring an automated data collection and liking that an external provider is responsible for the data collection. The respective respondents might think that both variables are connected to a more neutral, objective and unbiased data collection method. They might fear internal consequences if their own organization surveils them which is found to especially be a concern if their own organisation initiates this (Rigamoti et al., 2024) or if they self-report data in a way that could cause unfavourable consequences for them.

Supporting the attribute of smartphone apps collecting respondents' personal data relates to support for data being processed with the help of artificial intelligence (#3). This could indicate that this group of respondents generally have relatively high trust in such advanced tools and might believe that AI can process data more effectively. The latter aspect is a perceived quality of AI that is also reported by another study (Chew & Achananuparp, 2022). If respondents would like to have their personal data collected, it makes sense that they then would also like to have it processed as effectively and insightful as possible. Next, there is a significant relationship between liking that wearables collect personal data and liking that very personalized outputs can be given (#4) and also that the bodily parameters are measured (#5) by wearables. Perhaps they also infer that by providing personal information and by measuring bodily parameters, the respective tool would also provide a greater benefit for them. Melenhorst et al. (2004) also describe such a user's requirement to balance out a higher intrusiveness of smart tools with a higher benefit. Even though their study is restricted to a much higher age group (mean age of 70.8 years compared to 32.7 years in this study), it is insightful that younger respondents apparently have generally similar preferences regarding the trade-off of intrusiveness against benefits.

Having a favourable perception towards bodily parameters being measured, on the one hand, significantly correlates to also having a favourable perception towards wearables creating personalized outputs. On the other hand, these favourable perceptions also correlate to respondents liking to wear wearables on their bodies (#6, #7, #8). Once again, it can be seen that a benefit (personalized outputs) is expected in return for more intrusive data collection (measuring bodily parameters directly by wearing a body-attached device). This of course makes sense and matches with the prior findings of Melenhorst et al. (2004).

Smartphone apps produce personalized outputs. If respondents relatively like that, this perception relates to the disliking of the own organization being responsible for the data collection (#9). It can be speculated that respondents either anticipate that it is simply more common for an external organisation to provide such an app and, because they are used to that, are rather willing to give personal information to an external party. They could also not want their own organisation to produce personalized outputs with such a method as they may fear consequences for themselves (Rigamoti et al., 2024). Usually smartphone apps are personally downloaded onto the own phone which is why it may not be appreciated if the own organization plays a part in it.

In conclusion, it can be seen that a lot of variables of the attitude towards attributes of assessment tools that are logically linked to each other also often show a significant relationship. It is somewhat surprising that respondents who like automated data collection are also more willing to share personal data as this is contrary to previous studies. Generally, respondents who are relatively in favour of more advanced outputs of the tools (such as personalized insights) also seem to expect and accept a higher degree of intrusiveness in return (such as more personal information or bodily parameters being collected and sensors worn on the body). Moreover, these respondents also relatively prefer an automated measurement of data and like that data is processed with the help of artificial intelligence.

It is intriguing to see that respondents are seemingly already aware that these trade-offs are to be expected when having the respective tools present in the office. The result could have of course also been that respondents really like to have all the benefits of the advanced tools but still dislike all the drawbacks that come along with them. In the next chapter, it becomes clear that these attitudes also relate to the ranking of and desire for assessment tools.

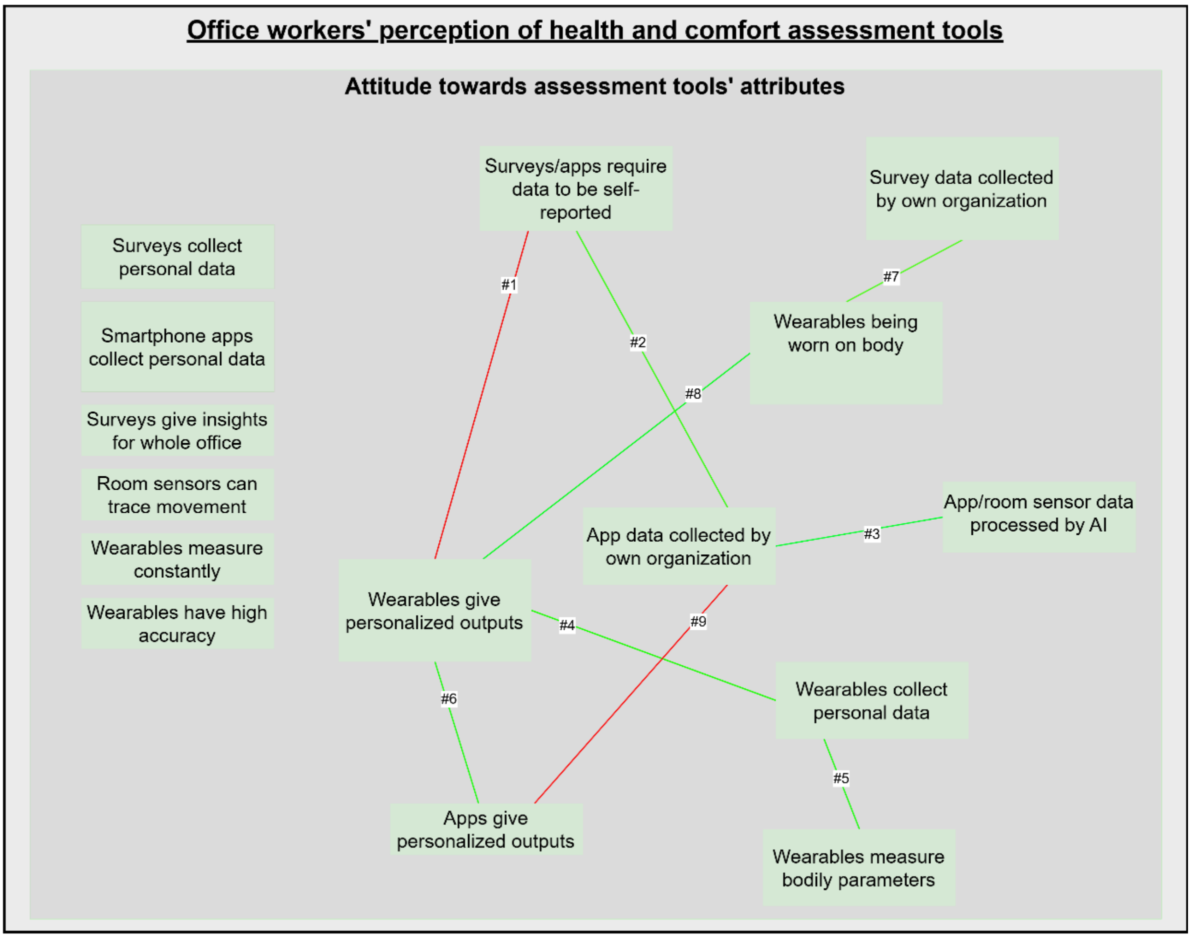


Figure 20: Significant relationships between variables of respondents' attitude towards attributes of assessment tools

Table 6: Significant relationships between variables of respondents' attitude towards attributes of assessment tools

#	Variable I	Variable II	Statistical test	Statistics	Sig.
1	Surveys collect personal data	Surveys/apps require data to be self-reported	Spearman correlation	r(44) = -.369	.012
2	Surveys/apps require data to be self-reported	Survey data collected by own organization	Spearman correlation	r(44) = .435	.003
3	Apps collect personal data	App/room sensor data processed by AI	Spearman correlation	r(44) = .326	.027
4	Wearables collect personal data	Wearables give personalized outputs	Spearman correlation	r(43) = .404	.006
5	Wearables collect personal data	Wearables measure bodily parameters	Spearman correlation	r(43) = .515	<.001
6	Wearables measure bodily parameters	Wearables give personalized outputs	Spearman correlation	r(43) = .591	<.001

7	Wearables measure bodily parameters	Wearables being worn on the body	Spearman correlation	r(43) = .567	<.001
8	Wearables being worn on the body	Wearables give personalized outputs	Spearman correlation	r(43) = .483	<.001
9	Apps give personalized outputs	App data collected by own organization	Spearman correlation	r(43) = -.312	.035

6.1.2 Relationships between respondents' attitude towards attributes of assessment tools and the desire for and ranking of assessment tools

Relationships also exist between the different dimensions of office workers' perceptions of health and comfort assessment tools (see Figure 21 & Table 7). A look at connections between attitudes towards attributes of assessment tools and the ranking of assessment tools is taken. Next to that, the attitudes are compared to the desire for assessment tools. Lastly, relationships are checked between the ranking of and the desire for assessment tools. Since a big majority would like to have room-mounted sensors installed in the office to measure comfort aspects and most respondents also rank this tool in the top spot, here no insights can be gained regarding relationships with the other variables.

A Spearman correlation is performed to evaluate the relationship between the ranking of surveys and the attitudes towards smartphone apps (#10) and wearables (#11) collecting private data. These variables are significantly related. If respondents rank the survey in a less favourable position (considering health-related aspects to be measured), they are also more inclined to like that these other tools collect their private data. As analysed in chapter 6.1.1, respondents being in favour of the collection of personalized data also generally expect a greater benefit for them as an output of the tool. Since Newell et al. (2004) observe that respondents distrust surveys because of their lack of meaningfulness, these types of respondents in particular might consequently prefer the other assessment tools over surveys expecting more useful and personalized outputs. It is then also reasonable to assume that these respondents generally have a more favourable opinion towards the attributes of the tools that are not surveys. This moreover goes in hand with the observations in chapter 6.1.1 that (dis)liking a specific tool also means that (most of) the tool's attributes are (dis)liked. Respondents with a more favourable attitude towards private data collection might also relatively dislike the type of surveys defined in the questionnaire as they simply do not collect any personal data.

Moreover, an aversion against the self-reporting of data, a main feature of surveys, relates to respondents ranking this tool (if health aspects are addressed) as relatively less favourable (#12). The respective respondents perhaps think the time spent on filling out the survey as part of the self-reporting process is an unnecessary burden which is analysed as another major factor for low response rates for surveys (Newell et al., 2004). Once again, this also suggests that the respondents who rank the surveys rather unfavourably also dislike many of the typical features of surveys as the disliking of self-reporting of the data also connects to the desire for personal information to be collected and an external provider to be responsible for the collection (see chapter 6.1.1). This can of course also be interpreted vice versa: Respondents liking surveys also more frequently like their typical attributes.

Respondents ranking wearables in a favourable position correlates with respondents liking that this tool is collecting their personal data (#13). This is certainly an expected outcome given that a greater benefit is expected in return for the intrusiveness of wearables. It also exemplifies that respondents who are more favourable towards a specific tool apart from the already discussed surveys (i.e., wearables) then also relatively like the attributes that are typically associated with this tool.

The attribute of wearables collecting bodily parameters is perceived positively by the majority of respondents (see chapter 5.2.1). The ranking of wearables and other tools (if health aspects are addressed) seems to be majorly related to the respondents' opinions regarding this attribute. Consequently, liking that the own bodily parameters are measured relates to wearables being ranked relatively favourably (#14). The Mann-Whitney U test is run. A significant difference between having a desire to wear wearables in the office and not having such a desire is found regarding the perception of the bodily parameters being measured (#15). Conversely, the Spearman correlation shows that respondents not liking that their own bodily parameters are measured correlates with them ranking the alternative tools smartphone apps (#16) and surveys (#17) more favourably. This certainly is to be expected and underlines that the willingness to use wearables could to some degree depend on whether a respondent feels comfortable with their own bodily parameters being measured. On the other hand, it could mean that the respondents who would like to use wearables do that because they believe they provide meaningful insights and acknowledge that data needs to be measured directly on the body to enable that. Perhaps they also have experience with wearing the respective devices on their body and do not mind the intrusive nature of them (anymore). That said, it is mentioned that preferences for wearables can also have completely different causes such as a possible increased self- and social perception of the user (Gao et al., 2015) that could relate to a relatively favourable perception of the attributes of wearables included in this study. It could therefore be that respondents are more accepting of the fact that bodily parameters are measured by wearables because they are so convinced about the positive effects of wearables.

A significant relationship is detected between approving that insights gained by surveys should be about the whole office rather than about individual users, and ranking wearables (if health aspects are addressed), the tool delivering the most personalized insights, unfavourably (#18). That, of course, is expected given that wearables are certainly not a suitable tool in case one would only want to have outputs given on the spatial scale of the office. Conversely, a favourable ranking of wearables (#19) and an unfavourable ranking for smartphone apps (#20) are both related to liking that wearables should have personalized insights. The result that wearables are a more trusted source for personalized insights compared to smartphone apps can be expected and could be because they in general indeed lead to very accurate results due to their uninterrupted data collection (Huhn et al., 2022) even though the accuracy differs per device and is certainly not perfect (Bent et al., 2020). Moreover, it can be expected that the smartphone apps included in the questionnaire are the more unknown and novel concept for many respondents which is why they may be more unfamiliar with or underestimate the capabilities of the apps.

Similarly, the Mann-Whitney U test reveals that respondents having a desire for wearables on average have a more positive attitude towards wearables giving personalized outputs compared to respondents that do not have such a desire (#21). Just like with other tools' attributes before, many of the significant relationships indicate that in case respondents rate a particular tool favourably, they also have a positive attitude towards a range of characteristic attributes connected to this tool.

A Spearman correlation is used to detect a relationship between the ranking of wearables and the attitude towards the own organization being responsible for the data collection. An unfavourable ranking of wearables (addressing comfort aspects) significantly relates to respondents liking that their own organization is responsible for the data collection (#22), an attribute that could be associated with surveys rather than wearables. It becomes clear that the attitude towards certain attributes can be independent of the specific assessment tool – these respondents presumably would like to have their own organization responsible for the data collection, perhaps because they have a higher trust in their own organization for collecting data adequately. And since wearables are usually operated by an external provider, these respondents are ranking wearables unfavourably, potentially then worrying about the external company causing data breaches or not handling data correctly (Segura Anaya et al., 2018; Ziccardi, 2020).

The Mann-Whitney U test is used to conclude that the attitude towards data being processed by artificial intelligence (AI) is more favourable among respondents who have a desire for smartphone apps being used in their offices compared to respondents without such a desire (#23). Moreover, respondents having such a positive attitude towards AI also relates to respondents ranking smartphone apps favourably (#24) and ranking surveys unfavourably (#25). These are the results of the Spearman correlation. In the questionnaire, it is not explicitly mentioned whether surveys also include AI in the data processing. However, respondents may infer that surveys do not use AI but a more conventional data processing approach which could be why they prefer the other tools. This therefore suggests that respondents in general not only use the descriptions given in the questionnaire to evaluate an assessment tool but also have their own prior opinions and ideas towards these tools. So while it is to be expected that conventional surveys are not perceived favourably if respondents like the use of AI, the reasoning behind the comparatively high ranking for smartphone apps in this regard is more obscure. It could perhaps be because smartphone apps could be perceived as the most novel approach among all the presented tools given their more recent emergence (see chapter 2.2.1). As AI can also be considered as a relatively novel concept in the workplace, early adopters of technology (Shoman et al., 2023) may be inclined to like smartphone apps most due to the relatively extensive integration of AI.

Having a favourable opinion towards sensors being worn on the body is unsurprisingly related to ranking smartphone apps and surveys (addressing health aspects) relatively unfavourably (#26 & #27). As mentioned earlier, these types of respondents could generally prefer the accuracy of data being actually measured by sensors to create precise outputs for them and therefore relatively dislike the subjective self-reporting used in smartphone apps and surveys. The Mann-Whitney U test is used to test whether significant relationships exist between a favourable ranking of an assessment tool and the desire to have the respective tool present in the office. It comes as no surprise that respondents who have a desire to have wearables present in the office also rank the wearables relatively favourably (if wearables address comfort aspects (#28) & if health aspects are addressed (#29)) compared to respondents that have no such desire. The same favourable ranking position but then for smartphone apps can be observed in case respondents have a desire for this tool (in case health aspects are addressed) (#30) in comparison to respondents that do not like to have this tool present in the office.

What is actually most interesting here are the non-significant relationships between the ranking of and desire for surveys. The descriptive analysis (chapter 5.2) reveals that even though surveys are usually ranked relatively unfavourably, a big majority of respondents would still like to have them present in the office. This seems conflicting and suggests that other tools might on average be more popular, but surveys are at the same time not perceived as very problematic and could therefore still be somewhat desirable for respondents. A possible explanation for that could be that although surveys do not necessarily provide the desired range of outputs and meaningfulness to many respondents (Newell et al., 2004) and other tools possibly perform better regarding this, surveys could still perceived as enjoyable and easy to use (Croteau et al., 2010). This would lead to the conclusion that the majority of office workers simply do not mind having surveys even though it is not their favourite tool to have in the office. Another reason why surveys could be viewed as relatively unproblematic and therefore respondents do not mind filling them out is that they are described as anonymous in this study's questionnaire which could be generally viewed positively by employees as suggested by Levenson (2014). Following this logic, smartphone apps and wearables are more polarizing (e.g., due to the great amount of personal information they collect and process) and respondents either like to have them and simultaneously rank them favourably or rather would not like to have them present at all. It seems that once respondents perceive that the possible drawbacks and risks associated with these more advanced tools are outweighed by their benefits, they then also would preferably like to use this tool in their office. At the same time, surveys could perhaps still be viewed as a tool that provides different kinds of insights due to their completely different data collection method.

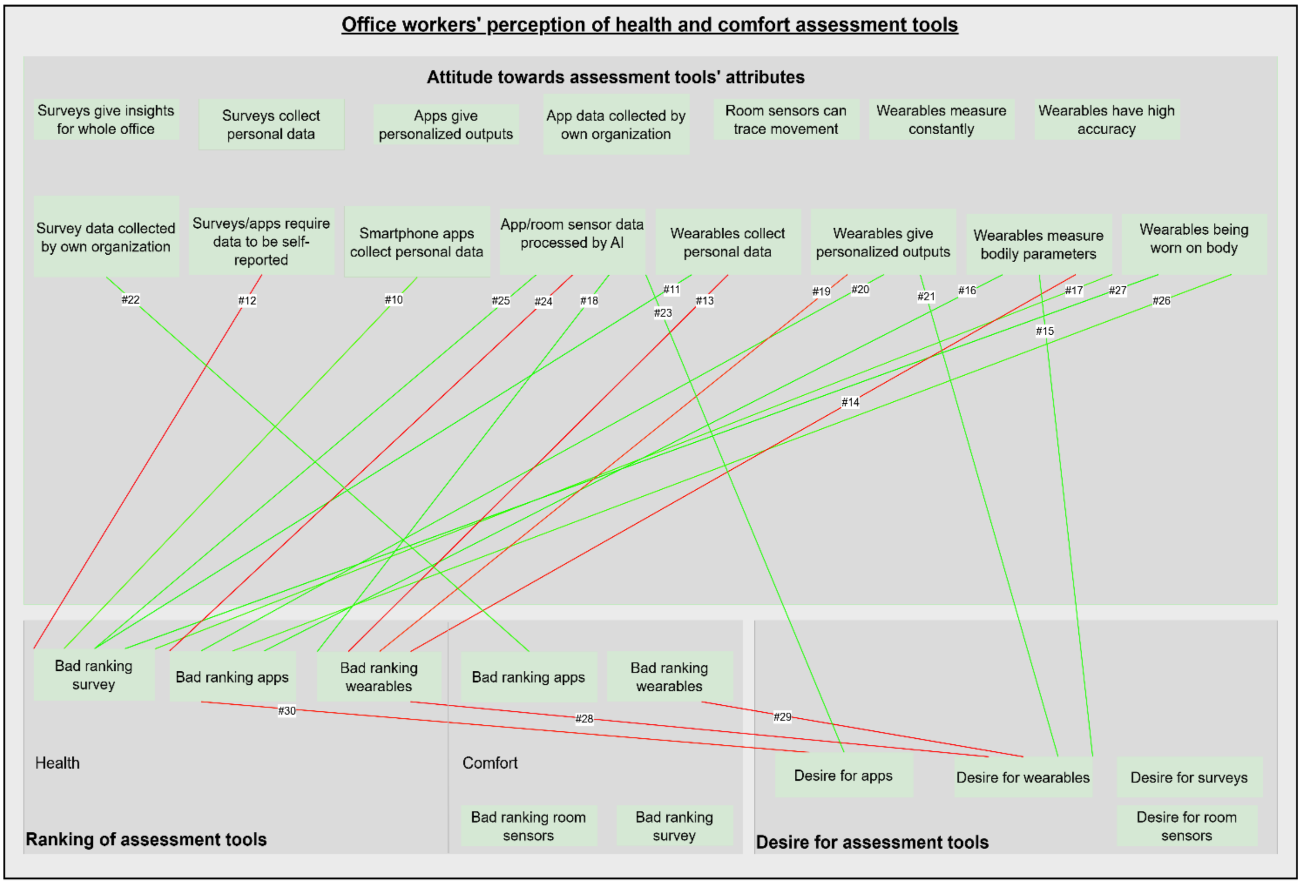


Figure 21: Significant relationships between respondents' attitude towards attributes of assessment tools and the desire for and ranking of assessment tools

Table 7: Significant relationships between respondents' attitude towards attributes of assessment tools and the desire for and ranking of assessment tools

#	Variable I	Variable II	Statistical test	Statistics	Sig.
10	Bad ranking survey (addressing health)	Apps collect personal data	Spearman correlation	r(42) = .314	.038
11	Bad ranking survey (addressing health)	Wearables collect personal data	Spearman correlation	r(42) = .412	.005
12	Bad ranking survey (addressing health)	Surveys/apps require data to be self-reported	Spearman correlation	r(42) = -.448	.002
13	Bad ranking wearables (addressing health)	Wearables collect personal data	Spearman correlation	r(42) = -.469	.001
14	Bad ranking wearables (addressing health)	Wearables measure bodily parameters	Spearman correlation	r(42) = -.575	<.001

15	Desire for wearables	Wearables measure bodily parameters	Mann-Whitney U test	U = 126.000 Mean rank (Desire) = 27.96 Mean rank (No desire) = 16.80	.012
16	Bad ranking apps (addressing health)	Wearables measure bodily parameters	Spearman correlation	r(42) = .313	.038
17	Bad ranking survey (addressing health)	Wearables measure bodily parameters	Spearman correlation	r(42) = .378	.011
18	Bad ranking wearables (addressing health)	Surveys give insights for whole office	Spearman correlation	r(42) = .377	.012
19	Bad ranking wearables (addressing health)	Wearables give personalized outputs	Spearman correlation	r(42) = -.442	.003
20	Bad ranking apps (addressing health)	Wearables give personalized outputs	Spearman correlation	r(42) = .317	.038
21	Desire for wearables	Wearables give personalized outputs	Mann-Whitney U test	U = 148.00 Mean rank (Desire) = 27.08 Mean rank (No desire) = 17.90	.009
22	Bad ranking wearables (addressing comfort)	Survey data collected by own organization	Spearman correlation	r(42) = .351	.019
23	Desire for apps	App/room sensor data processed by AI	Mann-Whitney U test	U = 147.00 Mean rank (Desire) = 28.38 Mean rank (No desire) = 18.18	.005
24	Bad ranking apps (addressing health)	App/room sensor data processed by AI	Spearman correlation	r(42) = -.338	.025
25	Bad ranking survey (addressing health)	App/room sensor data processed by AI	Spearman correlation	r(42) = .351	.020
26	Bad ranking apps (addressing health)	Wearables being worn on the body	Spearman correlation	r(42) = .325	.031
27	Bad ranking survey (addressing health)	Wearables being worn on the body	Spearman correlation	r(42) = .362	.016
28	Desire for wearables	Bad ranking wearables (addressing health)	Mann-Whitney U test	U = 76.000 Mean rank (Desire) = 16.04 Mean rank (No desire) = 31.00	<.001

29	Desire for wearables	Bad ranking wearables (addressing comfort)	Mann-Whitney U test	U = 118.500 Mean rank (Desire) = 17.74 Mean rank (No desire) = 28.76	.004
30	Desire for apps	Bad ranking apps (addressing health)	Mann-Whitney U test	U = 96.000 Mean rank (Desire) = 16.50 Mean rank (No desire) = 29.70	<.001

6.1.3 Conclusion

Key takeaways become clear regarding the relationships between the different dimensions of office workers' perceptions of the assessment tools. First of all, it really differs between individual office workers whether a specific assessment tool is liked or not with the exception of the room-mounted sensors which are perceived favourably by nearly all respondents. If a tool is liked, then the attitudes towards most of the specific tools' attributes are usually also relatively positive, even some of the more intrusive attributes. On the other hand, if respondents dislike a tool, they then also dislike most of its attributes. That said, the direction of these relationships is not clear: Whether respondents primarily like the tool and then because of that also have favourable attitudes towards its attributes or whether they like the combination of attributes and therefore rank the respective tool favourably cannot be determined with this statistical method and dataset.

Whether a tool is liked or disliked consequently mostly does not seem to be related to a single attribute of a tool but rather the whole 'package' of attributes. Respondents seem to infer that many attributes of a tool are mutually dependent on each other and therefore expect to gain more benefits (e.g., more detailed, personalized insights) given the downsides (e.g., intrusive collection of personal information) of a more advanced, smarter tool. This, however, also means that respondents in favour of these tools seem to be more tolerant towards the mentioned downsides of the tools compared to respondents not wanting the benefits of these tools as much. So respondents are apparently to some degree aware that a trade-off between intrusiveness and benefits is required. Nevertheless, the descriptive statistics (see chapter 5.2.1) show that the intrusive attributes of tools are perceived relatively less favourably overall and should therefore be mitigated whenever possible. Respondents also seem to have a somewhat preoccupied opinion about which kind of attributes the respective tools have even if it is not explicitly surveyed in the questionnaire. These opinions may be the result of unaccounted confounding variables connected to the perception of the tools. All in all, respondents seem to be inferring a lot of information about the tools relating to their attitude about the tools. Within the scope of this study, these underlying biases cannot be accounted for.

The attitude towards attributes of the assessment tools generally does not seem to differ depending on which assessment tool is used (e.g., the respondents' opinions towards the collection of personal information do not seem to depend on which type of tool collects them). Interestingly, a relatively unfavourable ranking of an assessment tool does not necessarily mean that there is no desire to have the tool present in the office. At least, this is the case for surveys, indicating that this tool is perhaps accepted by office workers as it is maybe a relatively established concept within offices and office workers do not have any strong adverse feelings against that tool.

6.2 Personal characteristics related to office workers' perceptions

In this chapter, relationships between personal characteristics and the different variables of office workers' perceptions of assessment tools are described. The personal characteristics are several non-technology-related variables that are specific to each office worker and could potentially have an impact on their perception of the assessment tools. Several constructs define personal characteristics. First, smart workplace health and comfort entails the office workers' perception of their own office regarding health and comfort and what their preferences are regarding the health and comfort aspects. Second, personal characteristics also include the gender, education level, and origin (country of work & nationality) of the office workers. Lastly, previous experiences regarding (the personal attitude towards and knowledge of) data privacy, the technology savviness (which includes the knowledge of and willingness to adapt to digital devices and the time of usage of digital devices) are examined. Moreover, it is checked whether the respondents' prior experiences with the respective assessment tools are related to the office workers' perception of the assessment tools.

Some personal characteristics do not significantly relate to any other of the variables in the model and therefore apparently are not useful for explaining office workers' perception of assessment tools or this is caused by some of the study's limitations. Office workers' perception of sedentary behaviour, lighting and noise conditions in their office do not relate to their perception of assessment tools just like the time they spend in the office, their education level, their origin, their attitudes toward data privacy and technology savviness and whether they have any prior experience with smartphone apps, room-mounted sensors and wearables (these are all the unconnected boxes in Figure 22 and Figure 23).

6.2.1 Relationships between personal characteristics and respondents' attitude towards attributes of assessment tools

The results of the Spearman correlation (see Figure 22 and Table 8) show that respondents reporting a higher perceived health and comfort level in their own office relates to them disliking wearing sensors on their own bodies to measure their health and comfort (#31). If the office is already perceived as healthy, it may not seem necessary to further improve this by wearing intrusive wearable technology. One could also interpret this the other way around. Respondents thinking their office scores relatively low on health and comfort would then like to improve that by using wearables worn on their own bodies.

Another relationship can be observed between ranking stress levels as relatively unimportant on the one hand and liking that their own organization is responsible for the data collection for surveys on the other hand (#32). An explanation could be that respondents who do not think that stress is important to them might simply not care who is responsible for the data collection. Another reason could be that office workers do not identify the indoor environmental conditions as the cause of stress in the workplace but rather relate this to other aspects such as the organisational climate (Sahni & Kumar, 2012). Office workers might even relate their stress level at work to activities outside the workplace such as self-image problems (Beehr et al., 2010). This could implicate that respondents who think stress is important to them would then rather have an external provider addressing these stress issues that they link to either company-internal issues (which perhaps should then be better addressed by an impartial third party) or even issues outside of work.

Age shows only one significant correlation with the attitude towards attributes of assessment tools. A relatively higher age (Mean = 32.7 years) relates to the respondent having a more positive attitude towards smartphone apps collecting personal data (#33). This is an interesting observation and not necessarily an expected one given that relatively young office workers could possibly already have a higher exposure to (other kinds of) smartphone apps which could then result in a generally more favourable attitude towards this tool and the tool's attributes. However, assuming younger age groups have a higher usage rate and therefore technology savviness and this being about the collection of private data, previous studies reveal that a higher technology savviness actually results in a more protective attitude towards data privacy (Mani & Chouk, 2017). While the findings of my study therefore somewhat overlap with previous studies, it has to be noted that the mean age of my study's sample is just 32.7 years. Just like with all the other results connected to the variable age found in this study, it has to be kept in mind that other studies likely have a very different age distribution making comparisons challenging. Students exclusively make up the sample of Mani & Chouk (2017) which should indicate that their sample is even younger on average. In general, it needs to be noted that other studies about a similar population reveal that a more representative average age for office workers in Western Europe is much higher in general (the sample of Kim & Bluyssen (2020) shows an average age of 43.8 years).

There are significant relationships between the gender of participants and their attitude towards tools' attributes. Possible differences in the answer patterns between women and men are analysed with the Mann-Whitney U test. It can be concluded that women have a more favourable attitude towards their own organisation being responsible for collecting data rather than an external provider in comparison to men (#34). Whether this is because women are more sceptical about external parties handling their data or relatively tend to have a lot of trust in their own organization is questionable. The findings of Shahzadi et al. (2019) support the latter hypothesis. Women are said to feel a stronger connection to their own company and company culture (Shahzadi et al., 2019) which could then relate to a higher trust in the internal data collection. Moreover, women do not mind wearing the wearables on their own bodies as much as men do who evaluate this attribute more critically (#35). Perhaps, this is also related to other confounding variables like the level of fitness or how much one takes care of their own health (e.g., women may be more interested in wearables because of that). While the study of Chandrasekaran et al. (2020) is not focused on office workers, it does reveal that improving their own health and fitness is the main reason why women are more willing to use wearables. That said, another previous study has investigated this relationship as well, but a significant correlation is not detected (Li et al., 2019). However, this study's sample is constituted very differently from my study by focusing on elderly Chinese people (Li et al., 2019). A completely different explanation for the differing perceptions of these assessment tools between men and women is provided by Konrad et al. (2000) revealing that self-reported attitudes can generally significantly differ between genders based on various gender roles and stereotypes.

There is a significant difference between respondents who already have surveys in use in their office and those who do not. The former group is comparatively less worried about the surveys collecting their personal data rather than collecting data anonymously (#36). This is an interesting insight which suggests that having used an assessment tool can potentially improve the perception of certain attributes of that tool. Choi et al. (2017) come to a different conclusion. Even though their study is only restricted to wearables, having previous experiences with the tool does not show any significant impact on the perception of the tool (Choi et al., 2017). Gummer & Daikeler (2020), on the other hand, find that the willingness to participate in a survey a second time mainly depends on whether the perception of the initial survey has been positive. All that being said, being familiar with a specific technology may generally create trust in this technology improving the perception of it even if this experience may not have been strictly positive (Abolarin & Jia, 2024). Another explanation could be that in my questionnaire, surveys are presented as anonymous and respondents could simply infer that the collected information cannot be traced back to them anyway which may result in a more relaxed attitude towards this attribute.

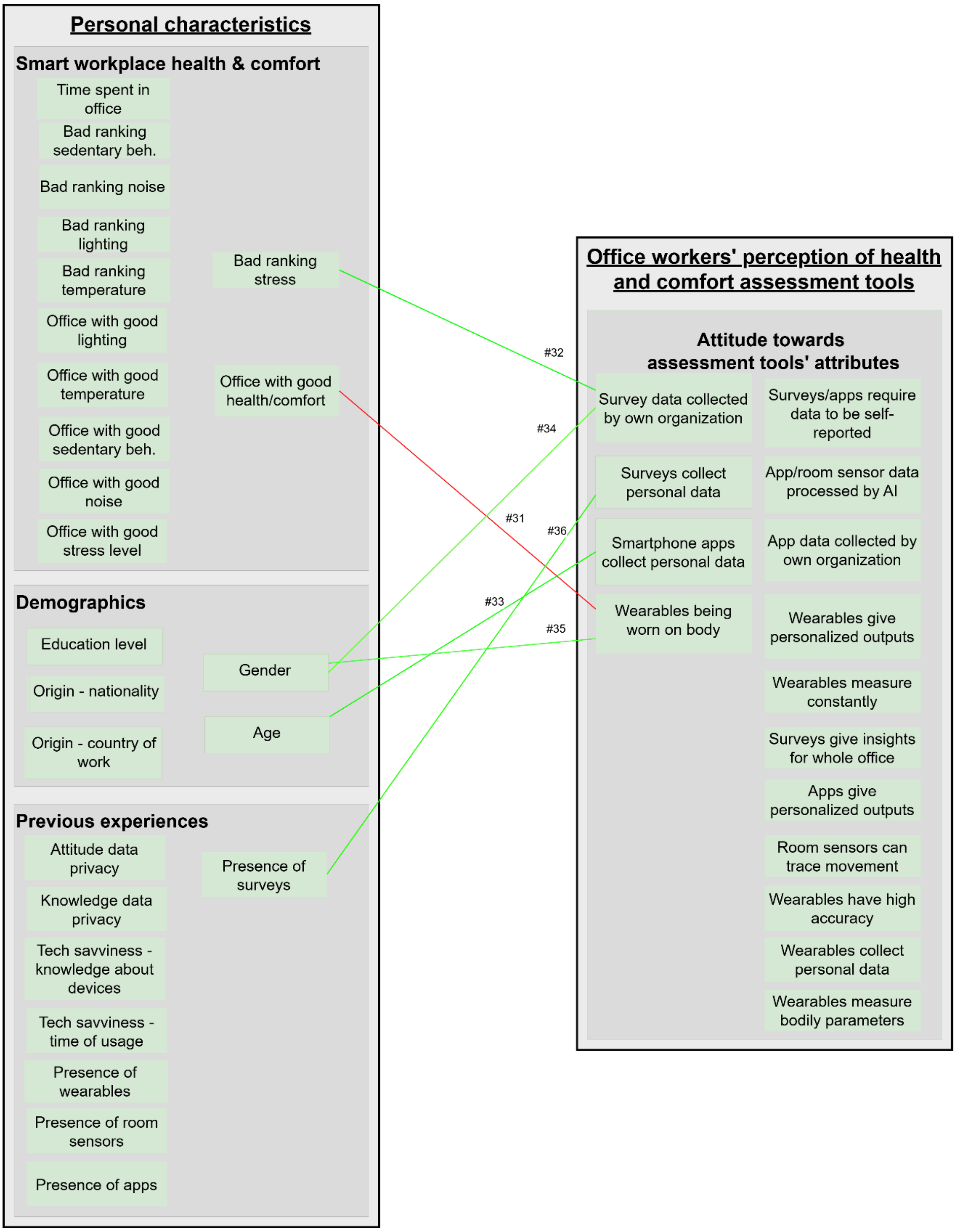


Figure 22: Significant relationships between personal characteristics and respondents' attitude towards attributes of assessment tools

Table 8: Significant relationships between personal characteristics and respondents' attitude towards attributes of assessment tools

#	Variable I	Variable II	Statistical test	Statistics	Sig.
31	Office with good health/comfort	Wearables being worn on the body	Spearman correlation	r(43) = -.301	.045
32	Bad ranking stress level	Survey data collected by own organization	Spearman correlation	r(44) = .304	.040
33	Age	Apps collect personal data	Spearman correlation	r(39) = .340	.030
34	Gender	Survey data collected by own organization	Mann-Whitney U test	U = 138.000 Mean rank (Female) = 24.89 Mean rank (Male) = 17.13	.034
35	Gender	Wearables being worn on the body	Mann-Whitney U test	U = 141.000 Mean rank (Female) = 24.78 Mean rank (Male) = 17.31	.037
36	Presence of survey	Surveys collect personal data	Mann-Whitney U test	U = 130.500 Mean rank (Present) = 29.14 Mean rank (Not present) = 21.73	.047

6.2.2 Relationships between personal characteristics and respondents' ranking of assessment tools

Table 9 & Figure 23 illustrate the significant relationships between personal characteristics and respondents' ranking of assessment tools. Spearman correlation is used to derive the significance of the following relationships. Thinking that the own office has a relatively positive impact on sedentary behaviour relates to ranking wearables relatively unfavourably (#37) and surveys relatively favourably (#38) as tools that should address health. Respondents who are already satisfied with the sedentary behaviour in their office might not see the necessity to have the additional monitoring and intrusiveness of the more sophisticated wearable technologies to measure health and therefore opt for surveys which are perhaps the least invasive options. Invasiveness as a possible criterion for indicating preferences is already discussed in chapters 6.1.1 and 6.1.2. On the other hand, this also means that office workers struggling with sedentary behaviour in the office rank wearables favourably perhaps thinking they are a more useful tool to improve their health. This insight suggests that the state of the indoor office environment and how satisfied the office workers already are with it could impact the perception of the assessment tools. An improved office environment could therefore even make certain assessment tools somewhat redundant.

One significant relationship exists between the preferences towards health and comfort aspects and the rankings of assessment tools. Indicating that the noise conditions are rather important relates to ranking smartphone apps rather unfavourably (#39) to address the comfort in the office. This suggests that respondents anticipate that smartphone apps are not really suitable for assessing noise conditions in the office. Perhaps out of all the health and comfort aspects, noise conditions stick out to respondents as the one that should be measured by sensors rather than self-reported via an app. Temperature and lighting conditions, which are the two other comfort aspects, are perhaps perceived more differently depending on the specific office worker in contrast to noise conditions which is why self-reporting the own perception of temperature and lighting via an app could be comparatively more effective.

In contrast to previous studies examining that men are more likely to perceive advanced assessment tools more positively than women (Jacobs et al., 2019), this study does not yield such results. No significant relationships are found between the gender and the ranking of assessment tools. Given the tendency that women are more favourable towards wearing wearables (see chapter 6.2.1), this result is even more surprising. Perhaps, men only have this particular problem with wearing the wearables while still ranking the whole tool similarly compared to women. The desire for this tool namely also does not differ between the genders.

Age is related to the ranking of assessment tools. A higher age relates to ranking wearables as assessment tools for comfort more favourably (#40). Moreover, a higher age also correlates with a less favourable ranking for surveys addressing health (#41) and comfort (#42). Again, the pretty low mean age within the sample (32.7 years) should be kept in mind. This is perhaps also why this rather surprising outcome can be noted compared to Röcker (2010) who reveals a completely opposite relationship. Röcker (2010) finds out that older age groups are less likely to like the relatively smart tools (such as wearables) compared to younger age groups. However, this study also has a much more homogenous distribution across all age groups with a higher mean age. Thus, there the comparability to my study is limited – relatively young respondents of their sample could be relatively old respondents in my sample.

Röcker (2010) also finds out that people with less formal education are less likely to prefer a more advanced assessment tool (such as wearables). This relationship cannot be examined within the dataset of this study. This perhaps is because the diversity of education levels is very low in the sample meaning that only a few respondents have a less formal education in the sample. Only measuring the perception of a very few respondents with a lower education level makes it difficult to find any insightful findings in this regard.

The Mann-Whitney U test reveals significant differences between respondents already using wearables in the office compared to respondents who do not. The former group ranks wearables (for addressing health aspects) as more favourable (#43). This adds to earlier observations (see chapter 6.2.1) that prior experiences with a tool can result in a more favourable perception of this tool or attributes connected to this tool.

Lastly, it is expected that a protective attitude towards data privacy leads to less desire to use wearables (Choi et al., 2017). This relationship cannot be found in my study. An important difference is that Choi et al. (2017) measure the perception of construction workers and not office workers and the set of items used to measure the attitude towards data privacy is also rather different which could alter the results. Overall, a lack of significant relationships between the attitude towards data privacy, but also the technology savviness on the one hand and office workers' perceptions of assessment tools on the other hand is noticeable in my study. An interesting possible explanation for that is given by Lutz et al. (2020). Their study suggests that people having uncertainties and mistrust towards organisations handling their private data can paradoxically stop caring about actually protecting their private data. Consequently, these people may have a protective attitude towards data privacy but they do not show related appropriate behaviours to also protect their private data (e.g., avoiding privacy invasive tools like wearables). This perhaps explains why the attitude towards data privacy does not relate to the ranking of and desire for assessment tools. Similarly, Makarem et al. (2009) detect that even people with high technology savviness can show aversions against new and innovative technologies and tools because other factors like the convenience of the technologies are more determining for the perception of the tools. Both variables could therefore not really be suitable for explaining office workers' perceptions of assessment tools.

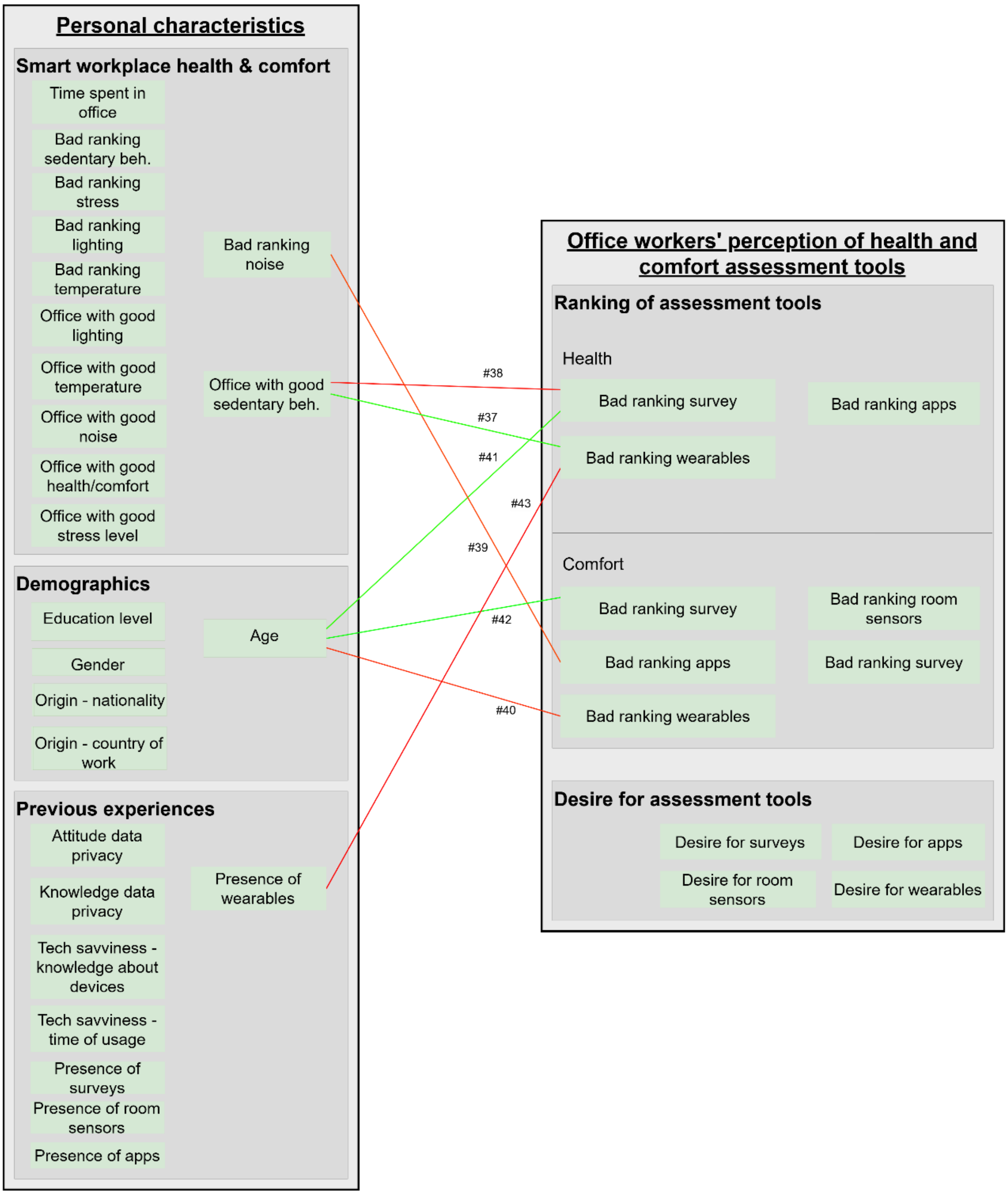


Figure 23: Significant relationships between personal characteristics and respondents' ranking of assessment tools

Table 9: Significant relationships between personal characteristics and respondents' ranking of assessment tools

#	Variable I	Variable II	Statistical test	Statistics	Sig.
37	Office with good sedentary behaviour	Bad ranking wearables (addressing health)	Spearman correlation	r(42) = .350	.020
38	Office with good sedentary behaviour	Bad ranking surveys (addressing health)	Spearman correlation	r(42) = -.450	.002
39	Bad ranking noise conditions	Bad ranking apps (addressing comfort)	Spearman correlation	r(42) = -.304	.045
40	Age	Bad ranking wearables (addressing comfort)	Spearman correlation	r(39) = -.346	.027
41	Age	Bad ranking survey (addressing health)	Spearman correlation	r(39) = .363	.020
42	Age	Bad ranking survey (addressing comfort)	Spearman correlation	r(39) = .344	.028
43	Presence of wearables	Bad ranking wearables (addressing health)	Mann-Whitney U test	U = 135.000 Mean rank (Present) = 17.14 Mean rank (Not present) = 25.00	.049

6.2.3 Conclusion

It should be noted that many personal characteristics do not show any relationships with office workers' perceptions of assessment tools or the relationships have a different direction than expected. This concerns respondents' education level, age and attitude towards and knowledge about data privacy as well as the technology savviness. This could of course be because of limitations of my study or differences to the other studies' design or sample constitution. In particular, the education level shows a low diversity of backgrounds within the sample. The average age, on the other hand, is rather low in my study's sample, making comparisons to other studies' findings difficult and maybe result in the surprising outcome that relatively older age groups of this sample prefer the smarter assessment tools. The lack of relationships between respondents' attitudes towards data privacy and technology savviness and the perception of tools could also be because these attributes are less suitable and influential than expected for determining office workers' perceptions.

Significant relationships also become visible between the gender, perceived health and comfort of the office of respondents as well as their prior experience with assessment tools on the one side, and office workers' perception of assessment tools on the other side. Women are more favourable towards wearing wearables and having their own organisation responsible for data protection. Existing prior experiences with a specific assessment tool sometimes lead to a more favourable perception of that specific tool. Another observation is that the perception of the current office environment relates to office workers' perception of assessment tools. If respondents are already satisfied with certain health and comfort aspects in their office, they sometimes feel less of a need for advanced assessment tools that are trying to tackle this problem.

These relationships are all connected to the attributes and ranking of assessment tools as dimensions of office workers' perceptions of the tools. Thus, the desire for tools is not significantly related to any personal characteristics. Perhaps it could overall be concluded that the researched personal characteristics of office workers are not very telling for how office workers perceive the different assessment tools as there are not many strong and significant relationships overall and some of them contradict the findings of previous studies.

6.3 Relationships between personal characteristic variables

Even though not directly related to any research questions, very few significant relationships between personal characteristic variables are detected (see Figure 24 & Table 10). Note that relationships between variables of the dimension of smart workplace health and comfort and the other two variables have not been tested as previously explained at the beginning of chapter 6. First, relationships between different variables of smart workplace health and comfort are described. Respondents are first asked about how they in general perceive their own office regarding health and comfort before being asked similar questions again but then regarding the 5 health and comfort aspects individually (after receiving additional information about them). The Spearman correlation shows that these two blocks of variables are all significantly related to each other (#44 to #48). Thus, respondents' initial perception of the health and comfort of their office relates to respondents' perception of all 5 health and comfort aspects individually. This is no big surprise given the very close similarity of the questions. Nevertheless, it is interesting to note that the additional information given in between the questions does not significantly change the answer patterns. This could mean that the respondents already have an accurate prior understanding of what constitutes health and comfort in the office. Moreover, none of the 5 health and comfort aspects seem to be perceived very differently so the answers would significantly differ from the ones given to the prior question about health and comfort in general. Considering that these aspects are somewhat different to each other, this is quite interesting and suggests that none of the health and comfort aspects particularly stick out and are perceived as especially positive or negative in the offices. Moreover, it could mean that the focus points regarding the health and comfort aspects are quite different depending on each office worker and their unique circumstances.

Respondents thinking that stress levels in their office are relatively low relates to them assigning relatively little importance to this aspect compared to the other health and comfort aspects (#49). The same observation can be made for respondents having a favourable perception of the temperature conditions in their own office which relates to them ranking temperature conditions unfavourably compared to the other aspects (#50). This is an interesting, yet understandable, relationship. It is reasonable to assume that one starts caring about a certain health and comfort aspect more if it is perceived relatively badly in the own office. Even though Vernet et al. (2019) do not conduct workplace-related research, they also find a general link between becoming aware of something which can subsequently raise the attention given to that matter. Respondents may thus give less attention towards the health and comfort aspect if it does not bother them during their time spent in the office. It has to be kept in mind though that this relationship has only been detected for two of the 5 health and comfort aspects.

Contrary to the results of other studies that find a relationship between the origin and cultural backgrounds of people with their attitude towards data privacy (Cvrcek et al., 2006; Röcker, 2009; Röcker, 2010), no such significant relationships are found within this data set. While Röcker (2010) mainly compares German and American workers with each other, the majority of respondents in my study originate from the two neighbouring countries of Germany and the Netherlands which perhaps share more cultural and workplace-related similarities with each other than Germany and the US. This is why Röcker (2010) could also perhaps find bigger differences in perception between the countries. While Cvrcek et al. (2006) compare workers of more comparable central European nations with each other, this study was conducted way before the introduction of the EU-wide GDPR which somewhat equalled the data privacy regulations amongst EU member states (Collins & Marassi, 2021). This could perhaps also have led to more similar attitudes towards data privacy in different EU member states that seem to be prevalent in my sample. Moreover, no relationship is found between high technology savviness and a protective attitude towards data privacy which is detected by Mani & Chouk (2017). The detected, possibly limited explanatory power of these variables (see chapter 6.2.2) could perhaps play a role in this lack of significant relationship as well. Lastly, it can also not be seen that an older age leads to less technology savviness (Röcker, 2010). As mentioned before (see chapter 6.2.1), the average age in the sample of Röcker (2010) is much higher than in my study making comparisons difficult. Given the low age of my sample, it could be that the majority of respondents have grown up with digital devices and are therefore all relatively technology savvy (even though not everyone reported this about themselves in the questionnaire). Of course, it could also be difficult for many to accurately evaluate themselves on how technology savvy they actually are.

These findings, while not central to answering the research questions, provide some further insights into the topic. Respondents' initial perceptions of their office's health and comfort closely align with their views on specific aspects of health and comfort, possibly indicating a relatively high prior knowledge about the topic. Low perceived stress levels and favourable temperature conditions are related to assigning lower importance to these aspects. As seen in chapter 6.2.2, this in turn relates to how the assessment tools are ranked which means that improving certain aspects of the indoor office environment could then have a relationship with how health and comfort aspects and assessment tools are perceived. Despite other studies finding cultural differences in data privacy attitudes, this study does not detect such relationships, possibly due to limitations of this sample's diversity or the other studies being outdated. Additionally, no link is found between technology savviness and protective attitudes towards data privacy or age and technology savviness. These findings, while not central to answering the research questions, provide some further insights into the topic.

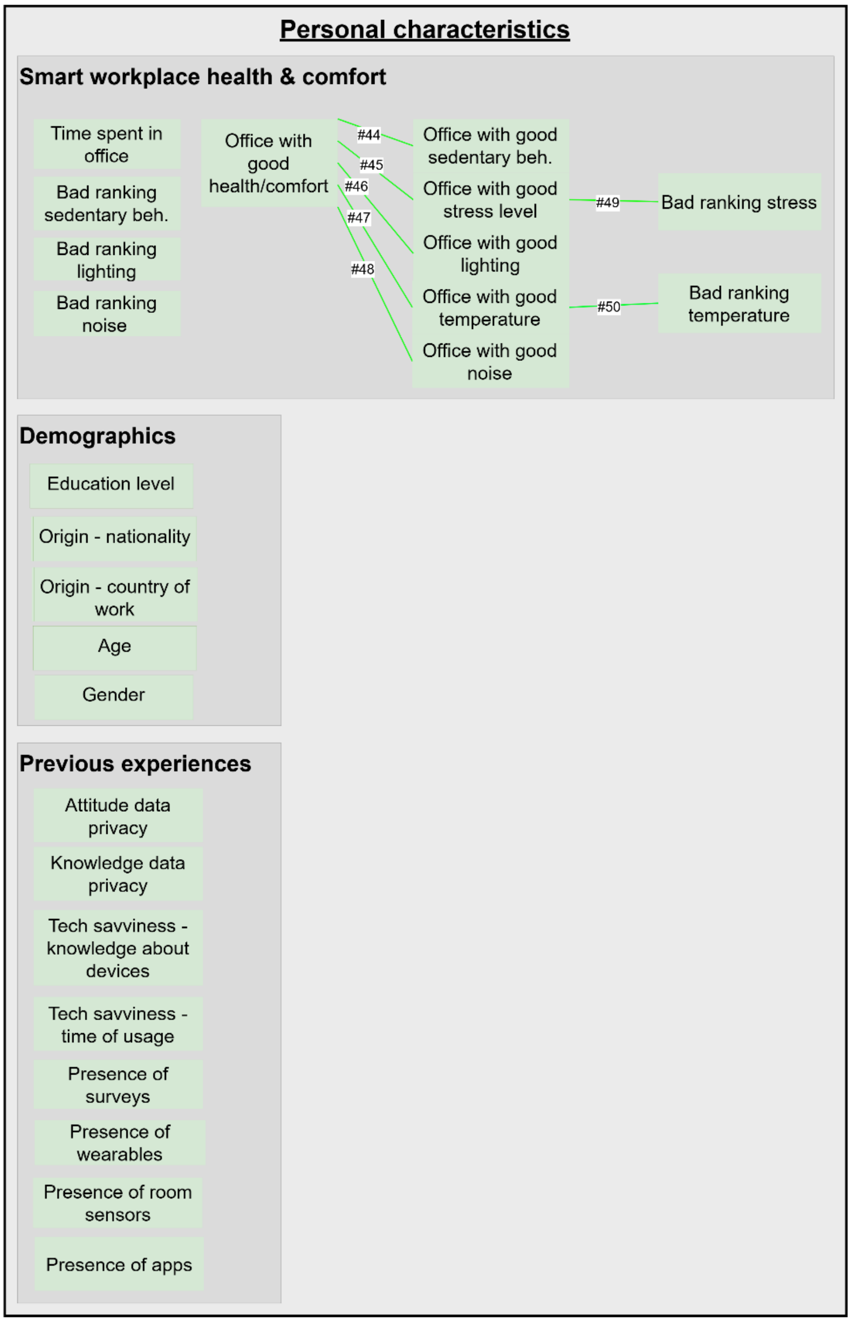


Figure 24: Significant relationships between personal characteristic variables

Table 10: Significant relationships between personal characteristic variables

#	Variable I	Variable II	Statistical test	Statistics	Sig.
44	Office with good health/comfort	Office with good sedentary behaviour	Spearman correlation	r(44) = .464	.001
45	Office with good health/comfort	Office with good stress level	Spearman correlation	r(44) = .429	.003
46	Office with good health/comfort	Office with good lighting condition	Spearman correlation	r(44) = .545	<.001
47	Office with good health/comfort	Office with good temperature condition	Spearman correlation	r(44) = .326	.027
48	Office with good health/comfort	Office with good noise condition	Spearman correlation	r(44) = .524	<.001
49	Office with good stress levels	Bad ranking stress level	Spearman correlation	r(44) = .338	.022
50	Office with good temperature conditions	Bad ranking temperature condition	Spearman correlation	r(44) = .369	.012

7. Conclusion

This exploratory study provides valuable and nuanced insights into office workers' perceptions of health and comfort assessment tools. It shows that there is no universally preferred assessment tool among office workers. Also, the perception differs depending on various variables associated with the assessment tools, the office workers' personal characteristics and, last but not least, which kind of health and comfort aspects are assessed. In particular, the balance between the intrusiveness and the utility of a tool plays a crucial role when designing or implementing a specific tool in the office. Office workers generally seem to be accepting of having smarter tools and the benefits they add to their office. However, whether a tool is accepted really seems to differ between individual office workers resulting in a sizeable amount of office workers that could at least initially have doubts about certain tools. This requires a nuanced and thorough approach when implementing such tools in the office. By integrating these findings into practice, organisations can enhance workplace well-being and foster a more accepting environment for advanced health and comfort management technologies. Future research should continue to explore these dynamics to build on the foundation laid by this study.

Subchapter 7.1 dives deeper into the main conclusions of the data analysis (chapter 5 & 6) to derive core takeaways and recommendations of this research for theory (chapter 7.2) and practice (chapter 7.3) while mentioning the limitations of this study. It goes without saying that these takeaways have to be viewed with care as this is an exploratory study and as a result, further research is required to substantiate the results.

7.1 Answering the research questions

The main research question is answered step-by-step throughout the thesis:

> *How do attributes of assessment tools and personal characteristics relate to office workers' preferences for assessment tools assessing their health and comfort in the office?*

This chapter summarizes the findings. From previous studies, it is derived that 5 relevant aspects of office workers' health and comfort are sedentary behaviour, stress, lighting, temperature and noise conditions (see chapter 2.2.1). These are not just important from an office worker's viewpoint but are at the same time also already being addressed by various assessment tools in practice.

Three dimensions that indicate office workers' perception of health and comfort assessment tools are distinguished. First, the attitude towards assessment tools' attributes. Second, the ranking of assessment tools. Third, the desire to have the assessment tools at the workplace. To allow for a comparison between different tools with differing levels of smartness, 4 representations of actually existing assessment tools are defined that are considered to be especially relevant in the office environment: anonymized surveys, personalized app-based surveys, room-mounted sensors and wearables (see chapter 4.3.2).

The assessment tools are characterized by 9 common attributes that on the one hand often become visible in real-life tools (see chapter 2.2.1), but on the other hand, have also sometimes been detected as influential variables for the office workers' preferences towards these tools by previous literature (see chapter 3.2): The amount of collected personal data (Collins & Marassi, 2021; Gorn & Shklovski, 2016; Harper et al., 2022; Lai et al., 2003; Neff & Nafus, 2016; Teebken & Hess, 2021; Zieglmaier et al., 2022), level of accuracy (Mani & Chouk, 2017), level of automatization (Ahmadi-Karvigh et al., 2017; Day et al., 2019; Donkers et al., 2023; Kwon et al., 2019; Lashina et al., 2019; Tuzcuoğlu et al., 2023), range of outputs, technological intelligence, data type collected, frequency of measurement, proximity to the user, responsibility for data collection.

The analysis (see chapter 5.2.1) concludes that a positive attitude exists towards these tools giving (very) personalized outputs, outputs being given for the whole office, environmental conditions and bodily parameters being measured, tools using artificial intelligence, the collection of data via the smartphone, tools being highly accurate and the very frequent measurement of data. On average, office workers feel neutral about tools collecting data that enable the tracing of movement patterns, whether their own organization or an external provider is responsible for the data collection and whether the data is self-reported or measured automatically. What office workers dislike about the tools is when personal information is collected and when the measurements are taking place directly on their own bodies (with wearables).

Each tool obviously has unique specifications for each of those attributes. Generally speaking, the higher level and smarter tools (such as room-mounted sensors or wearables) provide greater benefits for office workers with the drawback of being more intrusive. How office workers weigh up the mix of attributes against each other and evaluate these trade-offs, partly manifests itself in how the assessment tools are ranked against each other and which of the tools office workers wish to have present in their office. Two different rankings are created. One is concerned with the three tools that measure health aspects and the second contains the four tools assessing comfort aspects. Wearables are the most favoured tool to measure health aspects followed by smartphone apps and surveys (see chapter 5.2.2). Office workers favour room-mounted sensors the most to measure comfort aspects followed by smartphone apps and surveys. Regarding comfort aspects, wearables are the least favoured tool. Here, the only noticeable and significant difference becomes clear regarding whether health or comfort aspects are assessed by a tool. It can be assumed that office workers do not see a necessity to assess comfort aspects (e.g., temperature conditions) by wearables as finely-grained and close to the user as health aspects (e.g., stress). Office workers may not be aware that interesting insights can also be gained when measuring indoor environmental conditions for every desk individually (Abboushi et al., 2022; Martire et al., 2018; Silentium, n.d.).

It becomes clear that office workers' ratings of a tool usually significantly relate to whether the attributes' specifications of that tool are also rated favourably (see chapter 6.1.2). The attributes therefore seem to be very influential to office workers' preferences for the tools overall. Moreover, the perceptions do not seem to depend on the specification of a single attribute but rather the whole 'package' of attributes of the respective tool. Interestingly, office workers to some extent seem to acknowledge that a tool can only provide certain benefits of advanced tools if they at the same time are also relatively intrusive. If they are in favour of such tools, they also seem to be more likely to accept their drawbacks to some degree. An overwhelming majority of office workers desire to have room-mounted sensors present in their offices (see chapter 5.2.3). Most office workers also wish to have surveys in use in their offices. Less favoured are smartphone apps and wearables (about half of the sample vote for these tools to be present). Paradoxically, surveys are ranked unfavourably while still often being desired while nearly the opposite can be said about wearables. Presumably this is because surveys, the tool with a lower level of smartness are perceived as less polarizing and controversial compared to wearables which are very smart.

This study is not just about describing which tools and which tools' attributes are preferred by office workers but also about which other variables relate to these preferences. These so-called personal characteristics are subdivided into the three dimensions of smart workplace health and comfort, demographics and previous experiences. Fewer relationships between personal characteristics and office workers' perception of assessment tools are detected in comparison to the amount of relationships that can be observed in-between attributes of assessment tools (see chapter 6.2). This leads to the conclusion that the attributes of assessment tools could perhaps be more influential for office workers' overall perception of assessment tools. This study finds that if office workers are pretty satisfied with a certain health and comfort aspect in their office, they feel less need for a specific assessment tool that tries to tackle this specific health and comfort aspect.

Literature (see chapter 3.3) reveals that the demographic aspects of gender (Jacobs et al., 2019; Röcker, 2010), education level (Röcker, 2010), age (Donkers et al., 2023; Mani & Chouk, 2017; Röcker, 2010) and origin of office workers (Cvrcek et al., 2006; Röcker, 2009; Röcker, 2010) influence their perception of tools as well. However, this research only finds that gender and age relate to office workers' perception of assessment tools. Striking results are that older groups of this sample (the mean age is 32.7 years) tend to be more in favour of the very smart tools. Moreover, women are relatively more in favour of wearing wearables and their own organization is responsible for the data collection compared to men. To my knowledge, this has not been discovered by any previous studies.

Lastly, the previous experience of respondents is supposed to relate to office workers' perceptions. This includes the attitude towards data privacy (Choi et al., 2017; Mani & Chouk, 2017) and the technology savviness (Mani & Chouk, 2017; Röcker, 2010) of office workers. Surprisingly, these variables show no relationships to other variables in this study (see chapter 6.3). On the other hand, if office workers already have experiences with a respective tool, they are sometimes more likely to rank this tool or attributes of this tool favourably.

7.2 Limitations & recommendations for research

Several limitations of this exploratory study should be acknowledged when using the insights. Future studies could mitigate these limitations when designing their research. First, selection bias may have occurred due to the demographic composition of the sample (Heckman, 1990). This, in turn, could lead to a sample that does not fully represent the broader, global population of office workers. By recruiting respondents predominantly from personal and professional networks, the majority of the sample is constituted by highly educated office workers from the Netherlands and Germany, the majority of them being female and relatively young. It can be expected that the average population of office workers is somewhat older than the sample (the participants in a much larger study among office workers in the Netherlands have a mean age of 43.8 years (Kim & Bluyssen, 2020) compared to 32.7 years in this study) and only roughly half should be female (Kim & Bluyssen, 2020). Moreover, the age distribution in my study is skewed towards office workers under 30 rather than evenly distributed across the whole range of age groups Originating from neighbouring countries, the majority of workers in the sample share a comparable cultural background. That said, the work cultures between the Netherlands and Germany somewhat differ (Jimmink, 2022). However, no significant differences in office workers' perceptions depending on their origin are found in this study between the two countries or indeed in relation to a completely different country. It is possible that office workers from countries with very different cultural backgrounds then also have different perceptions about the assessment tools as work culture-related factors like hierarchy and autonomy can differ a lot between countries (Aycan et al., 2000; Mannix & Neale, 2005). Lastly, office workers without a university background are vastly underrepresented which again does not fully portray the whole population of office workers. Conclusions should especially be considered with care by companies and industries that employ a much lower percentage of highly educated office workers. It would be interesting to conduct similar research in a different demographic setting (e.g., within a different culture or with less educated office workers etc.) to compare the similarities and differences to this study.

Moreover, it can also be anticipated that a disproportionate number of respondents have a high interest in real estate and workplace-related topics given the predominance of these contacts in the personal and professional network. It can also be anticipated that office workers with stronger opinions towards the topics of this research are more likely to participate in the study compared to office workers who have a more indifferent opinion about these matters. It might be less likely for the latter group to fill out the questionnaire due to this disinterest. Office workers who are more engaged in workplace-related topics might logically have a deeper understanding and interest in health and comfort as well as technology-related matters in the office. Their assessment of those constructs might therefore differ compared to office workers who do not possess this knowledge and interest. The lack of significant relationships in-between these personal characteristic variables and the perception of assessment tools could be an indicator of this limited variability within the sample. Furthermore, the sample size of 46 in itself signals a limited diversity within the sample – different office workers with very similar demographic backgrounds can of course have very different opinions towards this topic. Moussaïd et al. (2013), for instance, detect that social interactions have a major influence on a person's opinion formation too which is not accounted for in this study. A larger sample size, something a bigger research project could address, could help to mitigate some of the selection bias. As such, it can also be recommended to recruit office workers from more diverse sources rather than mostly through their own social networks.

This leads to another important limitation of this study. As a lot of variations in the perception of the assessment tools cannot be explained with the existing personal characteristics variables, unaccounted confounding variables that are not part of the conceptual model could exist such as the above-mentioned social interactions of employees (Moussaïd et al., 2013), their trust in their organisation (Li et al., 2008) or their physical activity level (Rupp et al., 2018). This is especially likely given the general limitations of the chosen research methodology – questionnaires. To not overwhelm and fatigue the respondents, only a limited number of questions and therefore also only a few variables can be included. Given this is exploratory research that is only based on very few findings from previous studies, there are a lot of other personal and attributes of assessment tools that could potentially relate to office workers' perceptions. For instance, the relationship between the office workers and the organization they are employed at is not included (e.g., employees heavily trusting their organization could relate to how they perceive the tools (Li et al., 2008)). Other possible predictors for the office workers' perception could be the general psychological and physical state of the office workers (e.g., fitter employees could have a different perception of the tools (Rupp et al., 2018). Given the constraints, only those variables that seemed most relevant regarding office workers' perceptions could be included. Future research could focus more on variables that are not included in this study to find out whether confounding variables exist and which other personal characteristics relate to office workers' perceptions of assessment tools. A factor analysis could help to derive distinct configurations of assessment tools suitable for a specific group of people.

These quantitative limitations also apply to the number and type of assessment tools, attributes of tools and health and comfort aspects that are included in the questionnaire. In all cases, only the ones that seemed most relevant are presented. Air quality, for instance, is another health and comfort aspect for which it would be interesting to investigate office workers' perceptions about. For instance, Ortiz & Bluyssen (2022) find that certain groups of office workers actually perceive this aspect as very important even though the other 5 chosen aspects of this study might overall be more relevant. On the other hand, the way the 4 chosen assessment tools are defined in this questionnaire means that they are only somewhat representative of tools that exist in real life and should be viewed as abstractions of those actually existing tools. It is therefore possible that the findings of this study only partly apply to specific tools existing in real life. Yet again, other research projects could concentrate on other health and comfort aspects or define the tools differently. It may also be interesting to investigate preferences towards a very specific, actually existing tool in a future study.

Another limitation of using questionnaires as a methodology is that it cannot be determined whether respondents base their answer choices solely on the given information in the questionnaire or whether they use previous knowledge and perhaps false biases (e.g., about specific tools) when answering the questions (Razavi, 2001). Chapter 6 finds clues that respondents indeed are inferring certain attributes about tools even though they are not explicitly mentioned in the questionnaire. An option to counter this could also be to incorporate more qualitative elements such as open-ended answers or interviews in the research to make use of a relatively inductive approach (e.g., Dunwoodie et al., 2023).

Due to constraints about the length of the survey to not limit the response rate (Deutskens et al., 2004; Revilla & Höhne, 2020), the length and depth of descriptions, answers and background information are naturally limited and need to be reduced to the bare minimum. This, in turn, leads to a limited richness of the gained data (Kato, 2023).

Something that cannot really be avoided with this methodology, but is certainly something to note, is the possible misinterpretation of questions by respondents (Ashok et al., 2022). This could lead to inaccurate responses just like when respondents start to rush over questions without giving enough time to think about the answers due to fatigue or time constraints (Hess et al., 2012). A suitable approach could be to replace or combine the questionnaire with a group interview that leaves room to ask questions to clarify if everything is understood correctly (Sandelowski, 2000).

Other limitations are very specific to this particular questionnaire. Respondents are presented with a whole range of assessment tools' attributes, some of which are supposed to provide benefits to the respondents, while others should be perceived more negatively due to their intrusiveness. It can be expected that respondents to a certain degree rate the attributes in such a way that the combinations of attributes are very favourable for them. However, this might not at all represent a realistic combination of attributes for a tool that could exist in real life. An example of this becomes clear in the results section. Respondents often like that tools provide personalized outputs but the collection of personal information is perceived relatively critically. It is unrealistic to assume that an actually existing tool could achieve both of these simultaneously. For future studies, it could therefore be really interesting to look into these trade-off situations more thoroughly to find a preferred middle way between benefits and intrusiveness of assessment tools (e.g., in how far are respondents willing to have personal information collected to achieve a more personalized output).

Future research could not just focus on different tools, attributes or health and comfort aspects but could also make use of a completely different research design. Since the described tools in this study might remain somewhat abstract, especially to respondents without any previous experiences, it would of course be interesting to design an experiment that allows the respondents to gain actual real-life experience with the tools. This could ideally be integrated into an existing office environment of a company. Another innovative methodology would be to analyse the data collected by the tools to be able to directly connect the real-time usage patterns with context-related information like the personal characteristics of the users. Furthermore, a stated-choice experiment (Adamowicz et al., 1998) could help to dive deeper into how exactly office workers evaluate the trade-off between benefits and intrusiveness that currently seems to be an unavoidable characteristic of many advanced assessment tools.

7.3 Implications & recommendations for practice

Based on the research findings, this chapter depicts possible implications and recommendations for workplace managers responsible for implementing the assessment tools in offices and for the manufacturers designing these tools.

In conclusion, which health and comfort assessment tool would office workers ideally like to have? It needs to be mentioned that no definitive answer can be given to this question, and as can be seen in chapter 6, this also differs depending on various other variables. Nevertheless, it becomes clear that the sample of respondents slightly prefers one of the smarter tools that can give a lot of accurate and personalized outputs. Even though some attributes of these tools are presumably perceived negatively because of their intrusive nature, other attributes of such advanced tools are perceived surprisingly well. It can, however, also be derived that less intrusive assessment methods providing the same outputs would probably be most preferred. Of course, it would currently be difficult to create a tool with such specifications, but finding a balance between intrusiveness on the one hand and insights, on the other hand, is a possible strategy to pursue when developing a new tool. Given the apparent popularity of room-mounted sensors, one possible development trajectory could be to further develop this tool for it to be able to deliver more finely-grained, accurate and personalized information. This could perhaps also enable this kind of tool to assess the two health-related aspects stress and sedentary behaviours which is currently not the norm (chapter 2.2.1 shows that unintrusive sensor technologies for such purposes are scarce)

This research shows that the perceptions of assessment tools can generally differ a lot between different office workers which often cannot be related back to personal characteristics (at least often not to those that are tested in this study). Thus, the conclusion for workplace managers should be to avoid generalizations such as older office workers being possibly more reluctant to adapt to smart tools (this study actually showing the opposite even though the mean age is just 32.7 years) but, if possible, more focus on the specific needs of each individual office worker. While office workers seem generally open to receiving health and comfort benefits by a technological solution, there is not a most preferred way of how to achieve this. Therefore, it could be worthwhile to implement or test multiple tools that roughly target the same outcome to see which of them are preferred by individual office workers. This also requires constant feedback loops incorporating employees' opinions and adjusting the implementation process accordingly (Barisic et al., 2020; Kaur et al., 2023; Jones & Smith, 2002).

The next step for tool manufacturers would be to design adaptive tools that can be customized to meet the specific needs and preferences of different office environments and individual workers, making the tools more appealing and user-centred. For instance, users could get an option to individually choose which type of data is collected and processed. This approach could not only enhance user acceptance but also ensure that the tools provide meaningful insights tailored to individual needs. Given that concerns about data privacy are very important for office workers' preferences towards assessment tools, it could be an interesting approach to let employees have more control over their own data (as suggested by Koldijk et al. (2016)). Simultaneously, making them understand how data is protected can mitigate privacy concerns and enhance trust (Khakurel et al., 2018, Koldijk et al., 2016; Harper et al., 2022; Teebken & Hess, 2021).

This approach also relates to possible solutions for improving the perception of already existing tools. During the implementation process of such tools, office workers essentially should be persuaded to approve of the tool in their office. For workplace managers trying to implement an assessment tool, it could help to slowly get their employees accommodated to a specific tool (Delpechitre et al., 2019), perhaps by implementing it in a step-by-step approach and helping them get acquainted with it (e.g., by hosting trainings or workshops) rather than simply imposing the new tool upon the staff without considering their concerns (Jones & Smith, 2002). Given that office workers are seemingly more in favour of a tool being implemented if it provides personal benefits, these benefits should also be especially emphasized (Anaam et al., 2020). It becomes clear that office workers evaluate each tool based on a range of attributes rather than one single attribute. Manufacturers of the tools or the workplace managers implementing them into the offices could conclude that it does not necessarily result in a changed attitude of office workers towards a specific tool if only individual specifications of this tool are tweaked (e.g., reducing the intrusiveness of wearables). Office workers may not even notice or experience these changes, may not think that the tweaks would change the tool much, or may already be preoccupied with the tool anyway. In all of these cases, extensively communicating the specifics of a tool (e.g., how it works, what it delivers, what the risks are) could also be a strategy to gain more trust and increase the acceptance of a specific tool. The same approach of educating the staff could also be implemented regarding the health and comfort aspects. If office workers are becoming more aware and sensible of these issues, they are perhaps more likely to favour an assessment tool that fixes them. That said, literature shows that there is also a risk of increased transparency leading to office workers becoming more sceptical about very intrusive tools as soon as they learn about the large amount of data being processed (Zieglmaier et al., 2022). Of course, such a communication strategy could not be tested in this research as only very short statements and descriptions of the tools are provided as part of the questionnaire. The usage rate of such tools could also be improved by providing (monetary) incentives to office workers regularly using the tools. This has been discussed in a previous study as well (Jacobs et al., 2019) and could prove successful given the finding in this study that the perception of a tool seems to become more favourable as soon as office workers gain experience with using that tool.

Another observation is that the perceptions of the current office environments relate to office workers' perceptions of assessment tools. If respondents are already satisfied with certain health and comfort aspects in their office, they sometimes feel less of a need for specific assessment tools that are trying to tackle this problem (e.g., if the sedentary behaviour is satisfactory in the office, wearables are ranked relatively unfavourably among the assessment tools). For workplace managers, this could mean that improving the indoor office environment for the employees could make assessment tools unnecessary from the viewpoint of the office workers. The money and effort to implement certain tools could perhaps be saved if the office environment is exceptional to begin with. That said, the assessment tools presented in this research could still be useful to check whether the office is (still) considered a healthy and comfortable place for everyone. In any case, as described in chapter 2.2.1, the assessment tools are suitable for effectively monitoring and evaluating the health and comfort within the office long-term. A dynamic approach ensures that the tools remain relevant by continuously evolving around employees' needs and by incorporating technological advancements. After all, it is anticipated that new technological developments could fundamentally change the opportunities for addressing health and comfort with (smart) tools in the office which could also open up completely new areas of use (Barisic et al., 2020). Hopefully, in the future, more accurate and personalized assessments will become possible without the intrusive drawbacks that are still associated with them nowadays.

This study also provides some insights that are less about the assessment tools themselves. There is an apparent dichotomy in perceptions regarding sedentary behaviours and stress levels by office workers. These aspects of the office environment are either seen as very important or not important at all by respondents. This polarization could indicate that office workers are starting to understand the implications to their health when working in the office more so than they did in the past. This is in line with other research outcomes (e.g., Borsos et al., 2021). However, some office workers might not necessarily associate these health issues with the time spent in the office. This suggests a need for educating office workers more thoroughly about the adverse effects working in an office can have on their health.

Considering all observations made in this study, it is doubtful whether implementing such assessment tools alone is enough to persuade office workers to return to the office more regularly. Bringing employees back into the office, which is a concern since the COVID-19 pandemic (Barnes & Ferris, 2023), requires a more holistic approach that includes not just technological advancements but also other organizational changes. A main goal will be to increase office workers' satisfaction in the office, and that certainly involves prioritizing office workers’ health and comfort in some way.

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Appendices

Appendix A

Attached is the whole online questionnaire as it is presented to the respondents.

Part I: Upfront questions - Experience of your own office

This section contains questions about your own office that you are mainly working in. Please answer the questions according to your own experience.

***How many days do you currently work in the office in a typical week?**

Please only refer to the days per week that you are spending inside the office of a company (or a shared office / coworking space). Do not inlcude the days that you are working remotely or in any other location.

Choose one of the following answers

○ Almost never ○ 1 day ○ 2 days ○ 3 days ○ 4 days ○ 5 days

***To what extent do you agree with the following statements:**

	Completely disagree	Disagree	Neutral	Agree	Completely agree
"My current office is a healthy place to work in"	○	○	○	○	○
"My current office is a comfortable place to work in"	○	○	○	○	○

Part II: Preferences towards health, comfort and technology in the office

Part II of this survey consists of 4 STEPs.

1. a short introduction of common health and comfort related issues in the office.
2. questions how relevant each of these issues are for you.
3. diving into different technologies improving on these issues.
4. questions which of these technologies you would like to have in your office.

As every STEP builds upon the information given in the previous STEPs, please read through the whole section carefully and then answer the corresponding questions.

* STEP 1:

Introducing you to health and comfort related issues the office

Working in an office environment can have negative impacts on your health and comfort. A distinction can be made between health and comfort:

A **healthy** office environment promotes the occupants' physical and mental resilience and limits stressors that could cause diseases.

Two common health related issues in the office are:

Sitting and moving behaviour

Long periods of sitting in a fixed position, wrong sitting postures and a lack of standing up and moving around, could lead to negative health outcomes such as muscle stiffness, neck or back pain and decreasing fitness.

Stress level

Stressful situations and fatigue do not just occur due to heavy workloads but also because of long periods of monotonous work and a poor planning of the workday. Stress can, for instance, affect sleep quality, cause headaches or lead to high blood pressure.

A **comfortable** office environment is created with indoor environment conditions that facilitate a state of satisfaction of the occupants' bodily wants.

Three common comfort related issues in the office are:

Lighting conditions

Inappropriate lighting is characterized by a lack of day light, the presence of glare or a poor quality or long exposure to artificial light (lamps and computer screens). Such conditions can be harmful to the eyes, or cause nausea and headaches.

Temperature conditions

The indoor environment is too cold or too hot for the own liking.

Noise conditions

Noise can be emitted by exterior sources (such as cars) or originate from colleagues chatting, walking around, talking on the phone etc.

To what extend do you agree with the statement: "My everyday work in my current office is characterized by ...

	Completely disagree	Disagree	Neutral	Agree	Completely agree
... poor sitting and moving behaviours"	○	○	○	○	○
... high stress levels"	○	○	○	○	○
... poor lighting conditions"	○	○	○	○	○
... poor temperature conditions"	○	○	○	○	○
... poor noise conditions"	○	○	○	○	○

* STEP 2:

Indicating your preferences towards health and comfort

All of these 5 described health and comfort related problems are common in offices. However, different office workers generally have different opinions about how important each of these are to them.

Rank how important these 5 aspects of health and comfort in the office are to you:

Double-click or drag-and-drop items in the left list to move them to the right - your highest ranking item should be on the top right, moving through to your lowest ranking item.
Please select at most 5 answers

Available items	Your ranking
Sitting and moving behaviour	
Stress level	
Lighting condition	
Temperature condition	
Noise condition	

* STEP 3:

Introducing you to technologies improving health and comfort in the office

The negative impact of the office environment on the introduced health and comfort issues can be mitigated with the help of different technologies. Such technologies differ in their level of technological advancement. 3 levels are defined for this survey:

Level 1 has a LOW technological advancement (e.g. surveys).

Level 2 has an AVERAGE technological advancement (e.g. mobile phone apps, building sensors).

Level 3 has a HIGH technological advancement (e.g. wearables).

We start with level 1 of possible technologies (surveys). **Have you ever filled out a survey about the 5 health and comfort related aspects in your office?**

Select all that apply

- ☐ Yes, about **sitting and moving behaviours**
- ☐ Yes, about **stress levels**
- ☐ Yes, about **lighting conditions**
- ☐ Yes, about **temperature conditions**
- ☐ Yes, about **noise conditions**
- ☐ Yes, but I forgot which aspects it was about
- ☐ No
- ☐ I don't know

***Would you personally like to have a yearly, anonymized survey, initiated by your organization that addresses ANY of the 5 health and comfort related aspects in your office?**

Choose one of the following answers

- ○ Yes
- ○ No

*Please indicate below which health and comfort related aspect(s) the yearly, anonymized survey, initiated by your organization should address in your opinion.

Select all that apply

- [ ] Sitting and moving behaviour
- [ ] Stress level
- [ ] Lighting condition
- [ ] Temperature condition
- [ ] Noise condition

*We would now like to know which specific characteristics of the survey you like or dislike. Statements are presented to you that describe common characteristics of such a survey if it was to be implemented in your office.

Please indicate whether you agree or disagree with the following statements:

	Disagree	Neutral	Agree
"I like that the survey is anonymous and no personal information is collected"	○	○	○
"I like that the data is self-reported in a subjective manner and not measured in a more extensive way"	○	○	○
"I like that insights are gained for the office as a whole and not for me specifically"	○	○	○
"I like that my own organisation is responsible for collecting the data"	○	○	○

*Now we move to level 2 of possible technologies (mobile phone apps).

Have you ever filled out app-based surveys about ANY of the 5 health and comfort related aspects in your office?

Select all that apply

- [ ] Yes, about **sitting and moving behaviours**
- [ ] Yes, about **stress levels**
- [ ] Yes, about **lighting conditions**
- [ ] Yes, about **temperature conditions**
- [ ] Yes, about **noise conditions**
- [ ] Yes, but I forgot which aspects it was about
- [ ] No
- [ ] I don't know

***Would you personally like to have <u>frequent and personalized app-based surveys on your mobile phone</u> that address ANY of the 5 health and comfort related aspects in your office?**

Choose one of the following answers

○ Yes

○ No

*Please indicate below which health and comfort related aspect(s) the frequent and personalized app-based surveys on your mobile phone should address in your opinion.

Select all that apply

- Sitting and moving behaviour
- Stress level
- Lighting condition
- Temperature condition
- Noise condition

*We would now like to know which specific characteristics of the app-based survey you like or dislike. Statements are presented to you that describe common characteristics of such an app-based survey if it was to be provided to you in your office.

Please indicate whether you agree or disagree with the following statements:

	Disagree	Neutral	Agree
"I like that the data is processed with the help of artificial intelligence"	○	○	○
"I like that the surveys can be filled out on my own smartphone"	○	○	○
"I like that more personal data is collected"	○	○	○
"I like that the data is self-reported in a subjective manner and not measured more extensively"	○	○	○
"I like that personalized, individual behaviour changes can be suggested"	○	○	○
"I like that an external app provider is responsible for the data collection and not my organisation"	○	○	○

*Do you have room-mounted sensors (see picture below) installed in your current (or previous) office building(s) that measure lighting, temperature or noise conditions?

Select all that apply

- Yes, measuring lighting conditions
- Yes, measuring temperature conditions
- Yes, measuring noise conditions
- Yes, but I forgot which aspects were measured
- No
- I don't know

*Would you personally like to have room-mounted sensors installed in your office that measure comfort related aspects like the lighting, temperature or noise conditions?

Choose one of the following answers

- Yes
- No

*Please indicate below which comfort related aspect(s) the room-mounted sensors should address in your opinion.

Select all that apply

- [ ] Lighting condition
- [ ] Temperature condition
- [ ] Noise condition

*We would now like to know which specific characteristics of the room-mounted sensors you like or dislike. Statements are presented to you that describe common characteristics of such room-mounted sensors if they were to be implemented in your office.

Please indicate whether you agree or disagree with the following statements:

	Disagree	Neutral	Agree
"I like that the data is processed with the help of artificial intelligence"	○	○	○
"I like that I do not have to give any manual inputs"	○	○	○
"I like that the actual environmental conditions are measured in my room(s)"	○	○	○
"I like that specific adjustments for my individual rooms are possible"	○	○	○
"I like that such sensor technologies could also enable the tracing of my movement patterns in my room(s)"	○	○	○

*Lastly, we move to level 3 of technologies (wearables).

Have you ever used wearable sensors (e.g. a Fitbit) to measure ANY of the 5 health and comfort related aspects while you were in the office?

Select all that apply

- [ ] Yes, to measure **sitting and moving behaviours**
- [ ] Yes, to measure **stress levels**
- [ ] Yes, to measure **lighting conditions**
- [ ] Yes, to measure **temperature conditions**
- [ ] Yes, to measure **noise conditions**
- [ ] Yes, but I forgot which aspects were measured
- [ ] No
- [ ] I don't know

***Would you personally like to use wearable sensors** (e.g. a Fitbit) **that measure ANY of the 5 health and comfort related aspects?**

Choose one of the following answers

○ Yes

○ No

*Please indicate below which **health and comfort related aspect(s)** the wearable sensors (e.g. a Fitbit) should address in your opinion.

Select all that apply

- [ ] **Sitting and moving behaviour**
- [ ] **Stress level**
- [ ] **Lighting condition**
- [ ] **Temperature condition**
- [ ] **Noise condition**

*We would now like to know which specific characteristics of the wearable sensors you like or dislike. Statements are presented to you that describe common characteristics of such wearable sensors if they were to be implemented in your office.

Please indicate whether you agree or disagree with the following statements:

	Disagree	Neutral	Agree
"I like that the gained insights are very accurate and detailed"	○	○	○
"I like that the gained insights are very personalized"	○	○	○
"I like that very personal data is collected"	○	○	○
"I like that I have to wear the sensors directly on my body"	○	○	○
"I like that I do not have to give any manual inputs"	○	○	○
"I like that the measurements are taking place constantly"	○	○	○
"I like that my own bodily parameters are measured"	○	○	○
"I like that the actual environmental conditions at my desk are measured"	○	○	○

* STEP 4:

Technology preferences

In the beginning of the survey you were introduced to the 5 major **health and comfort related aspects** in the office.

You then got to know the different levels of technology that can help to improve these aspects.

Rank the discussed technologies indicating your preferred and less preferred options. **First, imagine that ONLY your sitting and moving behaviour in the office is addressed.**

Double-click or drag-and-drop items in the left list to move them to the right - your highest ranking item should be on the top right, moving through to your lowest ranking item.
Please select at most 3 answers

Available items	Your ranking
Surveys (Level 1)	
Mobile phone apps (Level 2)	
Wearables (Level 3)	

*Rank the discussed technologies according to your preferences again. Now, imagine that ONLY your stress level in the office is addressed.

Double-click or drag-and-drop items in the left list to move them to the right - your highest ranking item should be on the top right, moving through to your lowest ranking item.
Please select at most 3 answers

Available items	Your ranking
Surveys (Level 1)	
Mobile phone apps (Level 2)	
Wearables (Level 3)	

*Rank the discussed technologies according to your personal preferences again. Now, imagine that ONLY the lighting conditions in the office are addressed.

Drag or double-click images into order.
Please select at most 4 answers

Available items	Your ranking
Surveys (Level 1)	
Mobile phone apps (Level 2)	
Room mounted sensors (Level 2)	
Wearables (Level 3)	

*Rank the discussed technologies according to your preferences again. Now, imagine that ONLY the temperature conditons in the office are addressed.

Drag or double-click images into order.
Please select at most 4 answers

Available items	Your ranking
Surveys (Level 1)	
Mobile phone apps (Level 2)	
Room mounted sensors (Level 2)	
Wearables (Level 3)	

*Rank the discussed technologies according to your preferences again. Now, imagine that ONLY the noise conditons in the office are addressed.

Drag or double-click images into order.
Please select at most 4 answers

Available items	Your ranking
Surveys (Level 1)	
Mobile phone apps (Level 2)	
Room mounted sensors (Level 2)	
Wearables (Level 3)	

Part III: Follow-up questions

This is the final part of the survey.

Please answer these 7 quick questions about your own **demographic background** and your **personality**.

***What is your gender?**

Choose one of the following answers

- Female
- Male
- Other
- Rather not say

What is your age?

This question is not mandatory to answer

Only numbers may be entered in this field.
Your answer must be at most 99

***What is your highest finished education?**

Choose one of the following answers

- Less than secondary education
- Secondary education
- Applied science university degree
- University bachelor's degree
- Post-graduate degree
- Other:

I am a citizen of:

This question is not mandatory to answer

Choose one of the following answers

Please choose...

I am currently mostly working in:

This question is not mandatory to answer

Choose one of the following answers

Please choose...

*To what extent do you agree with the following statements:

	Completely disagree	Disagree	Neutral	Agree	Completely agree
"It usually bothers me if companies ask me for personal information."	○	○	○	○	○
"Companies should not use personal information unless it has been authorized by the individual who provided the information."	○	○	○	○	○
"When companies ask for private information, I think twice before providing it."	○	○	○	○	○
"I am concerned that companies are collecting too much personal information about me."	○	○	○	○	○
"I have a high knowledge of the data privacy regulations."	○	○	○	○	○
"I feel comfortable using digital devices that I am less familiar with."	○	○	○	○	○
"I am really excited discovering new digital devices or applications."	○	○	○	○	○

***How much time do you spend using digital devices (such as a smartphone, computer or TV) outside of work on a typical day?**

Choose one of the following answers

○ Less than one hour ○ 1-3 hours ○ 3-5 hours ○ 5 or more hours

Appendix B

This appendix includes the test results necessary to check for the internal consistency of the two sets of items introduced by previous studies.

Appendix B – Figure B1

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.733	.730	4

Appendix B – Figure B2

Correlations

		V125	V126
V125	Pearson Correlation	1	.397**
	Sig. (2-tailed)		.008
	N	44	44
V126	Pearson Correlation	.397**	1
	Sig. (2-tailed)	.008	
	N	44	44

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix C

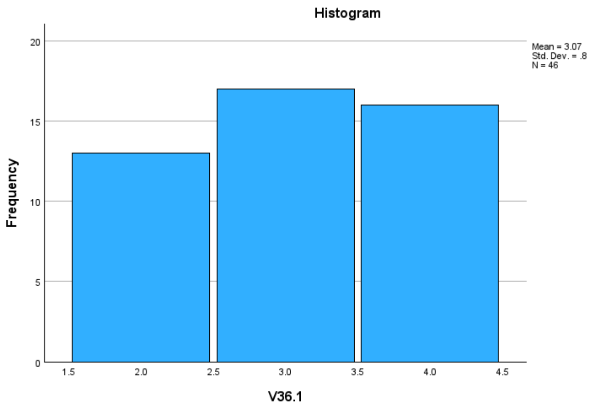
In this appendix, the tests are presented that check whether the answer patterns of the dependent variables in the model are normally distributed.

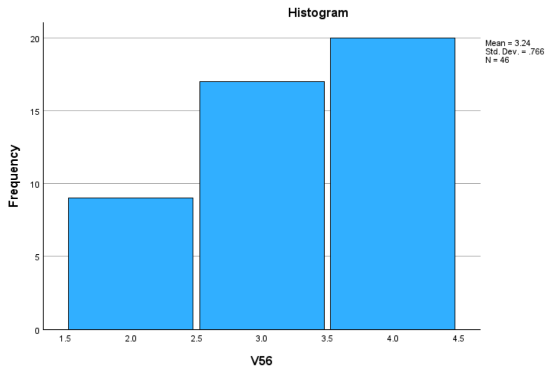
Appendix C – Figure C1

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
V36.1	.227	46	<.001	.800	46	<.001
V56	.275	46	<.001	.783	46	<.001

a. Lilliefors Significance Correction



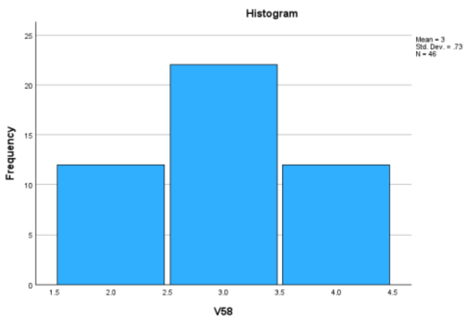


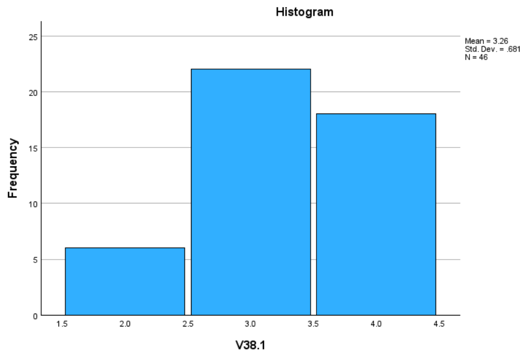
Appendix C – Figure C2

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
V38.1	.258	46	<.001	.784	46	<.001
V58	.239	46	<.001	.810	46	<.001

a. Lilliefors Significance Correction



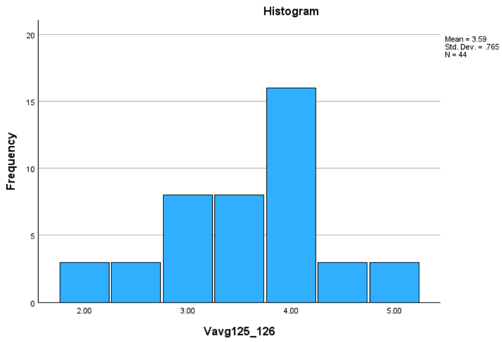


Appendix C – Figure C3

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Vavg125_126	.204	44	<.001	.931	44	.012

a. Lilliefors Significance Correction

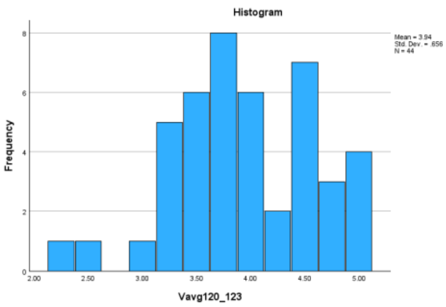


Appendix C – Figure C4

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Vavg120_123	.123	44	.095	.959	44	.117

a. Lilliefors Significance Correction

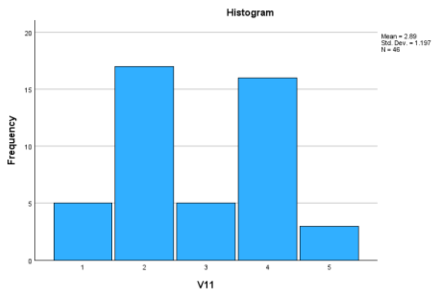


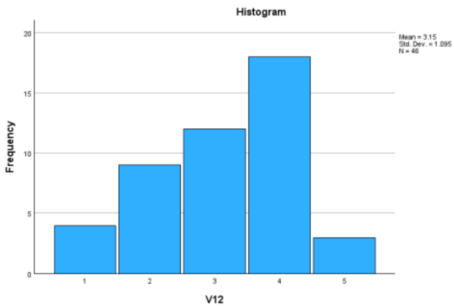
Appendix C – Figure C5

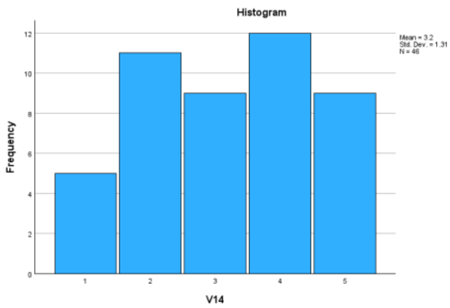
Tests of Normality

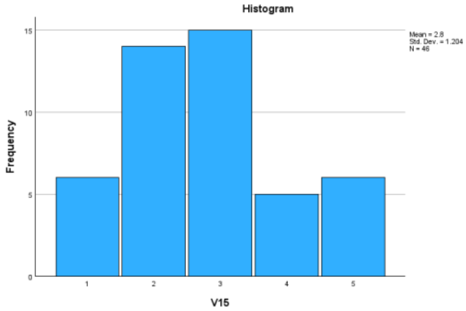
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
V11	.250	46	<.001	.868	46	<.001
V12	.237	46	<.001	.890	46	<.001
V13	.256	46	<.001	.858	46	<.001
V14	.187	46	<.001	.901	46	<.001
V15	.196	46	<.001	.899	46	<.001

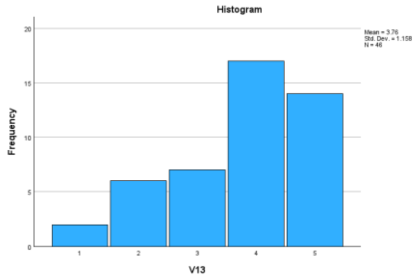
a. Lilliefors Significance Correction









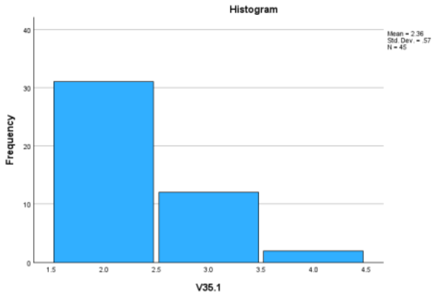


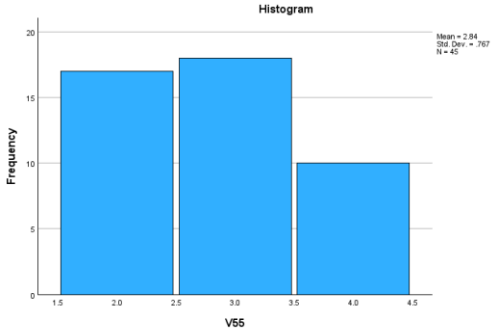
Appendix C – Figure C6

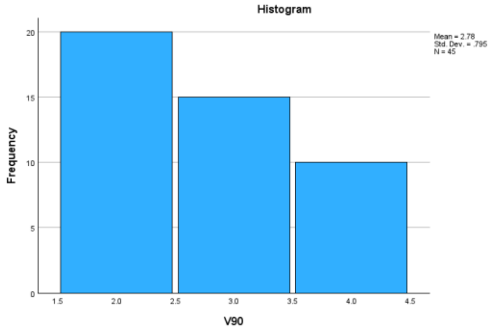
Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
V35.1	.422	45	<.001	.632	45	<.001
V55	.242	45	<.001	.799	45	<.001
V90	.281	45	<.001	.778	45	<.001

a. Lilliefors Significance Correction





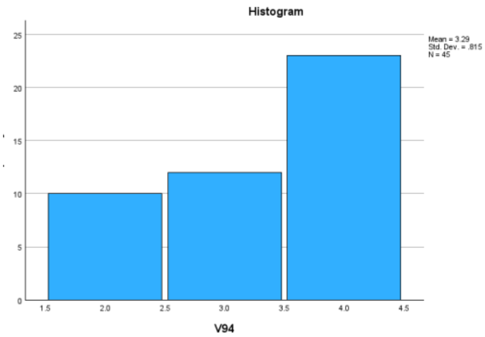


Appendix C – Figure C7

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
V94	.320	45	<.001	.747	45	<.001

a. Lilliefors Significance Correction

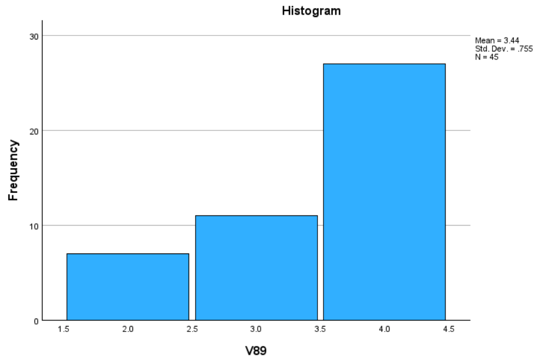


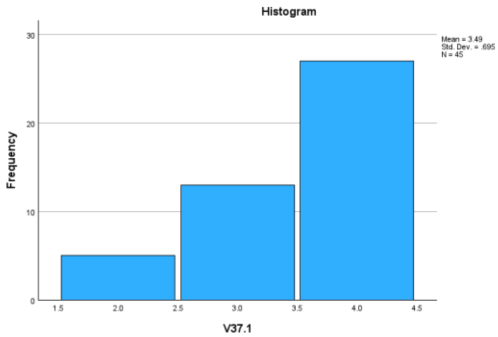
Appendix C – Figure C8

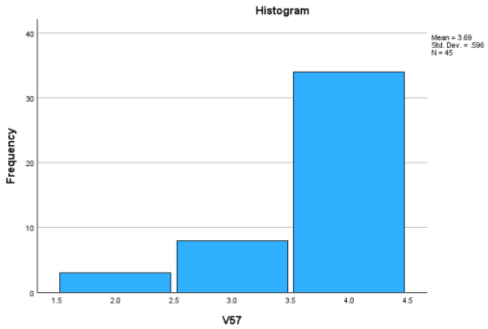
Tests of Normality

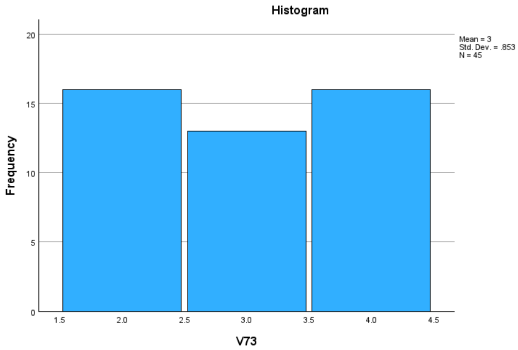
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
V37.1	.369	45	<.001	.704	45	<.001
V57	.455	45	<.001	.568	45	<.001
V73	.235	45	<.001	.781	45	<.001
V89	.369	45	<.001	.701	45	<.001

a. Lilliefors Significance Correction

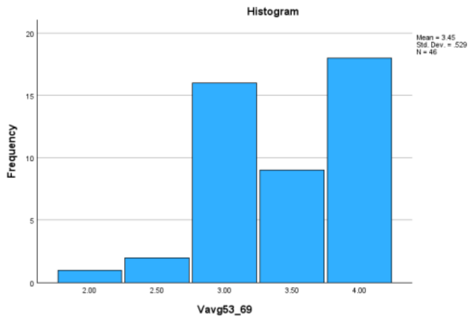








Appendix C – Figure C9



Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Vavg53_69	.244	46	<.001	.831	46	<.001

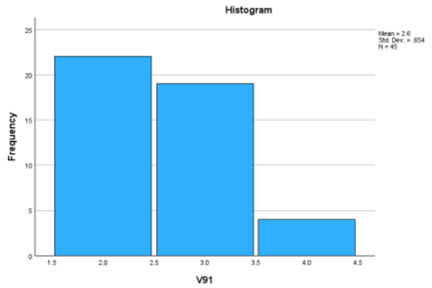
a. Lilliefors Significance Correction

Appendix C – Figure C10

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
V91	.310	45	<.001	.752	45	<.001

a. Lilliefors Significance Correction

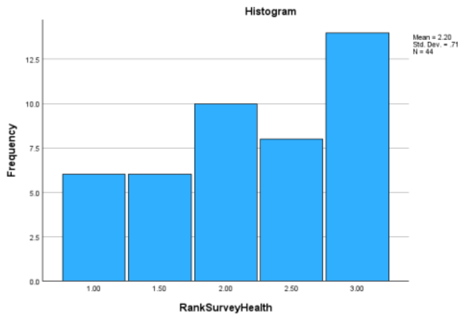


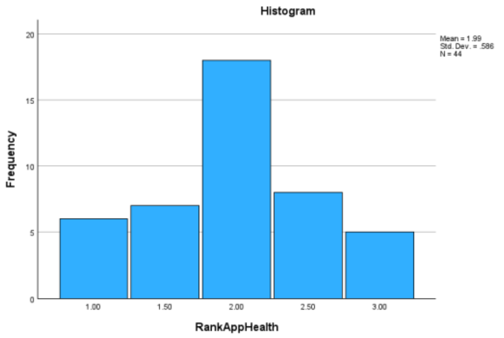
Appendix C – Figure C11

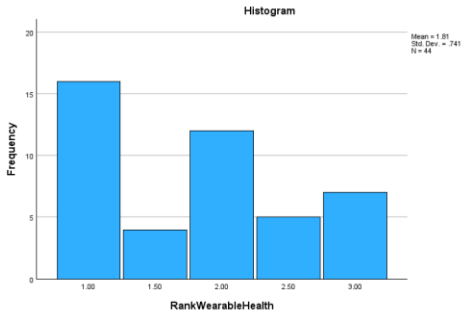
Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
RankSurveyHealth	.187	44	<.001	.868	44	<.001
RankAppHealth	.212	44	<.001	.907	44	.002
RankWearableHealth	.226	44	<.001	.846	44	<.001

a. Lilliefors Significance Correction





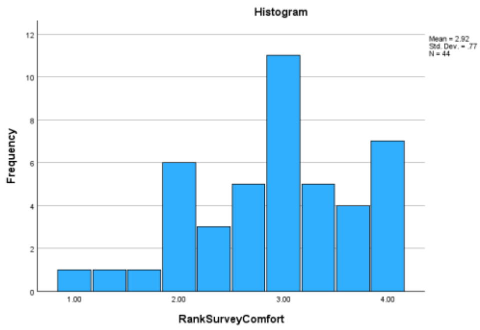


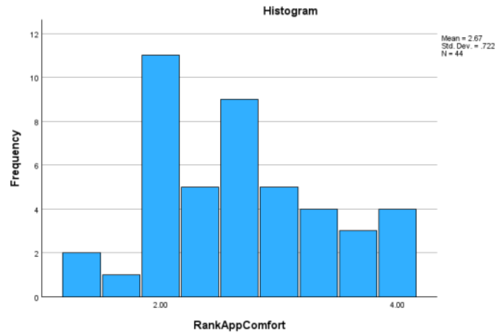
Appendix C – Figure C12

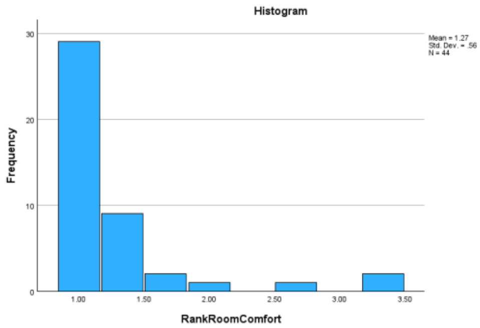
Tests of Normality

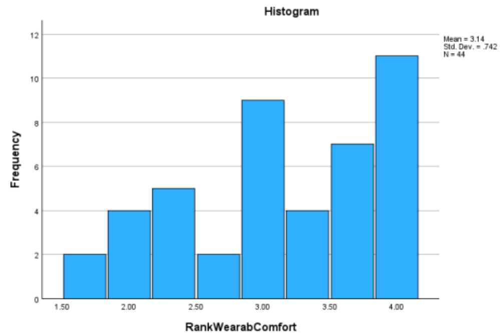
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
RankSurveyComfort	.153	44	.012	.944	44	.032
RankAppComfort	.140	44	.030	.942	44	.028
RankRoomComfort	.341	44	<.001	.530	44	<.001
RankWearabComfort	.169	44	.003	.899	44	<.001

a. Lilliefors Significance Correction


Histogram
Mean = 2.92
Std. Dev. = .77
N = 44
Frequency
RankSurveyComfort


Histogram
Mean = 2.67
Std. Dev. = .722
N = 44
Frequency
RankAppComfort


Histogram
Mean = 1.27
Std. Dev. = .56
N = 44
Frequency
RankRoomComfort


Histogram
Mean = 3.14
Std. Dev. = .742
N = 44
Frequency
RankWearabComfort

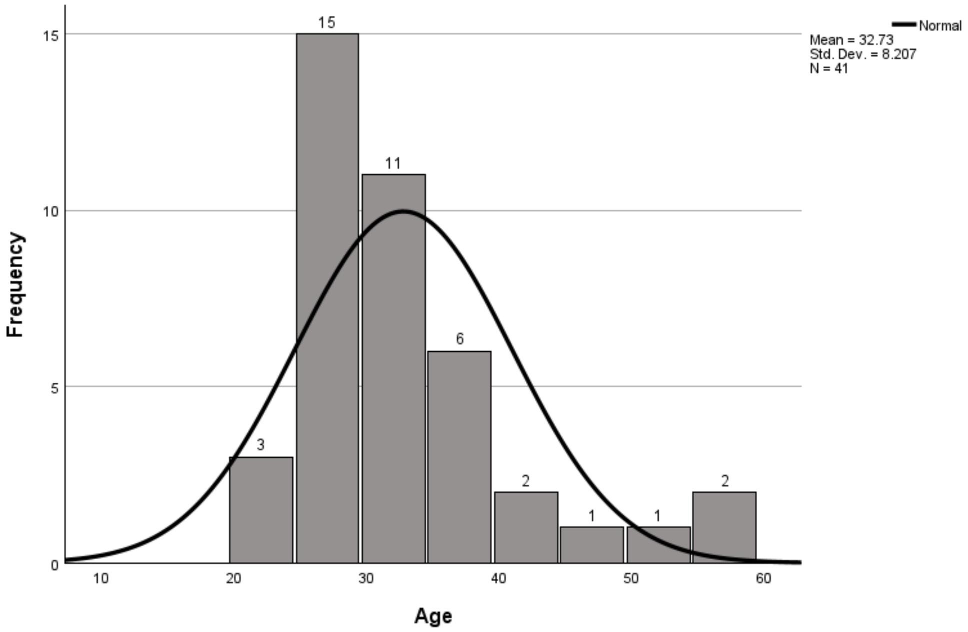
Appendix D

In this appendix further descriptive statistics with additional metrics for various variables are included complementing the findings in chapter 5.

Appendix D – Figure 1

Age	Statistics
**n = 44*	
Mean	32.73
Standard deviation	8.207
Minimum	22
Maximum	58

*refers to the number of respondents that answered the question(s) about this item

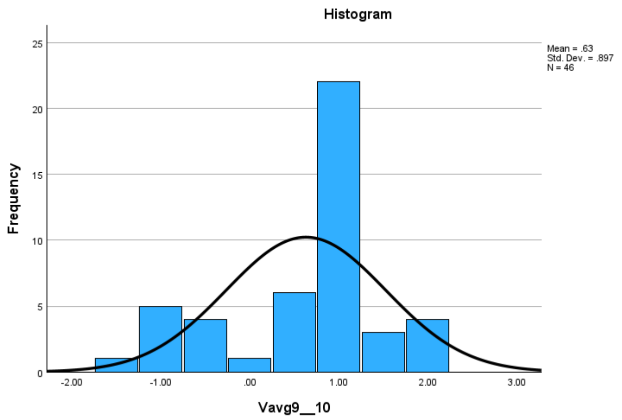


Appendix D – Figure 2

Perception of own office	Statistics		
	Mean	Median	Std. Deviation
**n = 46*			
Is the own office healthy & comfortable?	0.63	1.00	0.90

*refers to the number of respondents that answered the question(s) about this item

Explanation: -2 = Completely disagree; -1 = Disagree; 0 = Neutral; 1 = Agree; 2 = Completely agree

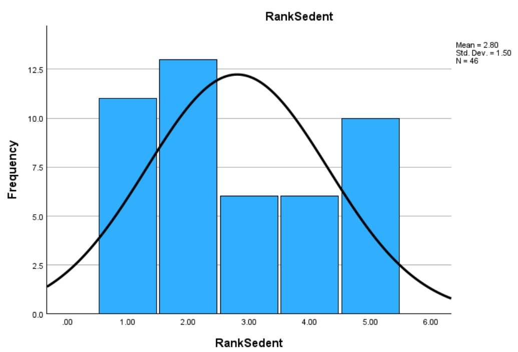


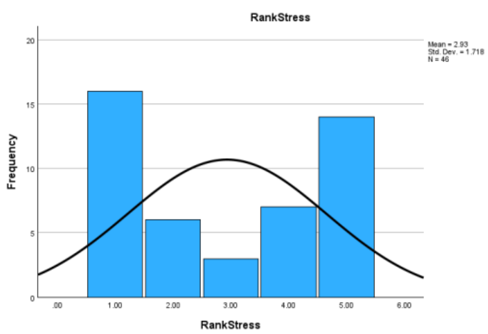
Appendix D – Figure 3

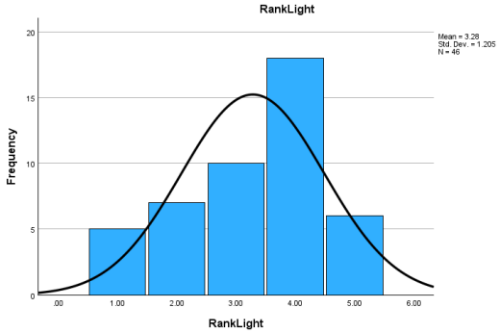
Ranking of health/comfort aspects	Statistics		
	Mean	Median	Std. Deviation
**n = 46*			
Sitting and moving behaviour	2.80	2.00	1.50
Stress level	2.93	3.00	1.72
Lighting conditions	3.28	4.00	1.20
Temperature conditions	3.11	3.00	1.27
Noise conditions	2.87	3.00	1.34

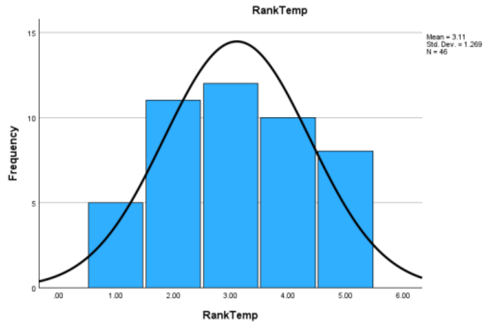
*refers to the number of respondents that answered the question(s) about this item

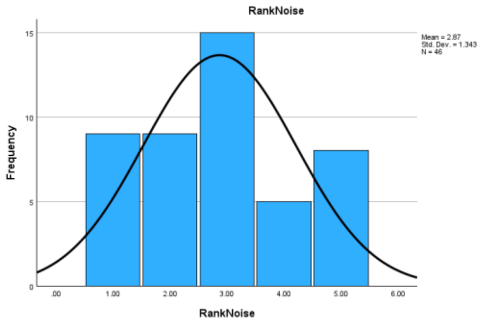
Explanation: 1 = Rank 1; 2 = Rank 2 etc.









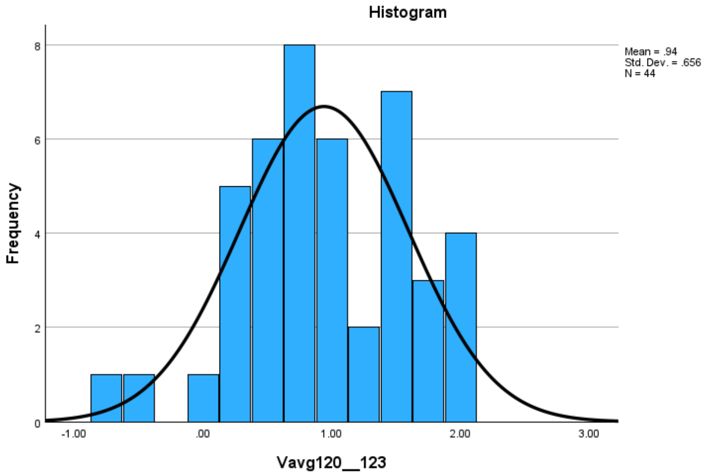


Appendix D – Figure 4

Data privacy	Statistics Mean	Median	Std. Deviation
**n* = 44*			
Protective attitude towards it	0.94	0.88	0.66

*refers to the number of respondents that answered the question(s) about this item

Explanation: -2 = Completely disagree; -1 = Disagree; 0 = Neutral; 1 = Agree; 2 = Completely agree



Appendix D – Figure 5

Data privacy	Frequency				
	Completely disagree	Disagree	Neutral	Agree	Completely agree
Knowledge about data privacy **n = 44* **"I have a high knowledge of the data privacy regulations."**	**5**	**14**	**11**	**10**	**4**

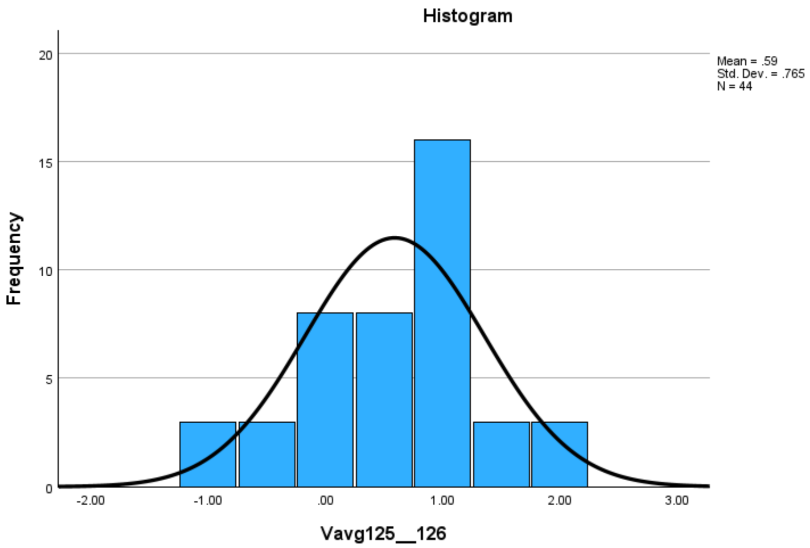
*refers to the number of respondents that answered the question(s) about this item

Appendix D – Figure 6

Technology savviness	Statistics		
	Mean	Median	Std. Deviation
**n = 44* High knowledge about & and high willingness to adapt to new digital devices	0.59	0.75	0.76

*refers to the number of respondents that answered the question(s) about this item

Explanation: -2 = Completely disagree; -1 = Disagree; 0 = Neutral; 1 = Agree; 2 = Completely agree



Appendix D – Figure 7

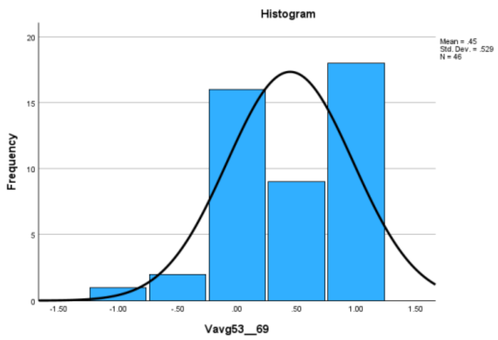
Smart application attributes & statements describing the attributes	Frequency: Survey (*n = 46) Disagree	Neutral	Agree	Smart phone apps (*n = 46) Disagree	Neutral	Agree	Room mounted sensors (*n = 46) Disagree	Neutral	Agree	Wearables (*n = 45) Disagree	Neutral	Agree	***Combind average Disagree	Neutral	Agree
Amount of collected personal information															
** "I like if personal data is collected"	32	12	2	17	18	11	-	-	-	20	15	10	23	15	8
Data type collected															
"I like that the actual environmental conditions are measured"	-	-	-	-	-	-	0	5	41	-	-	-	0	5	41
"I like that my own bodily parameters are measured"	-	-	-	-	-	-	-	-	-	10	12	23	10	12	23
"I like that the actual environmental conditions at my desk are measured"	-	-	-	-	-	-	-	-	-	3	7	35	3	7	35
Range of outputs															
"I like that insights are gained for the office as a whole and not for me specifically"	5	13	28	-	-	-	-	-	-	-	-	-	5	13	28
"I like that personalized, individual behaviour changes can be suggested / gained insights are very personalized"	-	-	-	3	8	35	-	-	-	7	11	27	5	10	31
"I like that specific adjustments for my individual rooms are possible"	-	-	-	-	-	-	0	2	44	-	-	-	0	2	44
"I like that such sensor technologies could also enable the tracing of my movement patterns in my room(s)"	-	-	-	-	-	-	16	13	17	-	-	-	16	13	17
Responsibility for data collection															
**"I like if my own organisation is responsible for collecting the data (and not an external provider)"	6	22	18	12	22	12	-	-	-	-	-	-	9	22	15
Proximity to user															
"I like that the surveys can be filled out on my own smartphone"	-	-	-	4	9	33	-	-	-	-	-	-	4	9	33
"I like that I have to wear the sensors directly on my body"	-	-	-	-	-	-	-	-	-	22	19	4	22	19	4
Level of accuracy															
"I like that the gained insights are very accurate and detailed"	-	-	-	-	-	-	-	-	-	3	10	32	3	10	32
Frequency of measurement															
"I like that the measurements are taking place constantly"	-	-	-	-	-	-	-	-	-	3	11	31	3	11	31

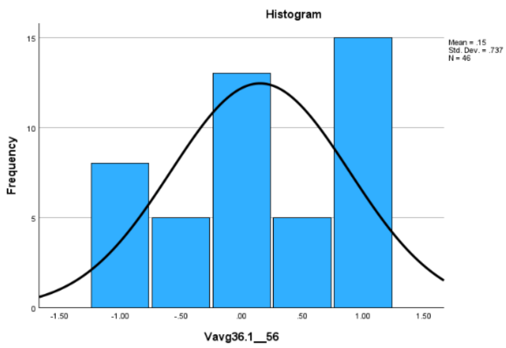
*refers to the number of respondents that answered the question(s) about this item for the respective smart application.
**these are "combined statements" as described in the main text.
***note that the combined average are presented here even if the inter-item correlations are not high for the answers to these statements.

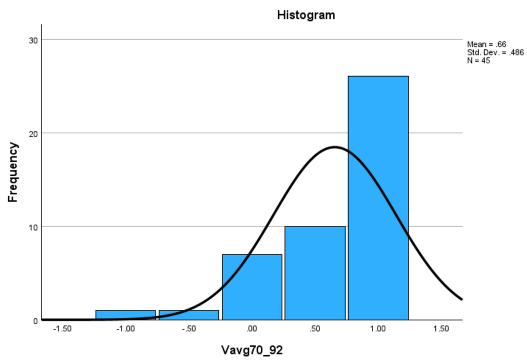
Smart application attributes & statements describing the attributes	Statistics		
	Mean	Median	Std. Deviation
Technological intelligence			
**n = 46*			
"I like that the data is processed with the help of artificial intelligence"	0.45	0.50	0.53
Level of automatization			
**n = 46*			
"I like that the data is self-reported in a subjective manner and not measured in a more extensive way"	0.15	0.00	0.74
**n = 45*			
"I like that I do not have to give any manual inputs"	0.66	1.00	0.49

*refers to the number of respondents that answered the question(s) about this item

Explanation: -1 = Disagree; 0 = Neutral; 1 = Agree



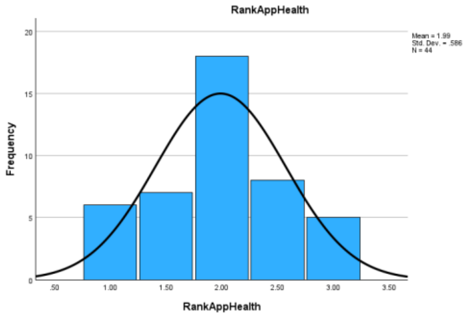


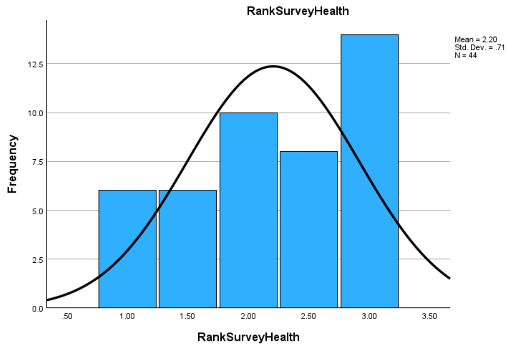


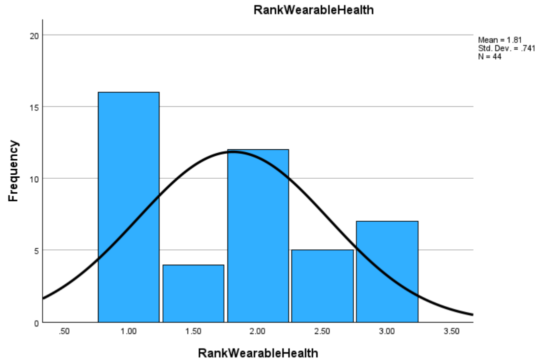
Appendix D – Figure 8

Smart application & ranking regarding health aspects	Statistics		
	Mean	Median	Std. Deviation
**n = 44*			
Survey	2.20	2.25	0.71
Smartphone app	1.99	2.00	0.59
Wearables	1.80	2.00	0.74

*refers to the number of respondents that answered the question(s)
Explanation: 1 = Rank 1; 2 = Rank 2; 3 = Rank 3

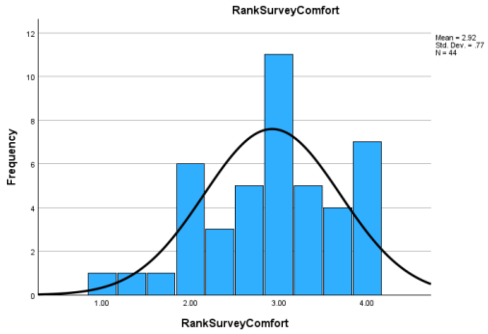


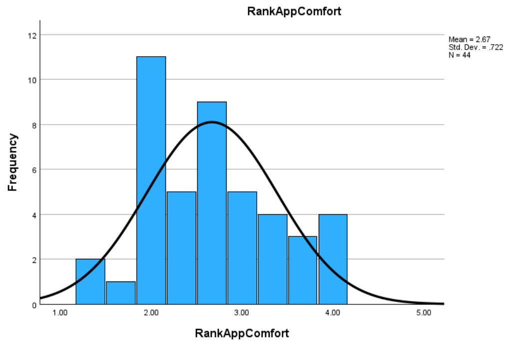




Smart application & ranking regarding comfort aspects	Statistics		
	Mean	Median	Std. Deviation
**n = 44*			
Survey	2.92	3.00	0.77
Smartphone app	2.67	2,67	0.72
Room mounted sensors	1.27	1.00	0.56
Wearables	3.14	3.17	0.74

*refers to the number of respondents that answered the question(s) about this item
Explanation: 1 = Rank 1; 2 = Rank 2; 3 = Rank 3; 4 = Rank 4


RankSurveyComfort
Mean = 2.92
Std. Dev. = .77
N = 44
Frequency
0
2
4
6
8
10
12
1.00
2.00
3.00
4.00
RankSurveyComfort


RankAppComfort
Mean = 2.67
Std. Dev. = .722
N = 44
Frequency
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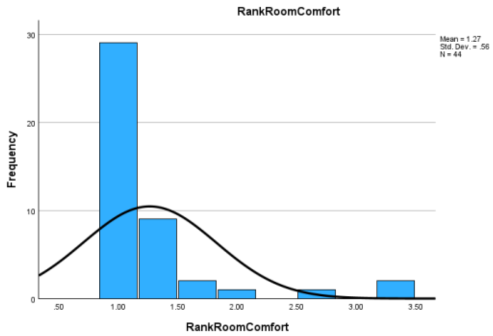
2
4
6
8
10
12
1.00
2.00
3.00
4.00
5.00
RankAppComfort


RankRoomComfort
Mean = 1.27
Std. Dev. = .56
N = 44
Frequency
0
10
20
30
.50
1.00
1.50
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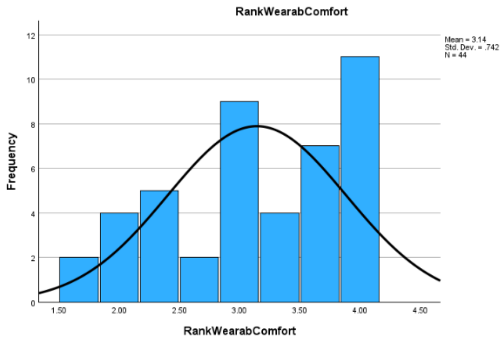
3.00
3.50
RankRoomComfort


RankWearabComfort
Mean = 3.14
Std. Dev. = .742
N = 44
Frequency
0
2
4
6
8
10
12
1.50
2.00
2.50
3.00
3.50
4.00
4.50
RankWearabComfort

Appendix E

In this appendix the utilized tests for the bivariate analysis are described.

Chi-square

The Chi-square test is a statistical test used to determine whether there is a significant relationship between two nominal variables (Ewens & Brumberg, 2023). It compares the observed frequencies (or counts) in each category of a contingency table to the frequencies that would be expected if the variables were independent. The null hypothesis for a Chi-square test therefore assumes that there is no association between the variables and the variables are independent of each other.

Several conditions must be met to use this test. To run a chi-square test the data of both the independent and the dependent variables must be categorical. The expected counts of each cell must be at least 1. No more than 20% of the expected counts must be below 5. If this condition is not met, the results of the test can be unreliable and should not be used. In that case, only a visual comparison of the histograms visualising the distribution of the answers for the two variables is possible. However, these observations are of course not statistically significant. Other conditions include that the observations should be independent of each other. This means that each observation should contribute to only one cell in the contingency table. Lastly, the data should be collected using a random sampling method to ensure that the sample is representative of the population.

Mann-Whitney U test

The Mann-Whitney U test is a non-parametric test used to determine whether there is a significant difference between the distributions of two independent groups (Ewens & Brumberg, 2023). Therefore, the null hypothesis is that the distributions of the two groups are equal and that there are no differences between the groups. It is an alternative to the independent samples t-test when the assumptions of normality are not met. The Mann-Whitney U test is used if the dependent variable is measured on an ordinal or continuous level and if the independent variable consists of two categorical independent groups. The independence of observations is another pre-condition for the test and means that no relationships exist between the observations in each group or in between groups. By considering the mean rankings for each group, the effect that the different groups have can be seen.

Kruskal-Wallis H test

Being another non-parametric test, the Kruskal-Wallis H test is used when the normality assumption of the one-way ANOVA is not met (Ostertagová et al., 2014). It is essentially an extension of the Mann-Whitney U test to more than two groups for the nominal independent variable and an ordinal/continuous dependent variable. It is consequently tested whether there are statistically significant differences between the distributions of three or more independent groups. As such, the null hypothesis assumes that the distributions of the groups are equal and that there are no differences between the groups. Once again, the independence of groups is a pre-condition. The mean rank can be used to derive the effect that a group has.

Spearman correlation

The Spearman correlation is a non-parametric measure of the strength and direction of relationships between two ranked variables (Sedgwick, 2014). The null hypothesis consequently assumes no relationships between the two variables. These variables should be measured on an ordinal or continuous scale and do not need to be normally distributed. An important assumption is that the relationship between the two variables should be monotonic, meaning that as one variable increases, the other variable either consistently increases or decreases. Moreover, each pair of observations should be independent. The strength and direction of the relationship can be determined by the correlation coefficient r (ranging from -1 to +1).