TECHNOSTRESS AMONG HEALTH PROFESSIONALS:

The blame game between health professionals and technology

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Technostress among health professionals: The blame game between health professionals and technology

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Christoph Golz

Supervisors

Prof. Dr. S.M.G. Zwakhalen

Prof. Dr. S. Hahn (Bern University of Applied Sciences)

Assessment committee

Prof. Dr. J.M.G.A. Schols (Chair of the Committee)

Prof. Dr. M. Hasseler (Ostfalia University of Applied Sciences)

Prof. Dr. J. de Jonge (Eindhoven University of Technology)

Prof. Dr. G.G. van Merode

Prof. Dr. M. Spreeuwenberg

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CHAPTER 1

General Introduction

The challenges of digitalization in healthcare

Health systems are increasingly being digitized because of the greater possibilities of technological solutions and the expected benefits for quality and safety [1], as well as for the planning and financing of health services [2-6]. As a result, information technology plays a central role in the everyday work of health professionals. Information technology is the “application of information and communication technologies tools including computer network, software and hardware required for internet connection” [7, p.139]. This includes the use of phones, computers, and laptops, as well as software such as email programs and programs for text processing. There is also technology that is specific to healthcare for storing, sharing and analyzing health information, such as electronic health records, which falls under the term healthcare information technology [8]. On average, nurses spend one third of their daily work with technology, and over 80% of this time is spent on direct patient care [9]. For physicians, the proportion of time spent using technology on a working day seems to be even higher, as they spend over 50% of their time solely on electronic health records [10], which is about 16 minutes per patient encounter [11]. However, the high proportion of time spent using technology does not mean that the digital transformation in healthcare is far advanced. On the contrary, the digital transformation of health systems has not gone as far as it could and should have, given the forecasted possibilities and ongoing strategic developments [3, 4]. Technological solutions to support health professionals and patients, such as wearables or health applications on patients’ smartphones to gather health-related data, are already available but are not implemented routinely in healthcare [12]. The reasons for this may be that the health applications are not validated and have poor applicability, and also that patient data security imposes high demands [12, 13].

There also seems to be a wide discrepancy between the expected and the empirically proven benefits of implemented health technology [14]. For example, the use of electronic health records is expected to enable patients to reach “information parity” with professionals [3, p.238] as a basis for shared decision making [5]. However, health professionals predominantly rely on paternalistic decision making, judging patients to be incapable of participating in the decision-making process [15]. Furthermore, poor user-friendliness and reliability of electronic health records seems to limit their extended use as a shared decision-making platform [16, 17]. In particular, the use of electronic health records has been found to increase the expenditure of time among health professionals instead of decreasing the administrative workload [14, 18, 19]. For example, physicians (16% vs. 28%) and nurses (9% vs. 23%) spent more of their work hours on documentation after the implementation of an electronic health record system [19]. However, the additional time required is due not only to the software but also to the hardware. For example, outdated computers may lead to a slow start-up of the system, or error messages may interrupt the tasks [20]. Another type of technology in daily use is business phones. Phone calls interrupt health professionals in their daily work. Although other interruptions such as face-to-face verbal communications are more frequent, interruptions by phone calls have been shown to have a significant impact for nurses on medication errors, such as giving the wrong dose or giving medication at the wrong time to a patient [21]. Nonetheless, there is evidence that technology also leads to improvements. Technology can, for example, improve patients' clinical outcomes: examples are better physical activity through a multiple-visit internet program for older adults, or fewer cardiovascular diseases through the application of an algorithm using patient data from electronic health records that gives prompts with recommendations [22].

In summary, the implementation of health technology may generate additional workload for health professionals but also contributes positively to better patient health outcomes.

One major reason for the discrepancy between the expected and the proven benefits of technology is found in the missing link between product innovation and health professionals' need for change in service delivery [6, 23]. Health professionals should be involved at the outset of the development or implementation of technology, in a cooperative process. This so-called co-creation is a process of involving the target population in the different design processes to reach a product which is useful, usable and meets the needs of the users [24]. Nevertheless, health professionals are often involved too late in the development and evaluation of technologies, resulting in technologies that are not very user-friendly [25-27]. If health professionals work with technologies that are not very user-friendly, they gain experience that may result in them having a resistant attitude to technology [28-30].

In addition to the discrepancy between the expected and proven benefits of technology described above, the ongoing digital transformation requires health professionals frequently and rapidly to adapt to new circumstances like the implementation of electronic health records or telemedicine [4]. This adaption includes the obligatory use of technologies at work and the ongoing improvement of knowledge and skills in order to use the technologies correctly [31, 32]. An inability to cope with new technologies can lead to technostress among health professionals [33].

Technostress

Technostress was first defined by Brod [34, p.16] as “a modern disease of adaptation caused by an inability to cope with the new computer technologies in a healthy manner.” It has further been described as a “mismatch between demands and available resources” [35, p.9]. The latest definition of technostress states that it is “a reflection of one’s discomposure, fear, tenseness and anxiety when one is learning and using computer technology” [36, p.3004]. For example, health professionals may feel stressed when using electronic health records because this requires additional working time and the software is not very user-friendly [14, 18, 19]. Technostress is influenced by individual and organizational characteristics as well as working conditions. Regarding individual characteristics, age is positively associated with technostress, meaning that being older leads to higher technostress [37]. Further, gender, profession and education have been found to be associated with technostress, but their relationships with technostress have been found to have different directions [37, 38]. The contradictory findings on individual characteristics might originate from the different organizational environments in which the studies were conducted, since technostress has also been found to differ between organizational environments [36].

Studies on the consequences of technostress among health professionals have not directly addressed technostress. Instead, the studies have elaborated on the stress induced by a specific soft- or hardware as an influencing factor for health professionals' physical and mental well-being, such as increased neck and back pain, burnout or lower job satisfaction [39-42]. The consequences of technostress are of relevance insofar as they may fuel the already high vulnerability to burnout or the thought among health professionals of quitting their job [43, 44], especially in times of workforce shortage. Technostress thus does not appear to be a phenomenon that can be viewed in isolation from other stressful working conditions when it comes to the well-being of health professionals. In 2005 Eurofound [45], which is the EU agency for the improvement of living and working conditions, was already acknowledging the potential for an increasing impact of technology in the workplace on work-related stress. A look at the latest European Working Conditions Survey of 2021, however, indicates a low emphasis on technology in the context of work-related stress, with only one question on the extent of technology usage in the main job [46]. This is in line with research on occupational health among health professionals, which neglects the relevance of technology in the workplace for health professionals [43]. Thus, studies on technostress among health professionals, and its inhibitors and consequences, are scarce [47, 48]. However, promoting digital competence is known to have a reducing effect on technostress among nurses [48].

Digital competence

Digital competence of health professionals seems to be necessary to cope with technostress [48]. In studies that are non-specific to the healthcare sector, digital competence was found to have a mitigating effect on technostress [33, 37]. As this relation was found across different sectors, it may also apply to the healthcare sector. One study from Germany looked at technostress across multiple sectors including that of health professionals, but these professionals were aggregated with professionals from other sectors such as public administration, education and social services, limiting the validity of the study for health professionals [33].

The competences needed for an occupation comprise knowledge, skills and social competences [49]. However, research on digital competence among health professionals has predominantly focused on knowledge and skills [50], neglecting the importance of the social component and its aspects such as attitude. A positive attitude towards technology usage is associated with reduced technostress [38]. A review of research on health professionals' digital competence summarized the key to digital competence as consisting of adequate knowledge and skills as well as motivation and willingness formed by the health professionals' attitudes [51]. In this thesis, the definition of health professionals' digital competence is based on the findings of this review. Health professionals' digital competence therefore comprises the theoretical understanding of how a technology can be used (knowledge), the ability to use that technology (skills) and social aspects, such as feelings towards technology or the way to behave when interacting with technology (attitudes) [51]. For example, a nurse using an electronic health record should know what happens to the data entered and what can be done with it (knowledge). Furthermore, the nurse should be able to open and close the program, edit the content, and communicate within the program (skills). Also, the nurse should not be reluctant to use the program for information exchange (attitude).

In short, technostress and the inhibitors of digital competence among health professionals have been addressed in selected cases regarding specific technologies like electronic health records or cellphones. Although technologies account for between 30% and 50% of the daily work of health professionals, research on occupational health among health professionals does not take this into account. Therefore, there is an absence of a theoretical foundation that would allow a comprehensive picture to be obtained that places technology-induced stress related to digital competences in the context of existing occupational conditions relevant to work-related stress.

Stress, determinants and consequences of technostress among health professionals

Within the context of work-related stress there are various theories and they each have their respective models. Althaus, Kop [52, p.97] conclude, in their critical review of theoretical models for the work environment, stress and health, that it is crucial to go "beyond the usual dichotomy" of the available models. This is in line with the literature on occupational stress models over the two last decades, which shifted the perspective "towards a holistic approach of studying and understanding the impact of occupational stress" [53, p.12]. This is also the approach taken by Eurofound, who base their European research on work-related stress on a comprehensive "model of causes and consequences of work-related stress" [54]. The aim of this model was to combine the best known and most commonly used stress models [55], which were the "Job Demand–Resource Model" (JDR model) of Karasek [56] and the "Effort–Reward Imbalance Model" (ERI model) of Siegrist, Starke [57]. The combination of the two models was found give a more comprehensive insight into occupational stress, and explained more variance than each of the models used separately [53]. However, none of these models include technostress. Thus, for the purpose of this thesis a revised "model of causes and consequences of work-related stress" including technostress and its known inhibitors is needed.

Model of causes and consequences of work-related stress

The model of causes and consequences of work-related stress by Kompier and Marcelissen [58], which was further adapted by Leka and Jain [55] and Russell, Maître [54], combines the JDR model and the ERI model and describes the causes of stress, stress reactions and the consequences of work-related stress on the individual as a mismatch between needs, resources and demands, influenced by the environment (Figure 1) [55]. The model is based on the premise that "stress is presumed to result from a complex set of dynamic phenomena and not just as a consequence of a single external event" [55, p.8]. In addition to the demands and resources, individual characteristics are included in the model, since it is known that differences in gender, age, and education are relevant to the extent of work-related stress [55].

The ERI model is included because it aims to identify the health-adverse effects of demanding working conditions. The ERI model is based on the assumption that an imbalance between effort and reward results in stress reactions and stress-related long-term consequences [57, 59]. Effort describes the job demands or the obligations at work, such as physical demands or responsibility. The employer rewards the employee with salary, esteem, promotion prospects, and job security [60]. An employee's overcommitment may amplify the health-adverse effects, as a highly committed employee is more sensitive to an effort–reward imbalance. For example, a digitally competent health professional may be committed to supporting team colleagues in the use of technology, but this additional effort is not recognized by the superior and thus not rewarded adequately.

The JDR model is included because it describes the imbalance between the demands on an individual and the individual's resources, or the offer made by the organization to cope with the demands. According to this understanding, a highly demanding job with low resources results in high work-related stress and low individual motivation [61]. For example, if a physician needs to enter a large amount of information into electronic health records (high demand) but the software is new, the necessary competences are missing (low resources), and the imbalance may lead to health-related consequences such as burnout.

The model of causes and consequences of work-related stress has been used to measure work-related stress among health professionals [62]. The results match the underlying theory, with higher demands, such as high quantitative demands, and lower decision latitude, such as low influence at work, being found to be associated with higher health-related adverse effects (e.g. burnout symptoms) or lower job satisfaction [43]. Regarding the imbalance between reward and commitment, the results also highlighted that higher rewards lead to fewer health-related adverse effects [43]. However, until now technostress has not been incorporated as a stress reaction of work-related stress into the model described above, and nor has this been done in the healthcare sector.

Technostress models

With the emergence of digital tools at work, models describing the influence of technology on stress at work began to be developed. Tarafdar, Tu [63] initially explained the concept that technology can cause stress, and they were followed by Ragu-Nathan, Tarafdar [64], who developed a model of technostress and its creators and inhibitors (Figure 2). The inhibitor literacy facilitation, for example, "helps users to understand [technologies] and their uses, and enables them to cope with the demands of learning new [technologies]" [64, p.472]. This is described in Chapter 2 as digital competence.

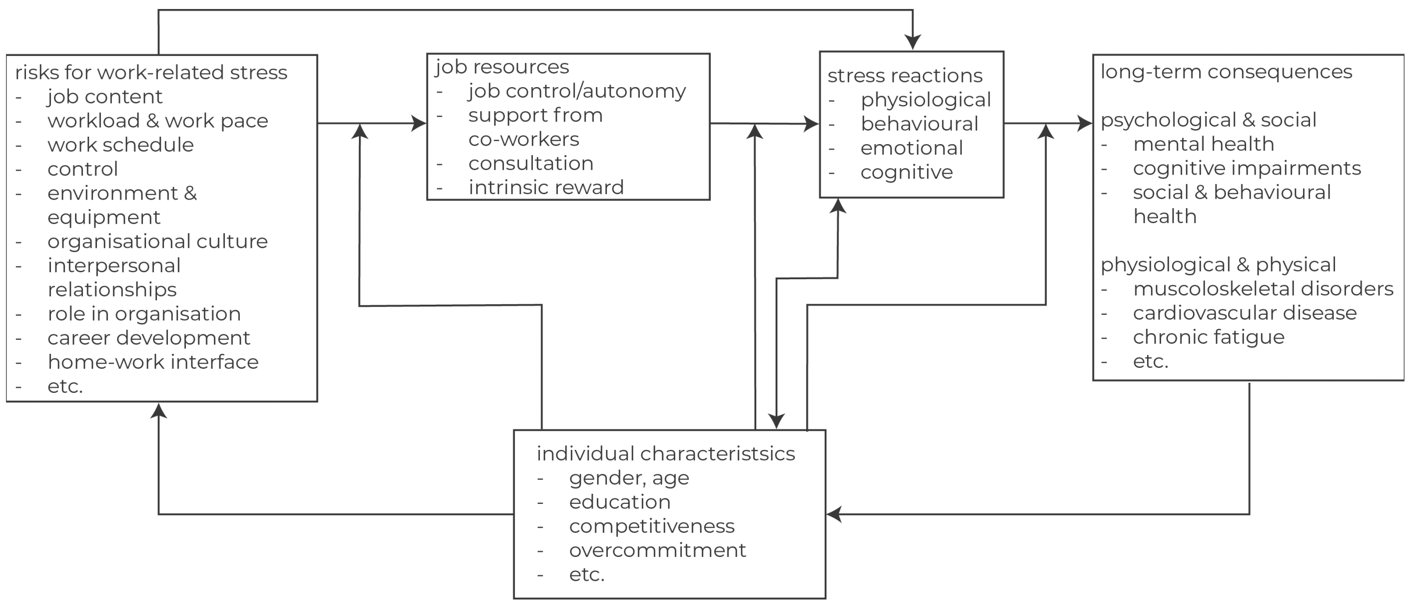

Figure 1: Model of causes and consequences of work-related stress by Russell, Maître [54] adapted from Leka and Jain [55]

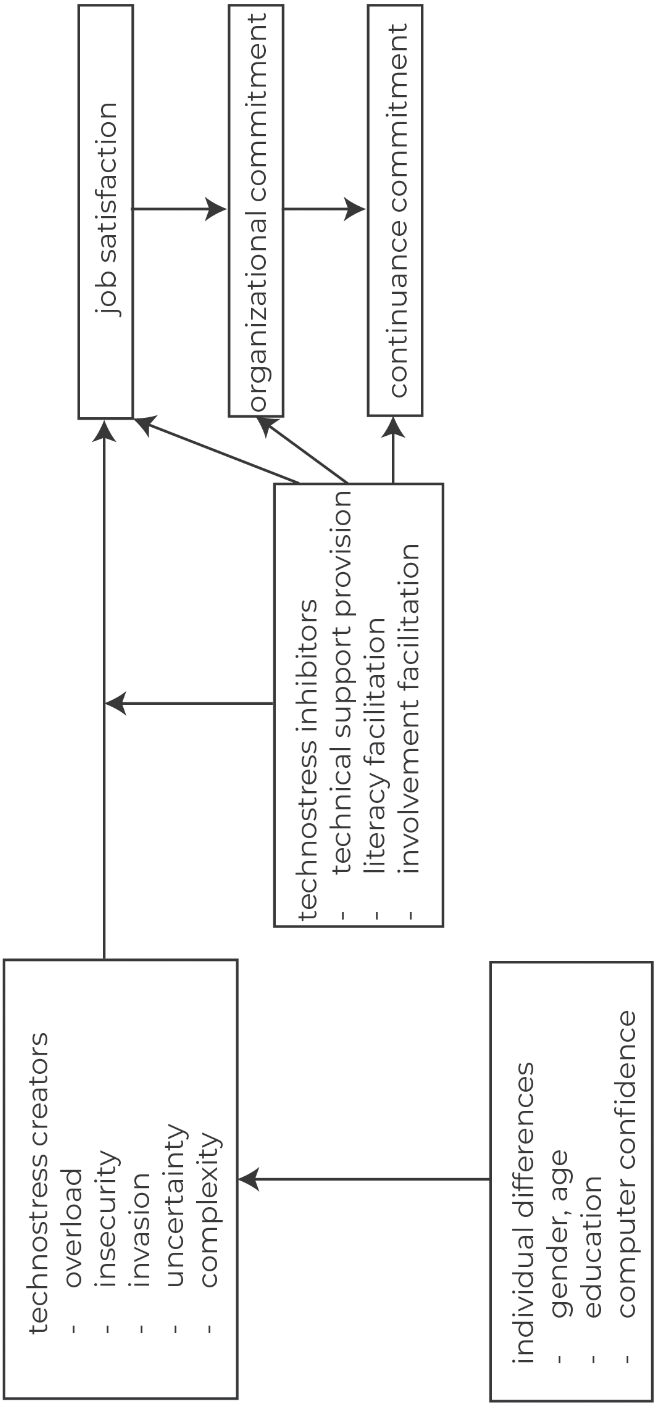

Figure 2: Conceptual model for understanding technostress by Ragu-Nathan, Tarafdar [64]

The model of Ragu-Nathan, Tarafdar [64] shows structural overlaps with the model of the causes and consequences of work-related stress of Russell, Maître [54], since it relates individual characteristics and risk factors / creators. It further describes the relationship between the risk factors / creators and the consequences, and shows that inhibitors / resources can have an impact on the consequences of the risk factors / creators. The latest contribution to the development of a technostress model was made by Gimpel, Lanzl [33], who added seven further technostress creators. There are currently 12 technostress creators in all: uncertainty (ongoing changes leading to uncertainty and constant learning); insecurity (feeling threatened about losing one's job); unreliability (unreliability of technology used); overload (technology forces users to work faster and longer); invasion (employees can be reached any time); complexity (users feel inadequate regarding their competences); performance control (feeling of being monitored and compared); ambiguity of the role (technical problems must be solved by the user); interruptions (malfunctions and unstable systems); non-availability (lack of technology that can reduce workload); no sense of achievement (feeling of lack of progress at work); and invasion of private life (feeling one's private life is affected).

In this thesis, the 12 technostress creators serve as the basis for explaining technostress. To illustrate what each creator means, I have created three case stories – those of Dora, Marc and Alice. All three will accompany us throughout the thesis.

Registered Nurse Dora – 50 years old: Dora works as a registered nurse in a nursing home. The management have informed the staff that they are going to implement some new software, which will be used to assess the quality indicators of the patients. Dora is concerned because the management have already recently implemented a new clinic information system. She has no capacity for new information since she is still learning to use that system properly (uncertainty). She sees that her younger colleagues have no problem with this innovation and feels that there is a threat that if she can't handle the new software the management could sack her (insecurity). She feels that she does not have the necessary competence to understand and use the implemented software (complexity). She experiences technostress and does not have the inhibitors she needs, which would be a greater digital competence and technical support to gain the ability to work with the implemented and the new technologies. Her age and gender play an amplifying role in her technostress, as being older and being female are known to be associated with higher technostress.

Registered Nurse Marc – 25 years old: Marc works as a registered nurse in psychiatry. He loves to use devices at work and in his free time, but when he compares the digital tools that he has at home with the tools he has at work, he gets disappointed (non-availability). His laptop at home boots up within seconds, and the battery lasts a long time. However, the laptop at work keeps crashing, and needs to be plugged in constantly because the battery is broken (unreliability). He works in the same team as Dora, and she often asks him to help her with opening the correct form or printing out a report. However, it is not only Dora but also other people from his team who ask him for help. He increasingly feels that this help is not actually part of his role. The other day, he had to reinstall a program for his boss because IT support didn't have time (ambiguity of the role). Marc also experiences technostress, but this is due to the imbalance between his high digital competence and the available technology, as well as the missing reward for his additional role of giving technical support to his team.

Physician Alice - 38 years old: Alice works as a physician in an acute care clinic. Since the implementation of a new clinical information system, she has the feeling that she is mainly entering data into the system rather than talking to her patients, leading to overtime (overload). Yesterday she left late. This morning her boss informed her that the needs assessment of a patient should already have been done. Alice starts feeling that her performance is controlled (performance control). She has a business smartphone with her, and the phone often rings during meetings with patients and colleagues. Alice finds it hard to get back to work after such calls (interruptions). Also, the feeling of constantly being reachable weighs on her (invasion). Additionally, her team uses a WhatsApp chat to inform each other about staff shortages or to ask for urgent decisions, even in her free time (invasion of private life). Lately, she has increasingly felt that she is not getting her job done because of using this technology (no sense of achievement). Alice is experiencing technostress. A lack of inhibitors leads to her feeling less satisfied with the job and less committed to the organization. Although her digital competence is sufficient, she is not involved in decisions such as the implementation of the WhatsApp chat.

Integrating technostress and digital competence in the adapted model of causes and consequences of work-related stress for health professionals

As there was no suitable model for this thesis, I merged the model of causes and consequences of work-related stress adapted for healthcare of Russell and Maître [54] with the technostress model Ragu-Nathan and Tarafdar [64], with the 12 technostress creators of Gimpel and Lanzl [33] having been integrated, to reach a conceptual model (Figure 3). The advantage of this synthesis is that it makes it possible to obtain a holistic understanding of technostress as part of occupational stress for health professionals. The model describes the influencing factors for stress reactions (both related to and not related to technology) with the long-term consequences and the relevance of individual characteristics. In this model, technostress is the reaction between the risks for work-related stress and the known technostress creators. Job resources and technostress inhibitors can have a positive influence on the impact on technostress of the risk factors and the technostress creators. The individual's characteristics influence each aspect in the model and are influenced by the technostress that is experienced and by its long-term consequences.

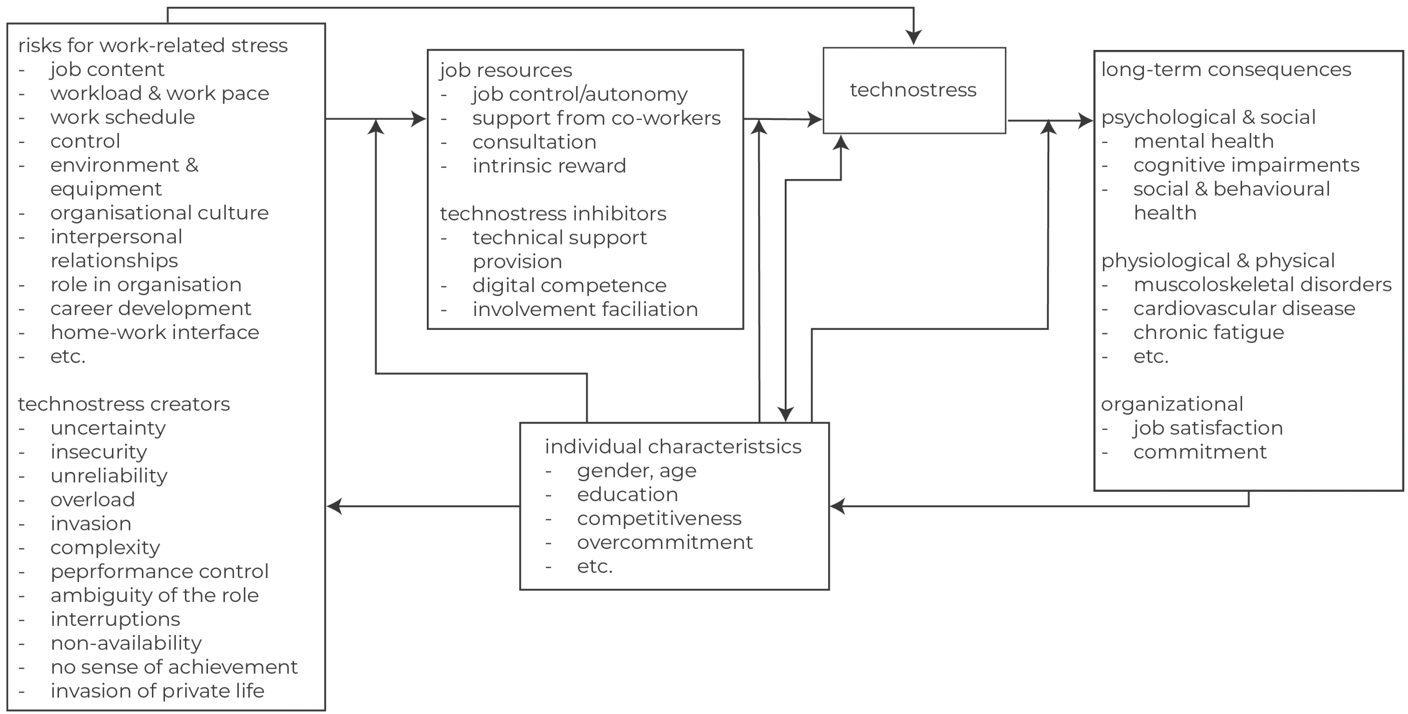

Figure 3: Conceptual model of causes of stress, resources, stress reaction and consequences of technostress among health professionals.

Aim and outline of the thesis

The thesis aims to investigate the impact on health professionals of technology in the workplace, through an analysis of (1) the extent of technostress and its influencing factors across health professional groups and settings, (2) the extent of technostress, its association with digital competence, and its long-term consequences in the psychiatric healthcare setting, and (3) the attitude of these health professionals towards technology at work. In addition, it presents the development of the Digital Competence Questionnaire for nurses in clinical practice.

All studies conducted in this thesis were in compliance with Swiss legal and regulatory requirements. In addition, the local ethical board in Bern confirmed that the studies do not warrant a full ethical application and do not fall under the Swiss Federal Act on Research Involving Human Beings (Req-2020-00179). All the studies were conducted on a voluntary basis for all the organizations, health professionals and panelists.

The aims will be addressed in the upcoming chapters. **Chapter 2** reports the results of a study on the extent of technostress and relevant factors influencing technostress, as well as the differences between health settings and health professional groups, using a cross-sectional study design. In Chapter 2 the association between the risks for work-related stress and technostress, as part of the underlying conceptual model, is described. **Chapter 3** reports the results from a study on technostress, its association with digital competence and its long-term consequences among psychiatric health professionals using a cross-sectional study design. In this chapter the associations between (1) individual characteristics with digital competence, (2) individual characteristics and digital competence with technostress, and (3) individual characteristics and technostress with long-term consequences are described, based on the underlying conceptual model. **Chapter 4** provides the results of a study on the attitude towards the use of technology at work among psychiatry health professionals using text mining analysis on single interview data. In this chapter we focus on attitude as part of the digital competence definition, and conclude that there are additional inhibitors such as support provision and involvement facilitation, based on the underlying conceptual model. **Chapter 5** presents the results of a Delphi study for content validation on the Digital Competence Questionnaire for nurses in clinical practice. The questionnaire is then evaluated for construct validity and internal consistency in **Chapter 6** in clinical practice in a cross-sectional study design. The findings are discussed in **Chapter 7** in the general discussion. Chapter 7 also gives implications for further research and practice. Finally, the impact of the thesis for science and society is described in **Chapter 8**.

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CHAPTER 2

Technostress Among Health Professionals – A Multilevel Model and Group Comparisons between Settings and Professions

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Abstract

Objective: Health organizations increasingly digitize. However, studies reveal contradictory findings regarding the impact of healthcare information technology on health professionals. Therefore, the aim of this study is to describe the prevalence of technostress among health professionals and elaborate on the influencing factors.

Participants: A secondary analysis was conducted utilizing cross-sectional data from the study, "Work-related stress among health professionals in Switzerland", which included 8,112 health professionals from 163 health organizations in Switzerland.

Methods: ANOVA for group comparisons followed by post-hoc analyses, along with a Multilevel Model to identify influencing factors for technostress ranging from "0" (never/almost never) to "100" (always), were conducted.

Results: Health professionals experienced moderate technostress (mean 39.06, SD 32.54). Technostress differed between settings ($p < .001$). The model explains 18.1% of the variance with fixed effects, or 24.7% of the variance with fixed and random effects. Being a physician ($\beta = 12.96$), a nurse ($\beta = 6.49$), or the presence of an effort reward-imbalance, increased technostress most ($\beta = 6.11$). A professional with no professional qualification ($\beta = -7.94$) showed the most reduction.

Conclusion: Health professionals experience moderate technostress. However, decision-makers should consider the cognitive and social aspects surrounding digitalization, to reach a beneficial and sustainable level of usage.

Keywords

Technostress; healthcare professionals; multilevel model; healthcare information technology; HIT

Introduction

Healthcare information technology (HIT) is increasingly being promoted to improve the working conditions of healthcare professionals and the quality of care [1]. The expected benefits are associated with an enormous acceleration of digital transformation [2–4]. HIT is "the application of information processing involving both computer hardware and software that deals with the storage, retrieval, sharing, and use of healthcare information, data, and knowledge for communication and decision making," [5, p.38] such as decision support systems, hospital information systems, or electronic health records [6].

Although this outlook sounds promising, the evidence regarding the expected effects on healthcare organizations, care providers, and patients remains contradictory [3, 7]. On the one hand, the implementation of HIT led to a significant increase of revenue enhancement (20% – 40%) for the organization, and health professionals reported an 80% reduction of turnaround time (waiting time for process completion) [8]. Furthermore, findings of a systematic review showed an improvement in health behavior and health outcomes among patients through the use of HIT [9]. Moreover, telehealth, one aspect of HIT, revealed several advantages for the patients, such as low costs, along with improved outcomes and increase in communication with care providers [10]. On the other hand, studies demonstrated that HIT use can result in stress in up to 73% of people employed in healthcare, and up to 40% experience moderate to high stress [11].

This stress is also known as technostress, which was introduced by Brod [12, p.16] as "a modern disease of adaptation caused by an inability to cope with the new computer technologies in a healthy manner." The concept is based on the transactional theory of stress and coping [13] and its components are: techno-invasion (employees can be reached anytime), techno-overload (technology forces users to work faster and longer), techno-complexity (users feel inadequate regarding their competences), techno-uncertainty (ongoing changes lead to uncertainty and constant learning), techno-insecurity (feeling threatened about losing one's job), techno-unreliability (unreliability of technology used) [14-16]. These advances in its conceptual development have led to the latest definition of technostress as "a reflection of one's discomposure, fear, tenseness and anxiety when one is learning and using computer technology" [17, p.3004]. With this background, Gimpel, Lanzl [15] developed a tentative model of digital stress, which places the components of technostress described above in relation to influencing factors (e.g. support, involvement, and competence) and resulting consequences (e.g. job satisfaction, work– life imbalance).

Studies elaborating on the stress-inducing effects of HIT and the consequences for health professionals and organizations are scarce and tend to focus predominantly on electronic medical records and their effects on physicians [3]. For example, among physicians, the implementation of electronic medical records with moderate functions resulted in increased stress levels, decreased levels of satisfaction [18, 19] and higher levels of frustration leading to more burnout symptoms [20]. Furthermore, the use of technology at work increases the level of dependence of the professional on the technology [16], thus promoting new risk factors, such as an ergonomically deficient environment or the amalgamation of privacy and work [21]. Unfavorable working conditions related to HIT, such as work–life imbalance, high workload, job insecurity, and high physical and emotional demands, are correlated with a variety of illnesses, such as back pain, headaches, and fatigue [15, 22]. There are also implications for patients which were identified, for example, in regard to the implementation of electronic medical records, which was associated with increased mortality rates among patients (odds ratio: 3.28; 95%-CI[1.94, 5.55]), due to delays in the treatment process [23].

Frey and Osborne [24] predicted that the digitalization of the working environment will result in vast task shifts from humans to technology. Although the healthcare sector will likely be less affected than other working environments [24], HIT can still be critically regarded as a double-edged sword by health professionals. HIT either reduces work-related stress, as promoted, or it eradicates jobs and increases stress through the improper implementation of technology.

These findings indicate that critical examination of digitization in healthcare organizations is crucial. The advantages of HIT for healthcare organizations, care providers, and patients are promising, and in times of scarce financial and human resources, they are an urgently needed solution. Moreover, contradictions regarding the current research situation, hamper implications for practice. Therefore, it is particularly important to obtain a more comprehensive description regarding the prevalence of technostress in healthcare organizations [25]. Hence, this paper aims to answer the following research questions:

- To what extent do health professionals experience technostress?
- Does technostress differ between healthcare settings?
- Does technostress differ between the health professions?
- What are the influencing factors of technostress on health professions?

Materials & methods

This study is based on a secondary analysis using data from the national STRAIN study, "Work-related stress among health professionals in Switzerland." The STRAIN study is based on a cluster randomized controlled trial (Clinical Trials registration: NCT03508596) and consists of three measurements (baseline, first, second). This study utilized the dataset of the STRAIN baseline-measurement (collected between September 2017 and March 2018), as published in Peter, Schols [26].

Study sample

Index-lists from all registered healthcare organizations in Switzerland were utilized for this study sample and included: acute care and rehabilitation hospitals (n = 239), psychiatric hospitals (n = 49), nursing homes (n = 1543), and home care organizations (n = 551). They were obtained through the respective association or the Swiss Federal Statistical Office, from the annual report of 2015. Small organizations (<7 employees and average number of beds <20) as well as specialized clinics (e.g. beauty clinics), were excluded. A geographically representative sample was achieved. A random sample of 100 organizations per setting was drawn from the total sample available, to ensure a sufficiently large sample size for the study.

Recruitment

An electronic invitation was sent to the Chief Executive Officers or the Human Resource Managers of the healthcare organizations and, upon request, the project was presented at a meeting. Detailed information of the recruitment process is described by Peter, Schols [26]. Overall, 163 organizations agreed to participate in the STRAIN study, in the following settings: acute care and rehabilitation hospitals (n = 24), psychiatric hospitals (n = 12), nursing homes (n = 86), and home care organizations (n = 41).

Data collection

Data collection in the STRAIN study was conducted as follows: An internal coordinator was appointed in each organization. This person coordinated the dissemination of information and surveys to the health professionals, which consisted of the following professional categories: physicians, medical therapeutic professions (e.g. physiotherapy, occupational therapy, nutritionists), medical technical professions (e.g. radiology, surgical technologist, laboratory assistant), nursing staff (e.g. advanced practice nurses, registered nurses, care aides, midwives), and others (e.g. administration, trainees). The internal coordinator could choose between paper and online questionnaires available in German, French, and Italian for the survey. For paper questionnaires, a pre-stamped envelope was enclosed for returning them to the project team. For online questionnaires, the link for the online survey using SurveyMonkey® and UmfrageOnline® was either sent individually by e-mail or published on the organization's intranet by the coordinator. Two weeks afterward, a reminder was sent electronically, or a paper-version was mailed to the health professionals organized by the internal coordinator. Upon completion of data collection, the data saved on the SurveyMonkey® and UmfrageOnline ® websites were deleted.

The questionnaire

The primary outcome was technostress. Technostress was measured with a single item developed and tested by the authors, "How often do you feel stressed by the use of technologies at your workplace, e.g. electronic patient record?" It was rated using a scale with a range from "0" (never/almost never), "25" (rarely), "50" (sometimes), "75" (often), and "100" (always), adhering to the questionnaire's scale structure. This single item was developed, since no suitable valid scale measuring technostress among health professionals was available at the time of the inquiry in the languages needed and the comprehensive STRAIN questionnaire could not be extended by multiple items for all dimensions of the concept in order not to affect the response rate negatively.

The other outcomes used in this study were all used to measure the predictor variables and stem from the STRAIN questionnaire. The STRAIN questionnaire [26, 27] used within the cross-sectional study included well known, valid, and reliable scales (Cronbach's alpha .64 – .94), focusing on individual characteristics, work stressors, stress reactions, and long-term consequences, as defined in the underlying "Model of causes and consequences of work-related stress", by Eurofound [28].

For this study, the following scales from the STRAIN questionnaire were chosen as predictor variables to cover the dimensions of the tentative model of digital stress by Gimpel, Lanzl [15]. Their model describes the correlation between technostress, private and professional demands, stress-inducing and stress-reducing factors, as well as the resulting stress reactions: Demographic information, personal environment [29], demands at work [30, 31], work organization and content [30], person– work interface factors [30], work environment [30], and the Effort–Reward Imbalance (ERI) [32] (see Table 1).

Table 1: Scales and items used for the data analysis

Scale	Items	Content
Primary outcome		
Technostress	1	e.g. perceived stress when interacting with technology
Predictor variables		
Demographic information	7	gender, age, education, profession, work experience, childcare, caring for relatives
Personal environment		
Social Support[1]	3	e.g. in private life, supporting those who are close if they are experiencing personal problems
Demands at work		
Quantitative demands[2]	3	e.g. work at a high pace, overtime
Emotional demands[3]	4	e.g. confrontation with death, aggressive patients
Demands for hiding emotions[2]	2	e.g. hiding feelings
Cognitive demands[2]	8	e.g. required knowledge, having to remember many things
Physical demands[4]	4	e.g. lifting or moving people or heavy loads

Table 1: Continued

Scale	Items	Content
Work organization and content		
Possibilities for development[2]	3	e.g. opportunity to develop skills
Influence at work[2]	3	e.g. degree of influence concerning work
Degree of freedom at work[2]	2	e.g. deciding when to take breaks / holidays
Rewards[2]	1	e.g. work is recognized and appreciated by the superior
Role clarity[2]	3	e.g. clear work tasks, objectives, area of responsibility
Role conflicts[2]	3	e.g. contradictory role requirements
Social support at work[2]	4	e.g. receiving support from colleagues/superior
Feedback[2]	2	e.g. receiving feedback from superior
Social relations[2]	1	e.g. possibility to talk to colleagues during work
Sense of community[2]	2	e.g. good atmosphere, co-operation
Person-work interface factors		
Insecurity of the working environment[2]	2	e.g. changes in shift schedules
Bond with the job[2]	1	e.g. being proud to belong to the organization
Family-work (im)balance		
Work – privacy conflict[2]	5	e.g. conflict between work and private life
Lack of boundaries[2]	2	e.g. being available in leisure time for work issues
Work environment		
Work environment[2]	5	e.g. being exposed to noise, cold, chemicals
Effort-Reward Imbalance		
Effort[5]	3	e.g. efforts given at work
Reward[5]	7	e.g. rewards received in turn

[1]Oslo Social Support Scale [29]
[2]Copenhagen Psychosocial Questionnaire [30]
[3]Nurses early exit study questionnaire [55]
[4]Sixth European Working Conditions Survey (EWCS Q30) [31]
[5]Effort-Reward Imbalance Questionnaire [32]

Data analysis

The items included from the COPSOQ were transformed from ordinal scales with five categories, on a value range from 0 (do not agree at all) to 100 (fully agree), as proposed by the publisher [30]. The scale scores were included if at least half of the items had no missing values [30]. Nominal and ordinal variables, such as education level and profession, were dummy coded for the multilevel model (MLM). The analysis was conducted using R version 3.5.1 and included descriptive statistics, ANOVA for group comparisons, and an MLM [33].

The ANOVA group comparisons used the Welch's t-test because the Levene's test showed unequal variances for comparisons of the settings (acute care and rehabilitation hospitals, psychiatric hospitals, nursing homes, home care organizations) ($p = .01$), as well as for the health professions (physicians, nurses, medical-technical professions, medical-therapeutic professions) ($p < .001$) [34]. Consequently, Games-Howell post-hoc analyses were computed for the group comparisons.

The MLM approach considers the natural structure in the data with health professionals (the lowest, level 1 units) nested in organizations (level 2 units). Hence, it is expected to result in a more accurate model compared to simple linear regression, as it ignores the hierarchy [35]. The dependent variable for the MLM was "technostress." The predictor variables for the working conditions were as follows: the ERI, commitment, demands (quantitative, cognitive, emotional, physical, hiding emotions), role clarity, role conflict, insecurity of working conditions, work-privacy conflict, lack of boundaries, working environment, setting, and employment level. The predictor variables for the stress-reducing factors at the workplace were as follows: possibilities for development, influence at work, freedom at work, appreciation, feedback, support at work, social support, and sense of community. Regarding the private conditions, the predictor variables were childcare and caring for relatives. The predictor variables for the individual characteristics were gender, age, education, profession, and work experience. The second level variable was clinic (see Figure 1). In order to minimize internal dropouts, the missing data for the numerical predictor variables in the MLM were filled based on multiple imputation with expecting data to be missing completely at random, using the mice package [36].

In a first step, a stepwise model selection with the MASS package was conducted with a lower Akaike Information Criterion, as the inclusion criteria [37]. The selected variables were then fitted using lme4 package [38]. For the MLM, beta coefficients with according p-values (2 tailed) and 95% confidence intervals (CI), as well as the marginal R-Squared (associated with fixed effects) and the conditional R-Squared (associated with fixed and random effects), were computed [39]. The assumption of heteroskedasticity was not met for the model. Hence, standard errors, p-values, and CI were bootstrapped (r = 999, bias corrected and accelerated, 95% CI).

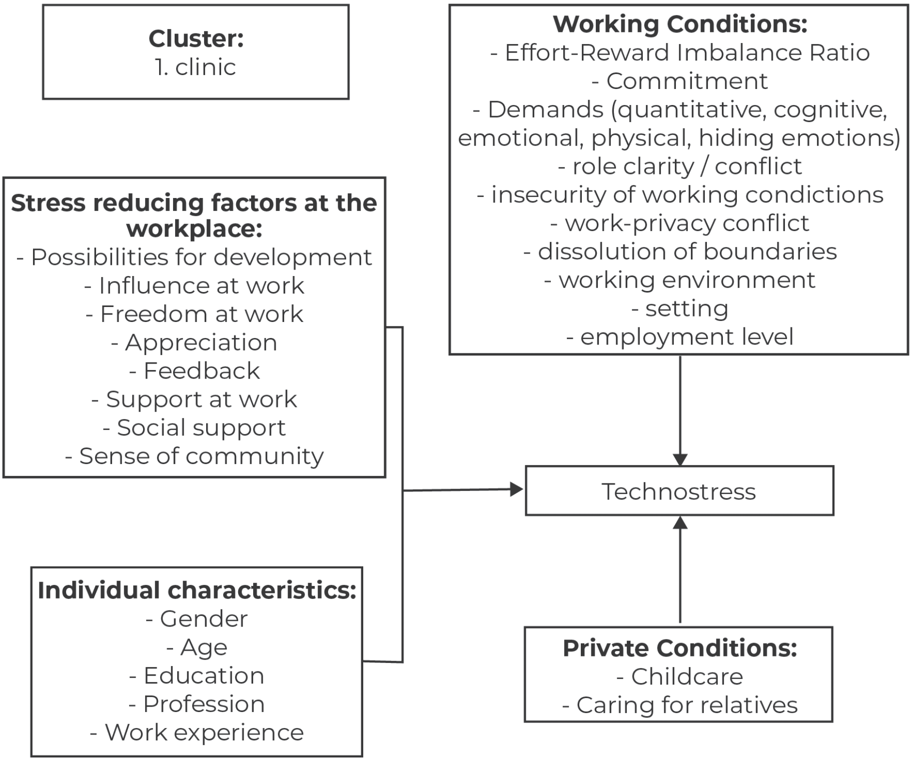

Figure 1: Scales used for the MLM based on the model by Gimpel, Lanzl [11].

Ethical considerations

The local Swiss ethical board confirmed, on 24th October 2016, that the study did not warrant a full ethical application and did not fall under the Swiss Federal Act on research involving human beings (Req-2016-00616). The participants are professionals and can take their responsibility for their participation. They were informed in writing at the beginning of the questionnaire about the contents and the voluntary nature of their participation.

Results

Overall, data of 8,112 health professionals were included in this analysis. Among the participants, 7% were physicians (n = 463), 4% medical-technical professionals (n = 241), 9% medical-therapeutic professionals (n = 628), 75% nurses and midwives (n = 4925), as well as 5% others (n = 346). Among the participating health professionals, 42% worked in acute care and rehabilitation hospitals, 26% in psychiatric hospitals, 21% in nursing homes, and 11% in home care organizations. The mean age of the participants was 42 years (SD 12) and the majority were female (82%).

Table 2: Technostress experienced among healthcare professionals

Setting	**Profession**	**N**	**Technostress* Mean (SD)**
Acute care and rehabilitation hospitals	Total	3398	46.38 (31.95)
	Nurse	1905	49.67 (31.56)
	Physician	229	53.85 (30.74)
	Medical-therapeutic profession	237	35.85 (30.82)
	Medical-technical profession	241	39.96 (29.49)
	Other	103	30.78 (28.98)
Psychiatric hospitals	Total	2075	37.90 (31.86)
	Nurse	952	43.01 (32.74)
	Physician	204	40.97 (30.35)
	Medical-therapeutic profession	319	32.55 (28.97)
	Other	158	25.15 (28.76)
Nursing homes	Total	1693	31.65 (32.49)
	Nurse	1317	32.80 (32.80)
	Physician	30	22.41 (30.14)
	Medical-therapeutic profession	72	20.96 (28.20)
	Other	13	25.51 (28.18)
Home care organizations	Total	946	31.90 (30.92)
	Nurse	751	32.40 (30.59)
	Other	72	34.34 (31.32)
Total		8112	39.23 (32.54)

*Range: 0 - 100

Technostress

In total, health professionals reported on the range from 0 (never/almost never) to 100 (always), a mean score for technostress at work of 39.23 (SD = 32.54). Table 2 summarizes the mean and standard deviation of technostress according to setting and profession.

Setting comparison

The extent of experienced technostress differed significantly between settings, Welch's $F(3, 3148.8) = 99.39$, $p < .001$. The Games-Howell post-hoc analysis revealed a significant difference ($p < .001$) between technostress experienced among health professionals, as follows: in acute care hospitals and psychiatric hospitals (8.48, 95%-CI[6.00, 10.90]), in nursing homes (14.73, 95%-CI [12.20, 17.30]), and in home care organizations (14.47, 95%-CI[11.50, 17.40]). This reveals, for example, that on average, health professionals working in acute care and rehabilitation hospitals have higher technostress (14.47 points), in comparison to health professionals working in home care organizations. Moreover, the psychiatric hospitals showed a significant difference in technostress among health professionals in comparison to nursing homes ($p < .001$) (6.25, 95%-CI[3.40, 9.10]), as well as when compared with home care organizations ($p < .001$) (5.99, 95%-CI[2.80, 9.20]). The difference between the nursing homes and home care organizations was not significant ($p < 1$) (.25, 95%-CI[−3.50, 3.00]).

Comparison of the health professions

The Welch's Test revealed a significant difference of technostress between the health professions, Welch's F (4, 933.04) = 47.30, $p < .001$. The Games-Howell post-hoc analysis also showed a significant difference of technostress between health professions. Physicians had significant higher technostress than medical-therapeutic professions ($p < .001$) (14.7, 95%-CI[9.54, 19.80]), medical-technical professions ($p = .003$) (7.00, 95%-CI[0.37, 13.50]) and nurses ($p < .001$) (5.80, 95%-CI[1.72, 10.00]). Furthermore, nurses had a significantly higher technostress than medical-therapeutic professions ($p < .001$) (8.80, 95%-CI[5.30, 12.34]).

Influencing factors on technostress

In regard to the regression analysis, cases with missing data in the included and not imputed factor variables (e.g. education, profession) were excluded. Hence, the dataset comprised 7,230 cases (89.13%). The estimated MLM explains 18.1% of the variance with fixed effects (marginal R-Squared) or 24.7% of the variance with fixed and random effects (conditional R-Squared). Working as a physician ($\beta = 12.96$, $p < .001$) or a nurse ($\beta = 6.49$, $p < .001$), or having a higher ERI was associated with increased technostress ($\beta = 6.11$, $p < .001$). However, working in a profession with no professional qualification, such as trainees, civilian service, and volunteers ($\beta = -7.94$, $p < .001$), was most significantly associated with a decrease in technostress (see Table 3). Furthermore, higher social support was associated with decreased technostress ($\beta = -0.64$, $p < .01$). Regarding binary variables, for example, with physicians, the data is interpreted as follows: if the individual is a physician, the technostress increases by 12.96 points. The interpretation for numerical variables, for example, with social support, is different: if social support increases by one point, technostress decreases by 0.64 points.

Table 3: Model for technostress in healthcare

Coefficient	**β**	**Std. Error**	**T value**	**p-value (*with bootstrap)**	**CI**
Intercept	-16.06	4.07	-3.94	<.001	-24.04 – -8.07
Physician	12.96	1.88	6.90	<.001	9.28 – 16.65
Nurse	6.49	1.18	5.52	<.001	4.18 – 8.79
Effort-Reward Imbalance Ratio	6.11	1.58	3.86	<.001	3.01 – 9.21
Medical-therapeutic profession	5.47	1.65	3.32	<.001	2.25 – 8.70
Work experience	0.31	0.04	8.32	<.001	0.24 – 0.39
Working environment	0.24	0.02	9.56	<.001	0.19 – 0.28
Emotional demands	0.12	0.03	4.04	<.001	0.06 – 0.18
Physical demands	0.12	0.02	5.15	<.001	0.08 – 0.17
Role conflict	0.12	0.02	5.01	<.001	0.07 – 0.16
Work-privacy conflict	0.11	0.02	4.69	<.001	0.07 – 0.16
Quantitative demands	0.09	0.03	2.92	.01*	0.03 – 0.15
Cognitive demands	0.08	0.04	2.24	.03*	0.01 – 0.15

Table 3: Continued

Coefficient	β	Std. Error	T value	p-value (*with bootstrap)	CI
Insecurity of working conditions	0.08	0.02	4.22	<.001	0.04 – 0.11
Feedback	0.05	0.02	2.19	.02*	0.00 – 0.09
Possibilities for development	0.04	0.03	1.26	.19*	-0.02 – 0.10
Appreciation	0.03	0.02	1.56	.13*	-0.01 – 0.06
Employment level	-0.03	0.02	-1.58	.11*	-0.07 – 0.01
Lack of boundaries	-0.06	0.02	-3.06	.01*	-0.10 – -0.02
Social support	-0.64	0.23	-2.82	.01*	-1.08 – -0.19
Education secondary II	-3.10	1.04	-2.99	<.001*	-5.13 – -1.07
No professional qualification	-7.94	2.50	-3.17	<.001*	-12.85 – -3.03
Random Effects					
Marginal R2:	0.181				
Conditional R2:	0.247				
Variance intercept	71.27				
Variance Residual	812.34				
ICC	0.08				

Discussion

This study revealed that health professionals in Switzerland experience moderate technostress in their daily work, which is comparable to the findings of Gimpel, Lanzl [15] from Germany. However, the technostress experienced among the health professions differs between settings and professions. Health professionals working in the acute care or psychiatric hospitals reported especially higher technostress than professionals in the other healthcare settings. This might be related to the fact that in Switzerland, the settings with higher technostress are also more advanced in terms of digitization. Therefore, they might be more exposed to the adjunct influencing factors of implemented HIT [40].

In this study, physicians showed significantly higher technostress in comparison to other included health professions, followed by the nurses. Additionally, the MLM revealed that with an increase in individuals' educational levels, the experienced technostress significantly increased. To our knowledge, comparable studies from the healthcare sector are missing. Other studies focusing on different sectors revealed contradictory findings regarding the correlation between education level and technostress [41]. Therefore, we assume that the influence of education level on technostress is sector specific [42]. For example, in industry, personnel with low education levels interact a great deal with technology, whereas personnel with a lower education level (e.g. care aides) in the healthcare system have less interaction with technology, which may explain their lower levels of technostress. The higher technostress reported among physicians could be explained to some extent, by the unwanted time spent with electronic medical records [43]. Previous studies showed that physicians spent more time with documentation than other health professionals [44]. This is related to the fact that they have an increasing number of mandatory forms to complete due to reimbursement regulations. This is also because they have an increasing number of patients to care for, with increasing levels of complexity in care [45].

According to the findings in the MLM, the ERI variable has been identified as a relevant predictor, regarding its impact on technostress, which is supported by Stadin, Nordin [46] Considering the tentative model of technostress [15], the dimension techno-overload and techno-unreliability could contribute to an explanation. Techno-overload might cause health professionals to conduct more and more tasks with HIT, without a noticeable increase in rewards (e.g. increasing reporting to health insurance companies). Moreover, the techno-unreliability of HIT (e.g. system crashes, connection errors) can also increase the effort required to achieve a task [14].

However, Patel, Ryoo [47, p.3] highlighted the “dual role of [technology] as a job demand and a job resource.” They argue that when elaborating on ERI’s association with technology, the ERI variable fails to differentiate between technostress-inducing and technostress-reducing resources of technology. Thus, they propose the use of the job demands-resources model in place of the ERI variable.

The MLM revealed that a higher level of social support (resource) results in decreased technostress. This corresponds with the proven fact, that social support has a stress-reducing effect [48] Hence, having a supportive community helps with managing HIT, broadening the theory of IT support as being a technostress-reducing factor. Health professionals might seek support from non-IT colleagues to manage HIT, thereby, respectively, also enhancing their digital competence [17, 47, 49].

This relationship between technostress and digital competence is supported by Gimpel, Lanzl [15], explicating that a mismatch of the digitization level with the individual's digital competence, led to an increase of technostress. International recommendations such as the Technology Informatics Guiding Education Reform (TIGER) Initiative or the DACH-recommendations for German-speaking countries propose a framework for the required digital competences. However, these recommendations require more elaboration and evaluation, along with further research [50, 51].

Terminio and Gilabert [52] stated that most professionals are not aware of the consequences of the ongoing disruptive processes regarding digitization. This lack of awareness might be noteworthy, along with the fact that Switzerland's healthcare system is much less digitized than several other countries [53]. This could underline the experienced low technostress among health professionals working in nursing homes and home care organizations in this study, which are sparsely digitized.

Strengths and limitations

This study compares, for the first time, technostress between the settings as well as between the health professions. Thus, it contributes to a more comprehensive understanding of the extent to which technostress is experienced in the healthcare sector. Moreover, the analysis gained a large study sample for each health professional's discipline and language region of Switzerland, as well as for the chosen analysis. Through conducting the hierarchical model analysis, the authors verified the added value of the analysis, by considering the natural structure of the data.

Technostress was, however, measured with a single item. This aggregated information offers only an insight into the complexity of technostress, which consists of multiple stress-inducing and - reducing dimensions [15, 47]. The use of this single item limits the interpretation of the findings, since no reference values exist and no measurement reliability has been estimated. However, the statistical differences could indicate a sufficient discriminant validity [54]. To test this hypothesis, further research is needed for psychometric testing of the single item using a reference questionnaire.

Moreover, not all factors which were required (as promoted in the tentative theoretical framework by Gimpel, Lanzl [15]) could be included into the MLM, since the used questionnaire was comprised of partly differing dimensions. This might have led to a lower explanation of variance for the MLM. Furthermore, the participation within the primary study was voluntary, which may have caused a selection bias. This could indicate that organizations, respectively, health professionals, which experience a higher technostress, did not participate in the study. In addition, the study sample comprised of healthcare organizations from Switzerland is less digitized than other industrial countries [53]. Moreover, no causal conclusion can be drawn, as this study utilized cross-sectional data. These implications need to be considered when interpreting the results.

Conclusions

The data provide a first insight into the prevalence of technostress among different health professions. To our knowledge, there are no other studies available on technostress comparing various settings and health professions. This study promotes awareness of this topic among health professionals and managers of healthcare organizations. HIT must be evaluated for reliability over a sufficient period of time before implementation, along with the involvement of the target group testing them to prevent techno-unreliability. Tasks could, furthermore, be assigned to new professions, or interfaces could be simplified for greater user-friendliness to manage techno-overload. Moreover, IT-specialists are gaining knowledge concerning the avoidable accompanying effects that HIT can have on health professionals. The findings suggest that IT-specialists and managers should consider the cognitive and social aspects of affected health professionals, to achieve sustainable and beneficial usage of HIT. Specifically, this means, considering the needs of the health professionals affected, involving them in the development and evaluation of HIT, offering continuous support, and formulating a long-term digitization strategy for the organization.

The healthcare sector is increasingly being digitized. Accompanying this process, an increase of technostress among health professionals is expected. Therefore, even though this study revealed moderate technostress among health professionals, longitudinal approaches as well as intervention studies to elaborate the change of technostress over time with regard to evidence-based measures (e.g. enhance digital competence), are needed.

The findings of this study need to be validated with further research, focusing in the first instance on physicians and nurses, as those professions showed the highest technostress among the professions included. Moreover, measures in intervention studies should address social support within teams, since it is expected to have a mitigating impact on technostress. Specifically, the relationship between ERI and technostress should be elaborated more comprehensively for a better understanding of its origins.

At this stage, technostress is an emerging topic in research. Its theoretical framework is still in development and will continue to evolve, due to the rapid pace of changes caused by digitization. Further research is needed to identify stress-inducing and -reducing factors of HIT among health professionals, and to develop a theoretical framework based on these findings. This is relevant, as digitization is on the agenda of healthcare organizations worldwide. Hence, the findings of this study should be compared to other studies internationally, thus broadening the discussion and facilitating international exchange. This is important since the transferability of technostress-reducing measures between the countries is expected to occur.

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Declaration of interest

The authors report no conflict of interest. The authors alone are responsible for the content and writing of the paper.

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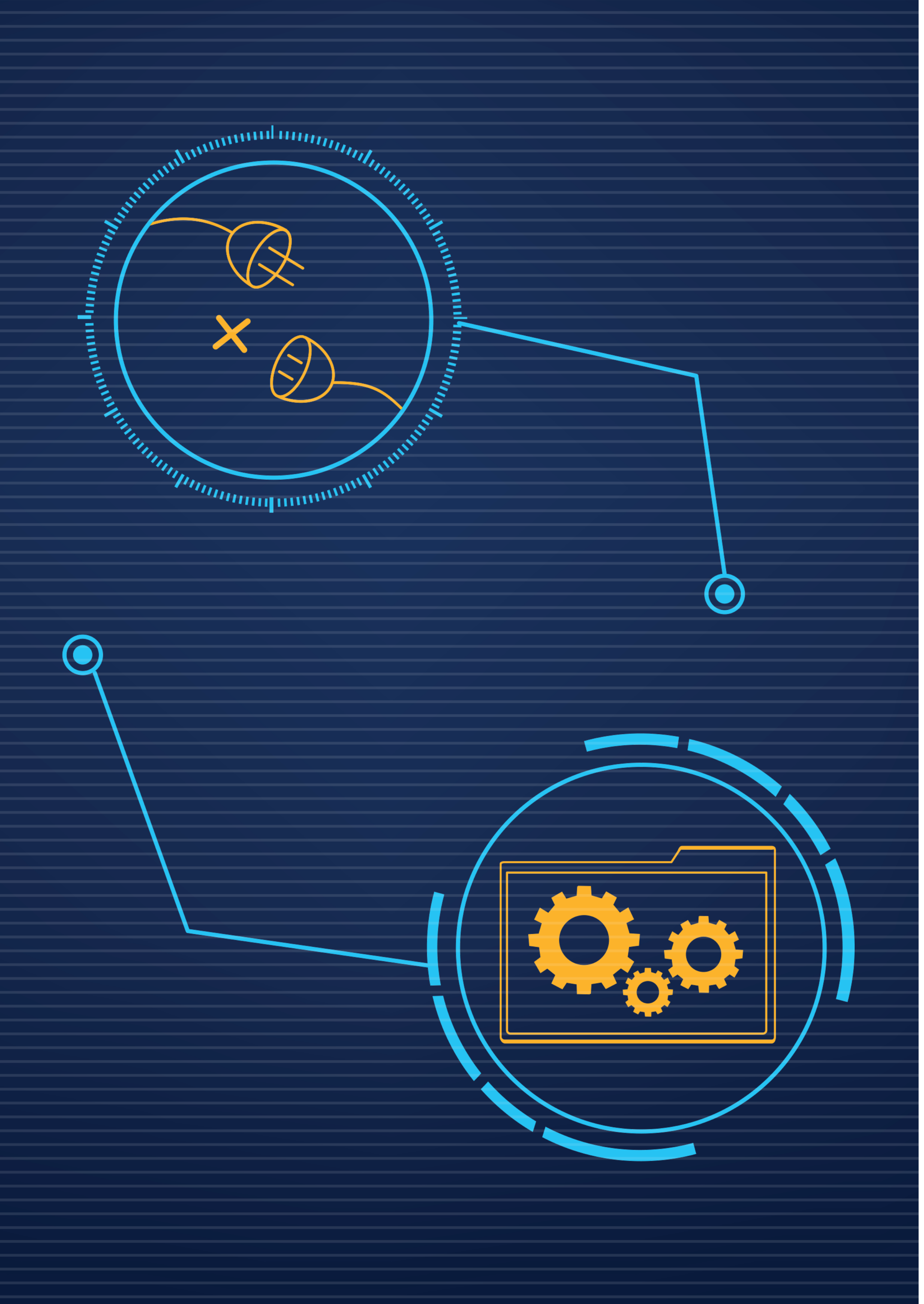

CHAPTER 3

Technostress and Digital Competence Among Health Professionals in Swiss Psychiatric Hospitals: Cross-sectional Study

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Abstract

Background: Psychiatric hospitals are becoming increasingly digitized because of the disruptive rise in technical possibilities. This digitization leads to new tasks and demands for health professionals, which can have an impact on technostress. It is unclear whether digital competence reduces technostress and how technostress affects health professionals' mental and physical health.

Objective: This study aims to assess the association between digital competence and technostress, considering individual characteristics and the association between technostress and long-term consequences for health professionals.

Methods: Cross-sectional data from 3 Swiss psychiatric hospitals were analyzed using multiple linear regression. The dependent variables for the models were digital competence, technostress, and long-term consequences (intention to leave the organization or the profession, burnout symptoms, job satisfaction, general health status, quality of sleep, headaches, and work ability). One model was calculated for each long-term consequence. The mean scores for technostress and digital competence could range between 0 (fully disagree) and 4 (fully agree), where a high value for technostress indicated high technostress and a high value for digital competence indicated high digital competence.

Results: The sample comprised 493 health professionals in psychiatric hospitals. They rated their technostress as moderate (mean 1.30, SD 0.55) and their digital competence as high (mean 2.89, SD 0.73). Digital competence was found to be significantly associated with technostress ($\beta=-.20$; $P<.001$).

Conclusions: Physicians and nurses who have more interaction with digital technologies rate their technostress higher and their digital competence lower than those in other professions. Health professionals with low interaction with digital technologies appear to overestimate their digital competence. With increasing digitization in psychiatric hospitals, an increase in the relevance of this topic is expected. Educational organizations and psychiatric hospitals should proactively promote the digital competence of health professionals to manage expected disruptive changes.

Keywords

Technostress; digital competence; psychiatry; health professionals; multiple regression

Introduction

Background

Psychiatric hospitals are increasingly becoming digitized because of the disruptive rise in technical possibilities [1, 2] and legal requirements, such as the obligation to use nationally shared electronic health records [3]. Moreover, the COVID-19 pandemic has underlined the need for additional digital services such as telemedicine or remote monitoring in mental health to avoid social exclusion through lockdowns or because of living situations in remote regions [4, 5]. Health professionals are thus increasingly confronted with digital technologies for clinical practice, interaction with patients, and administrative tasks.

Therefore, digitalization creates new tasks for health professionals and places demands on them that are not part of their education and training. These include, for example, the management of data privacy [1] or digital competences to enhance appropriate patient communication via internet [6]. In addition, new tasks make demands such as increasing time spent with documentation [7, 8] or with low usability electronic health records [9] and technical support among colleagues [10], which were previously beyond the scope of work of health professionals.

The demands for digital competences and associated changes in the role of health professionals also require a change in the perception of and attitude toward digital resources in everyday work [11]. Consequently, this transformation may have a stress-inducing effect on health professionals, especially because psychiatric health professionals tend to be hesitant regarding new technologies because of the expected deleterious effects on the relationship between health professionals and patients [12, 13]. For example, they may feel more disturbed by the digitization of their daily work than their colleagues in settings that are traditionally more digitized, such as acute care with intensive care units.

The phenomenon called technostress is “a reflection of one’s discomposure, fear, tenseness and anxiety when one is learning and using computer technology” [14, p.3004]. The term was introduced in 1984 by Brod [15] as “a modern disease of adaptation caused by an inability to cope with the new computer technologies in a healthy manner" during the rapid emergence of technology in everyday life. Studies on technostress among health professionals are scarce [16, 17]. A recent study revealed that psychiatric health professionals experience a moderate level of technostress [16].

Technostress is known to have an effect not only on the working life of professionals [10], such as reduced job satisfaction [18, 19], but also on their private life, such as psychophysiological reactions such as headaches and fatigue [20, 21] or burnout symptoms [22]. Exposure to stress-inducing technology can even result in reduced ability to work and an intention to leave the job, which could exacerbate the already-existing shortage of health professionals [23].

An important factor in technostress is expected to be an individual's digital competence, as higher digital competence has been identified as having a mitigating association with technostress [10, 24]. However, it was found that professionals with high digital competence tended to feel particularly stressed by the nonavailability or unreliability of the technologies used at work [24]. Research on digital competence among health professionals has quite a strong focus on the knowledge and skills of using digital technologies at work [25] or specific subgroups in nursing, such as nurse leaders [26, 27]. The TIGER Nursing Informatics Competencies Model, for example, consists of 3 parts: basic computer competences (eg, using the computer and managing files), information literacy (eg, evaluating information and its sources critically), and information management (eg, using electronic health records) [25]. However, additional factors, such as attitude, motivation, and experience of using digital technologies, are also thought to be relevant in the context of digital competence. A recent review of research on health professionals' digital competence summarized the key areas of this competence as "sufficient knowledge and skills [...], social and communication skills [...], motivation and willingness [...] and support for positive experiences in digitalization" [28, p.758]. Therefore, besides insufficient knowledge and skills for proper implementation and use of digital technologies, a lack of motivation and prejudice against digitalization are, for example, associated with reduced technology use. Moreover, health professionals must adapt their communication style, depending on whether they communicate face to face or via telemedicine [28]. Therefore, behavioral determinants are crucial for enhancing digital competence in addition to knowledge and skills [29].

Unfortunately, findings on digital competence and its association with technostress are not specific to health professionals in psychiatric hospitals. However, it is especially important for health professionals that information on their digital competence and technostress is needed, as they are considered to be reluctant adapters of digitization, despite increasing calls for adaptation to new tasks and requirements to keep up with their profession. These contradictions of reluctance and ongoing change need to be addressed at an early stage.

Objective

This paper, therefore, aims to answer the following research questions:

- How do health professionals in psychiatric hospitals rate their digital competence?
- How do health professionals in psychiatric hospitals rate their technostress?
- What is the association between health professionals' digital competence and their technostress, considering the individual characteristics of health professionals?
- What is the association between technostress and long-term consequences for health professionals?

Methods

This cross-sectional study was conducted in 3 psychiatric hospitals in the German-speaking part of Switzerland as part of the Work-Related Stress Among Health Professionals in Switzerland (STRAIN) study [23]. This study is based on a cluster randomized controlled trial (Clinical Trials registration NCT03508596) consisting of 3 measurements (baseline, first, and second) and investigating work-related stress among health professionals in Switzerland.

Sample and Recruitment

The study sample of the STRAIN study included acute care and rehabilitation hospitals, psychiatric hospitals, nursing homes, and home care organizations.

Detailed information on the STRAIN study sample has been published elsewhere [23]. For this study, a request to participate was sent to 12 psychiatric hospitals that had already participated in the STRAIN study. The internal coordinators of the psychiatric hospitals were contacted by email and asked whether their institution's health professionals might participate in this study, which would focus on technostress and digital competences. The project was then presented to decision makers at the psychiatric hospitals. Health professionals from the following work categories were included in this study: nursing staff, physicians, psychologists, medical therapeutic professionals, and social workers. Participants who labeled themselves as researcher or secretariat in the additional free text field were excluded. Overall, 1767 health professionals were eligible for participation in the study.

Data collection

The study was conducted along with the second measurement of the STRAIN study between June and September 2020. The questionnaires for health professionals from the institutions that had agreed to participate were expanded to include topic-specific scales measuring technostress and digital competence.

The internal coordinator of the participating psychiatric hospitals disseminated the information for the participants and the survey to health professionals. Participation in the study was possible via paper or web-based questionnaires in German. For the paper questionnaires, a prestamped envelope was enclosed to return the questionnaire to the project team. For the web-based questionnaire, the link to the web-based survey using SurveyMonkey and UmfrageOnline was either sent individually by email or published on the organization's intranet by the coordinator. A reminder to complete the questionnaire was sent electronically or on paper 2 weeks afterward by the internal coordinator.

The Questionnaires

The 3 questionnaires used in this study comprised a technostress questionnaire [24], an in-house-developed digital competence questionnaire, and the STRAIN questionnaire [23]. The questionnaires were estimated to take 45 minutes overall to complete.

Technostress Questionnaire

For the measurement of technostress, the scale created by Gimpel, Lanzl [24] was used. The scale, which shows satisfactory reliability (Cronbach α=.91), is based on the technostress model of Ayyagari, Grover [30]—a model widely used in research on technostress. It consists of 12 items using a 5-point Likert scale, with the end points 0 (fully disagree) and 4 (fully agree). For interpretation of the data, the mean score was calculated (min=0; max=4), where a high score indicates high technostress. The questionnaire covers the following 12 items, which are derived from the theory's dimensions: uncertainty (ongoing changes lead to uncertainty and constant learning), insecurity (feeling threatened about losing one's job), unreliability (unreliability of technology used), overload (technology forces users to work faster and longer), invasion (employees can be reached anytime), complexity (users feel inadequate regarding their competences), performance control (feeling of being monitored and compared), ambiguity of the role (technical problems must be solved by oneself), interruptions (malfunctions and unstable systems), nonavailability (lack of technology that can reduce workload), no sense of achievement (feeling of lack of progress at work), and invasion of private life (feeling one's private life is affected).

Digital Competence Questionnaire

To measure digital competence among health professionals, no suitable and compact questionnaire was available that focused on the 5 key areas of digital competence (knowledge, skills, communication, experience, and attitude) for health professionals [28]. Moreover, to not lengthen the already-long questionnaire excessively, thereby negatively influencing the response rate, a short self-assessment scale measuring digital competence was needed. Therefore, for each of the 5 key areas, an item was developed in-house. The 5 items covered the following topics: knowledge (eg, one's own knowledge of digital technologies at work), skills (confidence in using digital technologies at work), communication (eg, confidence in communication using digital technologies at work), motivation (eg, motivation to use digital technologies in everyday work), and attitude (eg, attitude toward potential improvements through digital technologies at work). Items were scored on a 5-point Likert scale ranging from 0 (fully disagree) and 4 (fully agree). For interpretation, the mean score was calculated (min=0; max=4), with a high score again indicating high digital competence.

The single items of digital competence were tested for construct validity by conducting exploratory factor analysis and reliability tests. The requirements for factor analysis were met with item correlations above 0.3 and a significant Bartlett test of sphericity ($\chi24$=39.4, P<.001) and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy with acceptable values above 0.6 (KMO=0.81). A scree plot was used to test for loadings on one factor. The reliability test for the 5 developed items on digital competence revealed satisfactory internal consistency (Cronbach α=.87; Multimedia Appendix 1).

STRAIN Questionnaire

The outcome variables (Figure 1) for long-term consequences stem from the STRAIN questionnaire [23,31], which comprises well-known, valid, and reliable scales such as the Copenhagen Psychosocial Questionnaire (COPSOQ) [32], the self-rated general health status [33], the Nurses' Early Exit study questionnaire [34], the von Korff questionnaire [35], and the workability index [36]. The scores from the COPSOQ, the Nurses' Early Exit study questionnaire, the von Korff questionnaire, and the general health status ranged from a value of 0 (do not agree at all) to 100 (fully agree) or from 0 (worst imaginable health state) to 100 (best imaginable health state) for the general health status and from 0 (no influence) to 100 (could no longer perform activity) for the von Korff questionnaire. The COPSOQ scale scores were included if at least half of the items had no missing values [37]. The total score of the workability index questionnaire ranged from 7 (minimum working capacity) to 49 (maximum working capacity).

Data Analysis

The analysis was conducted using R version 3.6.1 [38] and included descriptive statistics for technostress and digital competence. Multiple linear regression models were calculated using the MASS package [39]. The predictor and outcome variables were chosen to cover the dimensions of the DSM [24]. The model describes the correlation between technostress, inhibitors of technostress, and consequences of technostress. Furthermore, individual characteristics (eg, age, education, and sex) were added to the model, as they have been identified as relevant predictors elsewhere [10]. To answer the research questions, multiple linear regressions were conducted (1) with digital competence as the outcome and individual characteristics as predictors; (2) with technostress as the outcome and individual characteristics and digital competence as predictors; and (3) with long-term consequences as outcome variables and technostress, digital competence, and individual characteristics as predictors (Figure 1). For each of the following long-term consequences, a separate multiple linear regression was calculated: intention to leave the organization [23], intention to leave the profession [23], burnout symptoms [32], job satisfaction [32], general health status [33], quality of sleep [34], headache [35] and workability [36].

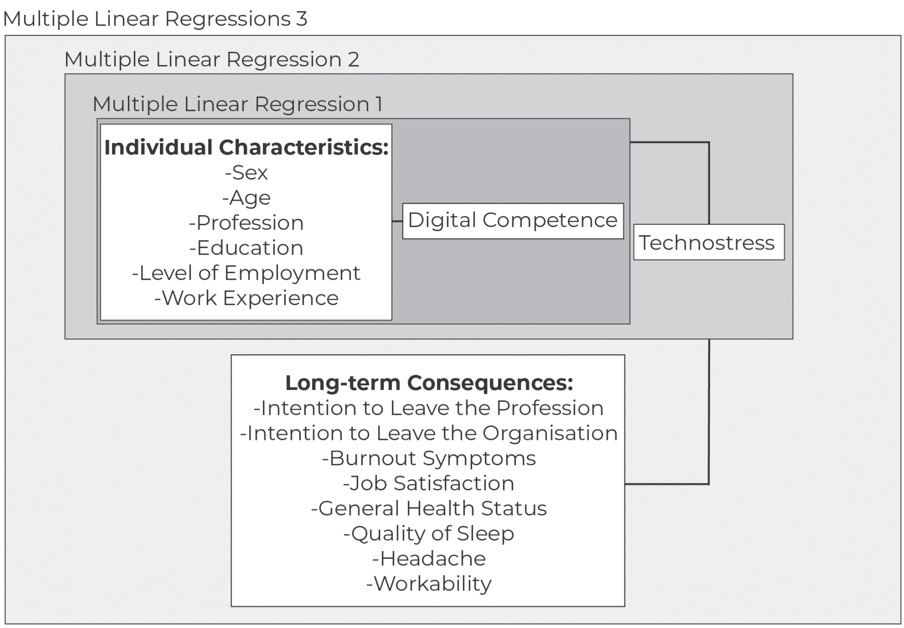

Figure 1: Scales used for the multiple linear regression models.

To minimize the effect of internal dropouts, missing data were filled in based on multiple imputation expecting data to be missing completely at random, using the MICE package [40]. To test for multicollinearity, the variance inflation factor was computed (1.06-1.70), which is regarded as acceptable to proceed if variables show values less than 3 [41]. The assumption of heteroskedasticity was tested using the Breusch-Pagan test. This was met for multiple linear regressions. Therefore, SEs, P values, and CIs were bootstrapped (r=999, bias corrected and accelerated, 95% CI). A stepwise model selection was conducted for the multiple linear regressions based on the Akaike information criterion [42].

Ethical Considerations

The local Swiss ethical board confirmed that the study did not warrant a full ethical application and did not fall under the Swiss Federal Act on research involving human beings (Req-2020-00179). The participants were professionals and could take responsibility for their own participation. They received written information before the start of the study regarding the subject, aim, and voluntary nature of their participation. Filling in the questionnaire was counted as informed participation. The data were gathered anonymously and could not be traced back to individual participants.

Results

In total, 493 health professionals participated in the study, corresponding to a response rate of 27.9% (493/1767). Among the participants, 60% (296/493) were nurses, 12.3% (61/493) were psychologists, 11.1% (55/493) were social workers, 8.7% (43/493) were physicians, and 7.7% (38/493) were medical-therapeutic professionals. The mean age of the participants was 41 (SD 12.33) years, and the majority were female (349/493, 71%). For technostress, health professionals reported a moderate mean score of 1.30 (SD 0.55). Nursing staff (mean 1.41, SD 0.54) and physicians (mean 1.41, SD 0.54) had the highest scores among the professions included, followed by medical-therapeutic professionals (mean 1.23, SD 0.60), social workers (mean 1.15, SD 0.57), and psychologists (mean 0.95, SD 0.40). Health professionals rated their digital competence high, with a mean score of 2.82 (SD 0.76): social workers were found to have the highest score (mean 3.18, SD 0.57), followed by medical-therapeutic professionals (mean 2.90, SD 0.84), psychologists (mean 2.89, SD 0.73), physicians (mean 2.82, SD 0.66), and nurses (mean 2.71, SD 0.78).

Technostress

Table 1 summarizes the results of the multiple linear regression, with technostress as the outcome variable. The regression model was shown to be significant $F_{5,487}=19.81$ ($P<.001$) and explained 20% of the variance (R^2). Being a physician (β=.22; P=.03) or a nurse (β=.17; P=.02) was shown to have an increasing association with technostress, compared with being a social worker (intercept), whereas being a psychologist was negatively associated with technostress (β=−0.23; P=.01). Digital competence was also negatively associated with technostress (β=−0.20; P<.001). This means that an increase in digital competence of 1 point results in a decrease in technostress by −0.20 points of the mean score.

Table 1: Multiple linear regression with technostress as the outcome [observations N=493; technostress: 0 (no technostress) to 4 (high technostress)].

Coefficient	**β**	**Std. Error**	**T value**	**p-value (*with bootstrap)**	**CI (95%)**
Intercept	1.63	0.15	10.86	<.001	1.62 – 1.64
Age	0.004	0.002	2.21	.03*	0.004 – 0.004
Physicians	0.22	0.10	2.22	.03*	0.22 – 0.23
Psychologists	-0.23	0.09	-2.53	.01*	-0.24 - -0.23
Nurses	0.17	0.07	2.30	.02*	0.16 – 0.17
Digital Competence	-0.20	0.03	-6.71	<.001	-0.21 - -0.20

Technostress: 0 (no technostress) - 4 (high technostress)

Digital Competence

The multiple linear regression with digital competence as the outcome was shown to be significant $F_{6,486}=10.47$ ($P<.001$) and explained 13% of the variance (R^2). Being male was shown to be positively but not significantly associated with digital competence (β=.11; P=.15). In addition, the level of employment was positively associated with digital competence (β=.006; P<.001). Age was negatively associated with digital competence (β=−0.014; P<.001), meaning that digital competence decreased marginally with increasing age (Table 2).

Table 2: Multiple linear regression with digital competence as outcome [observations N=493; digital competence: 0 (no digital competence) to 4 (high digital competence)].

Coefficient	β	Std. Error	T value	p-value (*with bootstrap)	CI
Intercept	3.25	0.21	15.52	<.001	3.24 – 3.26
Sex: male	0.11	0.08	1.45	.15*	0.10 – 0.11
Age	-0.014	0.003	-5.29	<.001	-0.01 - -0.01
Level of employment	0.006	0.002	3.21	<.001	0.006 – 0.006
Physicians	-0.46	0.15	-3.11	<.001	-0.47 – -0.45
Psychologists	-0.26	0.13	-1.92	.06*	-0.26 - -0.25
Nurse	-0.48	0.11	-4.55	<.001	-0.49 - -0.48

Digital competence: 0 (no digital competence) - 4 (high digital competence)

Long-Term Consequences

The results of the multiple regression models with long-term consequences as the outcome variables are shown in Multimedia Appendices 2 and 3. The models indicate that the independent variables predict the outcome burnout symptoms as best ($R2=0.16$, $F10,482=9.28$; $P<.001$), followed by intention to leave the organization ($R2=0.15$, $F13,485=6.37$; $P<.001$) and job satisfaction ($R2=0.15$, $F12,480=5.28$; $P<.001$). General health status turned out to have the lowest explanatory power with the included predictor variables ($R2=0.06$, $F3,489=9.88$; $P<.001$).

In all models, technostress was significantly associated with outcome variables. The highest impact was found for burnout symptoms, with an increase of 10.32 ($P<.001$) associated with an increase in technostress of 1 point. Technostress was also positively associated with headache ($β=6.58$; $P<.001$) and the outcomes intention to leave the profession ($β=4.53$; $P=.02$) and intention to leave the organization ($β=4.53$; $P<.001$). Moreover, technostress was negatively associated with job satisfaction ($β=−6.08$; $P<.001$), general health status ($β=−4.47$; $P<.001$), quality of sleep ($β=−5.87$; $P<.001$), and workability ($β= −1.40$; $P<.001$).

The predictor variable, digital competence, was included in 6 of the 8 models. The effect of digital competence was lower than that of technostress. Digital competence was positively associated with quality of sleep ($β=4.19$; $P<.001$), job satisfaction ($β=2.26$; $P=.02$), and workability ($β=.79$; $P=.002$). When interpreting the results, attention must be paid to the possible scores of the outcome variables. Thus, an increase in digital competence of 1 point leads to an increase in workability of 0.79, whereby workability can range from 7 to 49. An increase of 1 point in digital competence leads to an increase of 2.26 points in job satisfaction on a possible range of 0 to 100.

Discussion

Principal Findings

Health professionals in psychiatry rate their technostress as moderate, and their digital competence as high. Higher digital competence was also significantly associated with lower technostress. Individual characteristics differ in their relevance to the models. The age of health professionals is significantly associated with technostress and digital competence. Older health care professionals appear to experience higher technostress and perceive themselves as having lower digital competence. Physicians and nurses appear in the models to have higher technostress and lower competence compared with the other professions surveyed. Being a nurse was shown to have the highest estimates across all outcomes.

To answer the question of the association between technostress and long-term outcomes of health professionals, it should be noted that technostress has a nonnegligible impact on long-term consequences, such as burnout symptoms, job satisfaction, and headache. Thus, technostress has a measurable association with the mental and physical health of health professionals. In addition, technostress promotes the intention to leave the organization or the profession.

Comparison With Prior Work

The significant association of digital competence with technostress is in line with another study in which computer self-efficacy (ie, digital competence) is described as an antecedent of technostress [10]. This association highlights the potential of enhanced digital competence to reduce technostress. However, the β values in the technostress model were equally high for the professions, which could mean that health professionals need to interact with digital technologies to varying degrees at work.

Interestingly, physicians and nurses who are known to have higher technostress [16] and thought to have more interaction with digital technologies than other health professionals were shown to have lower digital competence. This is in contrast with the findings of Kuek and Hakkennes [43], who found that health professionals with high-frequency digital technology use also showed higher digital competence. However, they argued that the organization in which the study took place was digitized more than organizations in comparable studies. One reason for the reported lower digital competence in this study could be past experience with digital technologies rather than a lack of knowledge and skills. Past experiences could have been negative because of a lack of suitable rooms or technical equipment and failing support systems [28]. Furthermore, it raises the question of whether health professionals who have experienced fewer negative interactions rate their digital competence higher because of the absence of digital technologies at work. These results are somewhat at odds with the results of other studies in which people who have little contact with digital technologies show higher levels of technostress because they lack opportunities to adapt and develop their own skills in using them [24]. This phenomenon could be explained by the Dunning-Kruger paradigm for this study. Studies "repeatedly show that people with little expertise [in the specific field] often grossly overestimate how much they know and how well they perform" [44, p.98]. However, this study does not provide any insights into the extent of interactions of health professionals with digital technologies.

Furthermore, lower digital competence (ie, computer proficiency) has been found to be a barrier to successful implementation of electronic health records in psychiatric hospitals [11]. This would imply that Swiss psychiatric hospitals have a good precondition for the successful implementation of digital technologies, as the digital competence of health professionals was rated high. However, being an active user of electronic health records was one of the inclusion criteria for the study, which means that participants self-rated their digital competence by having sufficient experience of interaction with digital technologies. According to Staggers et al [45], there are 4 different levels of digital competence for nurses. They propose that experienced nurses (level 2) are “highly skilled in using information management and computer technology skills” [45, p.386]. This expands the understanding of the core competences necessary for consideration as an experienced professional and places a requirement on educational organizations and psychiatric hospitals to support health professionals in fulfilling this aim. Recent findings also highlight the importance of leaders investing in technical support for their employees, such as “receiving low support in learning and using digital tools” [46, p.11], which is expected to contribute to enhanced digital competence [28].

Concerning gender, there was no strong evidence as to whether males or females were more affected by technostress. However, the model for digital competence indicated that being male was slightly but not significantly associated with digital competence (P=.15). One reason for this result could be that the clear majority of participants were female (71%), which could have led to an underestimation of the potential difference between the sexes. Regarding the technical support described earlier, females seem to compensate for their lower digital competence by relying on the organization’s helpdesk, whereas males tend to exchange expertise [47]. This implies that health organizations might want to invest in a low-threshold helpdesk and train health professionals with an affinity for digital technologies to become peer supporters.

Evidence for the effects of individual characteristics is inconsistent, particularly with respect to age and sex [10]. This study contributes to the discussion by indicating that age is a relevant predictor of both technostress and digital competence. In terms of digital competence, the results of this study appear to confirm that younger health care professionals perceive themselves as having higher digital competency [48]. However, recent findings, albeit nonspecific to the health care setting, indicate that females tend to be more affected by technostress [49]. In this respect, a possible effect of sex should be considered in future studies that focus on health care professionals. If it turns out that women are more affected by technostress in the health care system, the intended measures must take this possible precondition into consideration.

In terms of the association between technostress and its long-term consequences, other findings from other sectors underline that higher technostress leads to higher intention to leave the profession or organization and lower job satisfaction [50]. Furthermore, additional influencing factors in health care appear to have a more important impact on long-term consequences for health professionals, such as work-private life conflict or quantitative demands at work [23, 51]. However, some aspects of private life conflicts are incorporated into the technostress scale used. One of the themes of technostress is techno-invasion, which measures the self-perceived aspect that one can be reached at any time. Also, the theme invasion of private life is part of the technostress scale, assessing the feeling that one's private life is affected by digital technologies at work. Although these aspects are included in the technostress scale, the findings in this study do not reach the explained variance of the study indicated above. Therefore, it seems that digital technologies do not currently play a vital role in the context of private life conflicts among health professionals in psychiatric hospitals.

In view of the fact that the Swiss health care system is still only partly digitized in terms of international comparison [52] and that psychiatry is not expected to lead the way in digitization, these findings seem logical. However, with a future increase of digitization in psychiatric hospitals [53], the topic's relevance is expected to rise. For example, a recent study described the empowerment and enslavement paradox of digital technologies for surgeons [54]. The study highlights the issue that with an increase in possibilities because of digital technologies, the danger of misuse increases, which negatively impacts the outcomes of health professionals and patients. The implication for psychiatric hospitals is, therefore, that technostress is not a major issue at the moment. However, psychiatric hospitals are encouraged to invest in monitoring the digital competence of their health professionals, especially along with the implementation of digital technologies, and offer suitable training to their employees. Furthermore, decision makers should involve health professionals in the development and implementation of digital technologies, as involvement has been identified as crucial for positive experiences with digital technologies, increasing motivation toward innovations and dismantling prejudices [10]. Health professionals must recognize that they are going to face digitization at their workplace. However, because many health professionals have a rather reserved attitude toward digital technologies at work, decision makers should approach this process thoughtfully.

Strengths and Limitations

This study contributes to the emerging topic of technostress among health professionals in a psychiatric setting. It provides first insights into the association of digital competence with technostress and the association of the two with long-term consequences. This study enriches the discussion on the potential influence of individual characteristics, such as age, sex, profession, and education. Furthermore, a digital competence scale with satisfactory properties was developed and evaluated in this study. This scale is made available to the community for use in further research (Multimedia Appendix 1).

However, this study had several limitations. First, convenience sampling was performed. Of the 12 psychiatric hospitals invited, only 3 agreed to participate. It cannot be excluded that psychiatric hospitals whose staff generally experience lower technostress agreed to participate because they were more sensitized to the topic. In addition, the sample did not reflect the typical distribution of health professionals in Swiss psychiatric hospitals. In this study, physicians were underrepresented (9%), compared with the usual proportion of 17% [55]. This might be because physicians are increasingly reluctant to participate in surveys for reasons such as information overload, survey fatigue, or privacy concerns [56]. In addition, a response rate of 27.9% (493/1767) is considered low but rather common for web-based surveys with health professionals [57, 58]. Unfortunately, forecasts indicate even lower average response rates soon [59]. Furthermore, participants could decide to use either a paper or web-based questionnaire. The comparability of paper and web-based questionnaires has been discussed in the literature. Psychological factors, such as mood state or fatigue during the inquiry, can have an impact on responses and can be influenced by environmental stimuli or distractions [60]. Especially in health care organizations in which the number of computers on the wards is limited and no quiet place is available to withdraw, this could have had a deleterious effect on responses. In addition, one organization opted exclusively for web-based inquiry. Staff members who feel highly stressed by digital technologies could have been excluded by this decision because they did not want to use the computer unnecessarily for longer than was required by their work. Moreover, no causal conclusions can be drawn, as this study used cross-sectional data. These implications must be considered when interpreting the results.

Conclusions

Health professionals in Swiss psychiatric hospitals experience moderate technostress at work. They rated their digital competence as high. It might be that health professionals with little interaction with digital technologies at work overestimate their digital competence. Therefore, to generate reliable results on this hypothesis in the future, the degree of digitization of the organization and the degree of contact with digital technologies at the individual level must be additionally assessed. In this context, research should evaluate whether self-rated digital competence corresponds to an objective assessment of digital competence at work, which would contribute to further development of the measurement tool for digital competence.

Technostress has been shown to have a relevant association with long-term consequences for staff, especially those with burnout symptoms. Further digitization in psychiatric hospitals is expected to have an increasing impact on the technostress experienced. Additional digital competence will be needed as an inhibitor of technostress for health professionals to sustainably cope with technostress and, thus, lower the risk of long-term consequences.

Health professionals and professionals in educational organizations do not yet recognize the need for future digital competences. Health and educational organizations are responsible for the adequate preparation of future health professionals; however, this should include training aimed at digital competence.

Psychiatric hospitals can draw conclusions based on these results. As digital competence significantly reduced technostress, further in-house education to promote digital competence should be established. Furthermore, the duties of younger health professionals could be extended to support older health professionals in managing digital technologies at work. Mutual support is demonstrably conducive to acquiring new competences and strengthening the sense of community in the team. However, this presupposes that such a duty is appropriately appreciated and remunerated.

Psychiatric hospitals in Switzerland are still in their early days in terms of the impact of digital technologies on health professionals. The necessary digital competences will emerge as the digitization process progresses. Researchers must continue to monitor this development and generate recommendations for measures to reduce technostress and develop suitable educational content from intervention studies.

Acknowledgments

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Questionnaire Digital Competence

1. In general, I rate my knowledge of digital technology as satisfactory.
2. I feel confident about finding relevant information using digital technology.
3. I feel confident about sharing information using digital technology.
4. I like to use digital technology at work.
5. I believe that digital technology has noticeable benefits for the quality of care.

Multimedia Appendix 2

Table 3: Multiple linear regression models with long-term consequences as outcomes part 1 (observations n=493)

	Intention to leave the professiona		**Intention to leave the organizationa**		**Burnout symptomsa**		**Job satisfactiona**	
	R2 = 0.08, F(7,485) = 6.37, *P* < .001		**R2 = 0.15, F(13,485) = 6.37, *P* < .001**		**R2 = 0.16, F(10,482) = 9.28, *P* < .001**		**R2 = 0.15, F(12,480) = 5.28, *P* < .001**	
	β	**se**	**β**	**se**	**β**	**se**	**β**	**se**
Intercept	24.84***	7.22	-1.01	12.72	16.34	10.87	76.77***	8.95
Technostress	4.53**	1.96	7.68***	2.02	10.32***	1.65	-6.08***	1.38
Digital Competence	-2.61	1.37			-2.46*	1.18	2.26*	0.02
Sex: male			-4.96*	2.32	-3.55	1.90		
Age	-0.25**	0.08	-0.26	0.14	-0.27***	0.07	0.21***	0.06
Level of employment					0.19***	0.48		
Work experience			-0.26	0.15				
Physicians	2.23	4.35	2.65	6.56			4.11	4.36
Psychologists	1.98	3.97	2.79	5.67			0.67	3.77
Nurses	8.78**	3.18	14.05***	3.57			-5.79*	2.32
Medical therapeutic professionals	-1.99	4.49	1.05	4.85			-3.48	3.19
Education: secondary level			9.16	11.67	9.85	9.27	-3.63	7.63
Education: tertiary level			22.28	11.45	16.33	9.10	-7.81	7.48
Education: Bachelor			28.73*	11.67	14.54	9.23	-13.05	7.65
Education: Master			29.86*	12.03	17.45	9.19	-11.98	7.89
Education: PhD			32.31*	12.70	15.82	9.37	-14.22	8.34

Significance level: *$P \leq .05$; ** $P < .01$; *** $P < .001$; β: estimated beta-values; se: standard errors

[a]Mean score range from 0 (do not agree at all) to 100 (fully agree)

Table 4: Multiple linear regression models with long-term consequences as outcomes part 2 (observations n=493)

3

Multimedia Appendix 3

	General health statusb		Quality of sleepa		Headachec		Work-abilityd	
	$R2 = 0.06$, $F(3,489) = 9.88$, $P < .001$		**$R2 = 0.08$, $F(3,489) = 13.25$, $P < .001$**		**$R2 = 0.10$, $F(5,487) = 11.07$, $P < .001$**		**$R2 = 0.12$, $F(9,483) = 7.64$, $P < .001$**	
	β	**se**	**β**	**se**	**β**	**se**	**β**	**se**
Intercept	95.26***	3.68	61.37***	5.48	23.43**	7.43	37.84***	1.49
Technostress	-4.47***	1.33	-5.87***	1.60	6.58***	1.88	-1.40***	0.34
Digital Competence			4.19***	1.15	-3.00*	1.36	0.79**	0.26
Sex: male					-8.38***	2.18	0.79	0.41
Work experience	0.12	0.06						
Age			0.17*	0.07	-0.32***	0.08	0.04**	0.015
Level of employment	-0.15***	0.39			0.13*	0.06	-0.03*	0.01
Physicians							0.80	0.81
Psychologists							0.77	0.73
Nurses							-0.70	0.59
Medical therapeutic professionals							-0.30	0.83

Significance level: * $P \leq .05$; ** $P < .01$; *** $P < .001$; β: estimated beta-values; se: standard errors
[a]Mean score ranges from 0 (“do not agree at all”) to 100 (“fully agree”),
[b]Mean score ranges from 0 (“worst imaginable health state”) to 100 (“best imaginable health state”),
[c]Mean score ranges from 0 (no influence) to 100 (could no longer perform activity),
[d]Total score ranges from 7 (minimum working capacity) to 49 (maximum working capacity).

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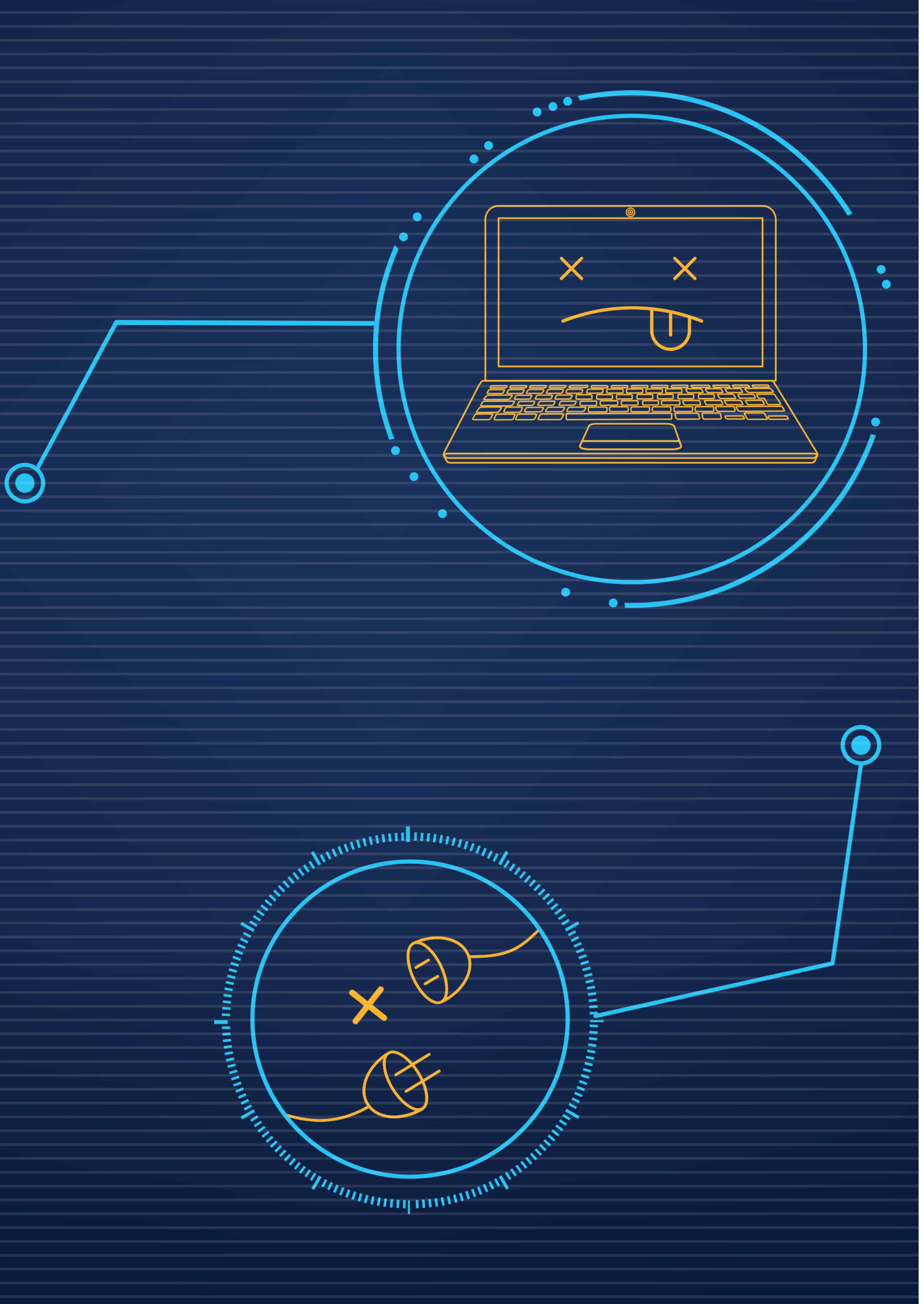

CHAPTER 4

Health professionals' sentiments towards implemented information technologies in psychiatric hospitals: a text-mining analysis

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Abstract

Background: Psychiatric hospitals are increasingly being digitalised. Digitalisation often requires changes at work for health professionals. A positive attitude from health professionals towards technology is crucial for a successful and sustainable digital transformation at work. Nevertheless, insufficient attention is being paid to the health professionals' sentiments towards technology.

Objective: This study aims to identify the implemented technologies in psychiatric hospitals and to describe the health professionals' sentiments towards these implemented technologies.

Methods: A text-mining analysis of semi-structured interviews with nurses, physicians and psychologists was conducted. The analysis comprised word frequencies and sentiment analyses. For the sentiment analyses, the SentimentWortschatz dataset was used. The sentiments ranged from -1 (strongly negative sentiment) to 1 (strongly positive sentiment).

Results: In total, 20 health professionals (nurses, physicians and psychologists) participated in the study. When asked about the technologies they used, the participating health professionals mainly referred to the computer, email, phone and electronic health record. Overall, 4% of the words in the transcripts were positive or negative sentiments. Of all words that express a sentiment, 73% were positive. The discussed technologies were associated with positive and negative sentiments. However, of all sentences that described technology at the workplace, 69.4% were negative.

Conclusions: The participating health professionals mentioned a limited number of technologies at work. The sentiments towards technologies were mostly negative. The way in which technologies are implemented and the lack of health professionals' involvement seem to be reasons for the negative sentiments.

Keywords

Technostress, information technology, psychiatric hospital, text-mining

Introduction

The increasing possibilities through technological innovations and their expected benefits have accelerated the digital transformation in health care [1]. This increasing use of and reliance on digital transformation in health care is underlined by research [2]. Marques and Ferreira [2] highlighted that there has been an exponential increase in studies over the last decade, with a focus on exploring the potential of technological solutions to improve the quality and safety of health care. However, the majority of studies included were conducted in the acute medical care setting. This indicates an imbalance in the research conducted into digital transformation process across the different health care sectors.

The mental health care setting is just at the beginning in the digitalisation of patient care or of the administrative processes [3]. Developers and researchers often fail to develop, implement, and evaluate Information Technology (IT) in mental health care mainly due to barriers in engagement, effectiveness, equity, access, ethical concerns and concerns of worsening the therapeutic relationship [4-8]. Furthermore, missing infrastructure (e.g. no suitable devices or Wi-Fi) as well as insufficient skills of health professionals hamper successful implementations [5]. IT is defined as the "application of information and communication technologies tools including computer network, software and hardware required for internet connection" [9, p.139].

The expected advances of technological solutions like artificial intelligence, wearables, e-health or standardised data formats through electronic health records are seen as the promotors of the future of digital psychiatry [3, 8, 10]. Despite the difficulties in the development and implementation of some digital technologies, advantages of already implemented technologies could be identified. For example, the use of electronic health record in the mental health care setting led to a significant increase of timely access and availability of patient information for the health professionals [11]. Furthermore, the implementation of telemental health led to enhanced accessibility of the services – of equivalent therapeutic quality – for immobile patients or patients living in rural regions [12, 13]. However, the use of technology resulted in several adverse effects among the health professionals working in the mental health care setting, such as higher burnout-symptoms, increased intention to leave the organisation or physical stress reactions [14].

One reason for adverse effects of technologies at work on health professionals' health is the lack of attention to the health professionals' attitude (e.g. anxiety, uncertainty) towards technologies during the development and introduction of technologies at work [15]. A positive attitude towards technology usage is associated with reduced technology-related stress [16], which in turn is a relevant influencing factor on multiple health-related outcomes among health professionals [14]. Attitudes are based on a feeling about a situation or a way of thinking about something – expressed by individuals verbally, in writing or in gestures – and are the sentiment of this person [17, 18]. Sentiments can be either negative, neutral or positive [19]. In this context, sentiments can describe the feelings towards technology or the way of behaving when interacting with technology at work.

So far, research on health professionals' sentiments towards technology in psychiatric hospitals is limited [20]. However, a more in-depth understanding of health professionals' sentiments may give a better insight into their feelings towards technology.

The aim of this study, therefore, was (a) to identify the implemented information technologies in psychiatric hospitals and (b) to describe the health professionals' sentiments towards technologies.

Methods

A text mining analysis of semi-structured interviews to describe health professionals' sentiments about already implemented technologies in psychiatric hospitals was conducted. Text mining is an umbrella term for computational processes to analyse unstructured text data [21]. Within the text mining, the data pre-processing and analysis is automated, which enables the identification of new information and relationships within comprehensive unstructured datasets [21]. The text mining approach can be used to count word frequencies and to identify patterns or sequences of used words, as well as sentiment analysis. Sentiment analysis is a text mining method that quantifies the emotional value in a text [18]. It is an objective and reproducible way of assigning a number about how negative or positive a piece of text is. Text mining has been recognised in health science as a suitable method to extract information from electronic health records [22] or from transcripts of single or focus group interviews [23-25].

Study Sample

A convenience sample of nurses, physicians and psychologists working in psychiatric hospitals was considered. The study was first presented to the management of three psychiatric hospitals in the German-speaking part of Switzerland, two of which thereupon indicated their interest in participating in the study (one private and one public psychiatric hospital each). After managerial decision to take part in the study, the management of each psychiatric hospital provided an internal coordinator to assure adequate information provision. The internal coordinator confirmed that technologies are applied in the workplace. The internal coordinators were either the medical director or the person responsible for the nursing development of the participating psychiatric hospital. They were asked to provide the employed health professionals with an informative letter about the study and to invite them to participate in the interviews. Physicians, nurses and psychologists subsequently contacted the researcher directly if they were interested in participating. To meet the inclusion criterion, participants had to have been employed by the current employer for at least 1 year, in order to ensure that these professionals had had sufficient experience with technology in their work.

Data Collection

Data were obtained in semi-structured individual interviews between June 2020 and March 2021 in person using an interview guide. An interview guide is defined as 'a list of questions, which directs conversation towards the research topic during the interview' [26]. Its' form is considered 'loose' and 'flexible' with topics, covering the main topics of the research subject [26]. The interview guide (Multimedia Appendix A) was developed based on the technology acceptance model [27]. This model describes the influence of attitude on the behavioural intention to use an IT [27]. The used interview guide covers the determinants of the dimensions from the model, such as 'perceived usefulness' (e.g. How does the [technology] influence your performance?), ‘perceived ease of use’ (e.g. How do you assess your competence in dealing with digital technologies in your workplace?) and ‘computer anxiety’ (e.g. How do you experience the overload caused by digital technologies in your work?). It also covers the moderators of the dimensions, as they influence the ‘behavioural intention’ of the user [27]. We included questions for the following moderators in the interview guide:

‘Experience’ (e.g. What digital technology has been implemented recently and how did you experience this implementation?), ‘management / organizational support (e.g. How do you experience the change in your role due to digital technologies?), ‘design characteristics (e.g. How do you feel about the possibility of another person being able to monitor all your performance through a digital technology?) and ‘user participation’ (e.g. What digital technologies would you like to have to better manage your work?). These aspects form the individual’s attitude towards the technology, which leads to the intention to use or non-use of the technology [19]. The interviews were conducted in Swiss German and audio recorded with a recording device after written consent of the participants.

Data Analysis

Transcription and Translation

The audio files were transcribed verbatim by one researcher, to textualize them as unstructured data in interview transcripts [28]. The Swiss German (a spoken German dialect with no direct written equivalent) was translated into the German language by one research member with German as native language and cross-checked by another research member with Swiss German as native language. In this process, the translations were also checked for correct spelling, to meet the requirements for data pre-processing, which is based on German vocabulary (e.g. ‘practical’ [gäbig bzw. praktisch]).

Data Pre-processing

The interview transcripts were pre-processed and analysed by using the statistical software R version 4.0.4 with Studio 1.4.1106 [29] with the following packages: spacyr [30], tm [31] and tidytext [32]. The data pre-processing comprised several steps: (a) deletion of the interviewers' text from the transcripts – that is, transcribed questions and statements of the interviewer. (b) The unstructured text data were transformed into a list, where each word was placed in one row. This process is referred to as tokenisation [32]. (c) The words were reduced to their dictionary root (base form) by using the spacyr package [30] with the German-language-specific package 'de_core_new_lg'. Word forms with the same root, such as 'makes' [macht], 'made' [gemacht] and 'make' [mache] are aggregated in the basic form 'to make' [machen]. This process is known as lemmatisation [21]. (d) Umlauts (ä, ö, ü) were transformed to (ae, ou, ue). Stopwords (e.g. I, and, it) predefined in the package tm [31], numbers, punctuation marks and other words not relevant for the analysis (e.g. names, greetings) were deleted.

4

Frequency and Sentiment Analysis

After data pre-processing, frequencies of the mentioned technologies and the sentiments using the 'SentimentWorschatz' (SentiWS) [33] were calculated. The sentiment analysis quantified the attitudes, opinions and emotions of the participants towards the technologies [18]. The current version of SentiWS consists of 1650 positive sentiments in their basic word form and 1800 negative sentiments in their basic word form. The sentiments' values are interval-scaled and range between -1 (strongly negative) and 1 (strongly positive) [33]. For example, the word 'great' [super] has a positive polarity with a value of 0.5012 and the word 'bad' [schlecht] has a negative polarity with a value of -0.7706. To avoid misclassification of sentences with negation, the identified sentiments were screened for their potential relation with the words 'not' [nicht] and 'no/none' [kein]. Sentiments with a negation in the sentence were recoded accordingly and added to the SentiWS with reversed polarity [34], for example 'not bad' [nicht schlecht] with a value of 0.7706. The identified sentiments were used for three different analyses. (a) For the first analysis, the means of words that describe negative (µ_neg) or positive (µ_pos) sentiments were calculated to compute the average proportion of negative sentences about technologies at work per interview and across all interviews (µ_neg / µ_pos- µ_neg). (b) For the second analysis, the frequency of the sentiments per technology was calculated and multiplied with the sentiments' value from the SentiWS. The relation between sentiment value and frequency emphasises that a few sentiments with a higher value have a stronger impact on the quantified attitude towards a specific technology than many sentiments with a low value. (c) As a third analysis, n-gram (n = 5) analysis of sentences describing sentiments per technology was conducted for a better understanding of the context in which a sentiment has been mentioned. The n-gram analysis is a sequence of n elements from a given text. The n elements are in the word order close to a defined keyword in the text, where the keyword is also one word of the n elements. Analysis was conducted in an iterative process in which new interview transcripts were added sequentially to evaluate when data saturation was achieved [35].

Frequency and Sentiment Analysis

For credibility, preliminary findings and interpretations were checked and discussed within the research team. For dependability, the data analysis was audited by two co-researchers. Furthermore, replicability was enabled through the provision of the statistical software script file [36]. The script file is available as Multimedia Appendix B. The visualisation was conducted by using the package ggplot2 [37]. The frequencies of the mentioned technologies have been displayed in table form and for the sentiments in a bar chart. The average proportions of negative sentences were visualised in a scatterplot with one point per interview transcript and the average across all interview transcripts. The results of the sentiment analyses for each identified technology were visualised in a bar chart, displaying how often a sentiment related to a technology for all interviews.

Results

In total, 20 health professionals participated in the study: 11 nurses (55%), 5 physicians (25%) and 4 psychologists (20%). Most of the participants were female (n = 16; 80%) and the mean age was 39 years (SD = 13.05 years). The mean duration of a single interview was 42 minutes (SD = 7.89 minutes).

The keyword density per technology ranged between 0.32% and 0.01% in the interview transcripts. The overall density of mentioned technologies in the interview transcripts was 1%. The health professionals mentioned hardware and software when asked about technologies they used. In the interviews, the participants mainly talked about the computer (28%), followed by the phone (18%) as the hardware. Regarding software, the majority of the participants talked about email using Microsoft Outlook (22%), followed by the electronic health record (18%; Table 1).

Table 1: Hardware and software that was mentioned in the interviews ordered by frequency.

	Information Technology	Frequency of mentioning, n (%)
Hardware	Computer	203 (28)
	Phone	130 (18)
	Laptop	52 (7)
	Electrocardiogram	12 (1.7)
	Voice recorder	2 (0.3)
Software	Email	161 (22)
	Electronic health record	129 (18)
	Shift planning tool	14 (2)
	WhatsApp	11 (2)
	Wi-Fi	6 (1)

Sentiment Analysis

Overall, 4% of the words in the transcripts had a non-zero positive or negative connotation. The remaining words were identified as neutral. The majority of words with a non-zero sentiment were identified as positive (73%). The most frequently used word with a positive polarity was '*know*' [wissen] (11%), followed by '*good*' [gut] (10%) and '*fast*' [schnell] (8%). The most frequently used word with a negative polarity was '*problem*' [Problem] (8%), followed by '*difficult*' [schwierig] (5%) and '*old*' [alt] (4%) (Figure 1).

The majority of the identified words with a non-zero sentiment indicated small values on the polarity from -1 (negative) to 1 (positive). The overall mean value for the positive sentiments was 0.11 and the mean value of the negative sentiments was -0.26. There was a negative sentiment towards technologies among the participants. The average proportion of negative sentences about technology at work in the transcripts was 69.4% (SD = 7.73%) (see Figure 2).

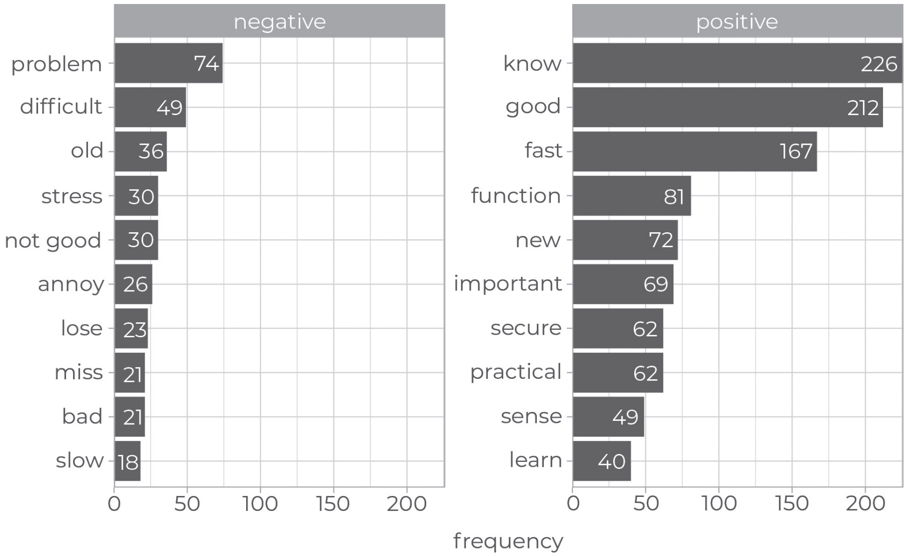

Figure 1: SentiWS sentiments from the interviews ordered by their frequency. The left bar chart displays the sentiments with a negative polarity. The right bar chart displays the sentiments with a positive polarity.

For several technologies (i.e. shift planning tool, WhatsApp, voice recorder and electrocardiogram), the sentiment analysis did not yield statistically significant results because these were hardly mentioned by the participants and therefore not related with any sentiment (see Table 1). The participants mentioned positive and negative properties for the electronic health record, computer, phone, email and laptop. The participants perceived computer work mostly negatively. This can be seen from the fact that although more positive sentiments were used in the context of the word '*computer*', negative sentiments clearly outweighed positive sentiments in terms of polarity. The participants used the word '*computer*' in the context of the positive sentiments '*fast*', '*practical*' and '*integrative*' [schnell, praktisch and integrieren] but also in the context of the negative sentiments '*old*', '*problematic*', '*not good*', '*unfortunately*', '*destroy*' and '*burden*' [alt, problematisch, nicht gut, leider, vernichten and belasten, respectively].

Figure 3 summarises the sentiment analyses for the above-described technologies with their related sentiments. The polarity multiplied by the frequency of the sentiments highlighted that a few sentiments with a higher value have a stronger impact on the quantified attitude towards a specific technology than many sentiments with a low value.

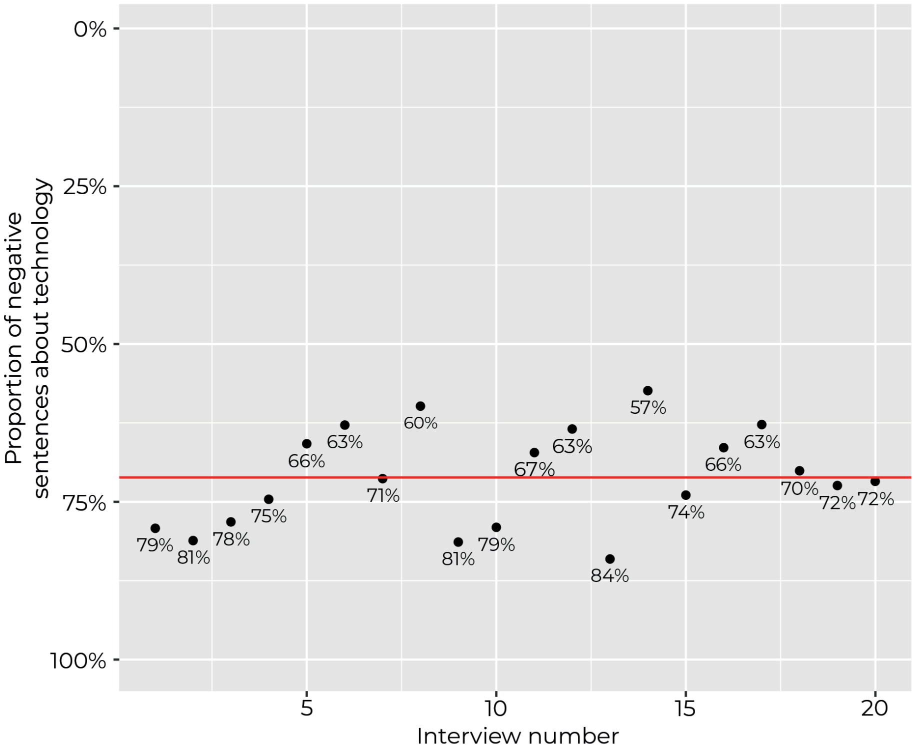

Figure 2: Average proportion of negative sentences about technology at work. The horizontal line indicates the average proportion of all interviews. The points indicate the average proportion per interview.

The n-gram analysis for words in their consecutive order related to a keyword revealed that although the participants could use '*laptops*', the devices, unfortunately, needed to be '*connected to the power*' or the '*internet*' due to '*weak batteries*' or '*missing Wi-Fi*' options at work. The work with the '*phone*' was experienced mainly as positive. However, answering the phone while being occupied in a conversation with a patient was mentioned as an '*avoidable interruption*'. As indicated in Figure 3, '*writing email*' was a frequent activity among the participants, which predominantly was associated with positive sentiments. On the other hand, the health professionals experienced an '*overload*' of emails and an '*interruption*' of their work.

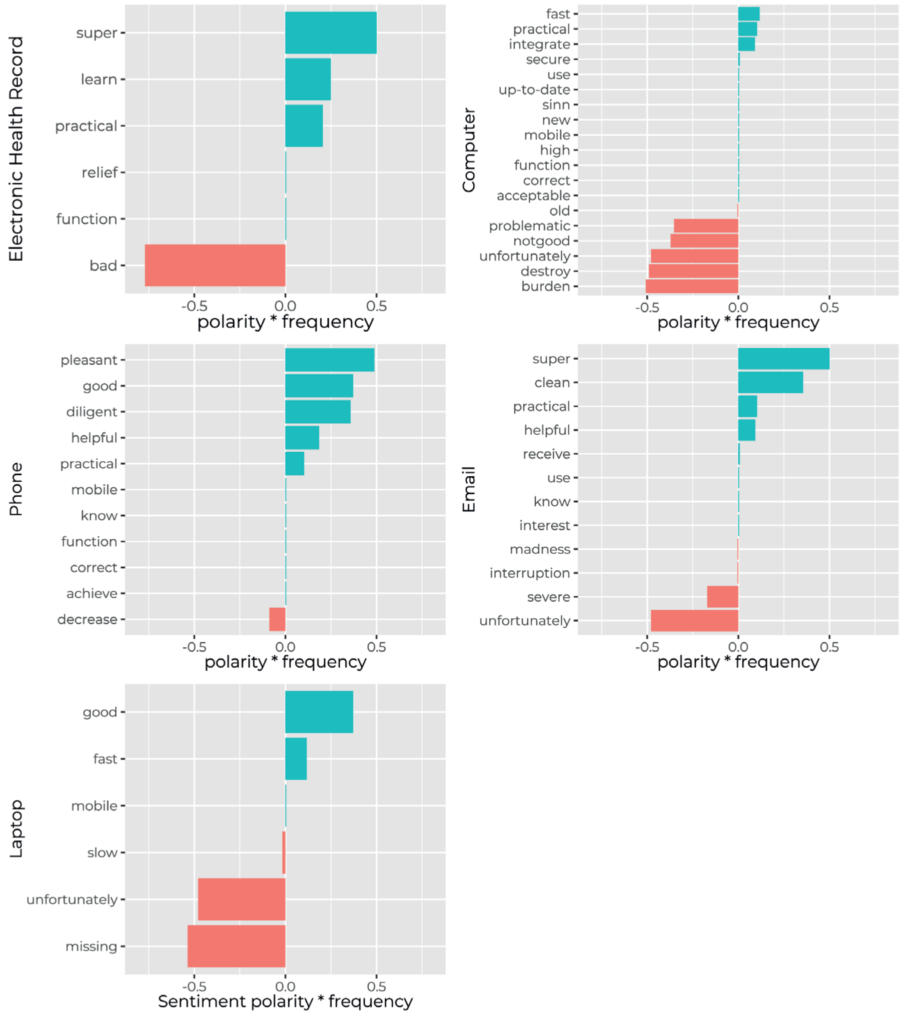

Figure 3: Results of the sentiment analyses for each technology with identified sentiments. The X-axis displays the frequency of the sentiments multiplied by the sentiments' polarity from the SentiWS. The Y-axis displays the sentiments.

Discussion

The current study focused on identifying the implemented technologies in psychiatric hospitals and exploring the health professionals' sentiments towards technologies. The results showed that computer, phone and email were used at work. Findings showed that the participants at the same time had both positive and negative sentiments towards each discussed technology. The majority of the identified sentiments were rather negative regarding technologies at work. The findings underline the influence of the user's experience on the attitude towards using technology, as demonstrated in the technology acceptance model [27]. In our study, the five topics 'Job Relevance', 'Output Quality, 'User participation', 'Management support' and 'Organisational support' from the technology acceptance model derived, acknowledging their statements based on their experience.

Job Relevance & Output Quality

Despite being aware of the positive attributes of the technologies, health professionals reported being confronted with issues during the interaction with technology at work that led to rather negative sentiments towards them. The duality of the sentiments towards technologies – that one sees the benefits but cannot take full advantage of them due to barriers – is consistent with the existing literature regarding health professionals' attitudes towards information systems [38, 39]. Job relevance and output quality are known to have an interactive effect on perceived usefulness [27]. In this context, health professionals seem to believe that technology is an added value for their work. However, the inadequate output quality leads to an overall negative attitude toward technology at work.

In our study the negative sentiments regarding, for example, the technology 'laptops' were mentioned in the context of lack of mobility due to lack of Wi-Fi or because of the fast battery discharge. This shows that the negative sentiments regarding 'laptop' were related to the quality of the technology or the connectivity and less to the fact that technology is used. Thus, it might be argued that health professionals have positive sentiments towards technologies in general, but this positivity is diminished by a lack of user-friendliness or expediency.

User participation

In a recent study, nurses perceived electronic health records as supportive during the provision of care, but they also rated the user-friendliness as low [40]. One reason for the low user-friendliness might be the lack of attention to the evaluation of technologies during development and implementation alongside the health professionals [41]. In this study, the negative sentiment '*unfortunately*' [leider] was mentioned in connection with various technologies. '*Unfortunately*' in this context can be interpreted as a regret or a disappointment of the participant that the technology does not meet the expectations. User involvement in the development and evaluation of technologies often starts too late [41], so this discrepancy between expectation and experience cannot be given adequate attention. This might have contributed to the fact that negative sentiments towards technologies outweighed positive ones. The involvement and contribution by health professionals to technology that is useful at work should serve as the basis to reduce the health professionals' reluctance towards technology, which might be the reason why digitalisation is progressing more slowly in mental health than in other health settings [5-7].

Organizational support

Poor battery life and weak Wi-Fi could underline the findings that the IT-departments are insufficiently involved in the implementation processes of technological innovations [42]. The IT departments of health organisations have reported several barriers for successful implementation of technology: a lack of resources, the absence of 24/7 IT services for health professionals and not being involved in technology-related decisions by the management [42]. Our findings suggest that before the digital future of psychiatry can be pondered [43], technical requirements must be met. For example, if wearables should be implemented to measure patient data [3], a reliable Wi-Fi for data transmission is crucial.

Psychiatric hospitals are acknowledged to be just at the beginning of the most innovative and potentially disruptive changes through digital transformation [3]. To master this expected change in the long term, the mostly negative sentiments towards technology among health professionals must be converted to positive sentiments [7].

Management support

To achieve this change, decision-makers in psychiatric hospitals need to be committed and assess the health professionals' needs of technologies, in particular the functionality and suitability for everyday use. For this endeavour, they should involve health professionals early in the development and implementation process [41] and learn from their point of view towards the technologies at hand. Theoretical models, such as the technology acceptance model 3 [27], should be used as a foundation in order to understand the systemic connectedness of factors, which influence the sustainable use of technology at work.

Implications for practice

Not all aspects from the technology acceptance model emerged from our findings. One reason could be that statements are made in interviews that affect several aspects of the theoretical construct equally and overlap. For an overall understanding of the attitudes towards technology, a complementary quantitative approach based on the TAM3 would be suitable. However, we found that, in particular, the 'user participation', 'management support' and 'organizational support' are seen as relevant by the health professionals.

The model highlights that user experience highly influences all aspects of intention to use a technology. Bourla, Ferreri [20], for example, indicated that psychiatrists' resistance to technology is due to fear of loss of control because of missing involvement and knowledge. To achieve the supportive effect of digitalisation for health professionals, the technologies must function according to the health professionals' expectations. In addition, health professionals must be trained in the usage of these technologies. Also, guidelines for using technologies at work must be made available to the health professionals [44]. For example, the guideline for work-specific emails within the organization should define, which information should be sent to who, during which time slot and who should be in carbon copy (cc). With regard to the phone, the guideline should define, during which tasks a forwarding of the phone is allowed and for which questions one reports to the responsible person by phone. Such clarification should lead to a reduction of interruption at work [44].

Strengths and Limitations

One strength of this study is that it has given the health professionals' a voice regarding their experiences with technology at work. The results highlight that the health professionals have a clear attitude towards technologies but that those attitudes are not being met accordingly. Moreover, trustworthiness has been established by aiming for credibility, dependability and confirmability [45]. Researchers and data managers of health organisations can use the script file to conduct projects with comparable aims without the need for major adjustments of the data pre-processing and analysis. The data set can be extended by additional transcripts without additional effort, or the analysis can be re-evaluated with new transcripts on a recurring basis. Confirmability was extended by reducing the researcher's influence on the result by replacing part of the manual work by systematic computational processes.

The current results should also be viewed in terms of some limitations. One limitation of the study is the number of transcripts included. No generalizability is possible due to small sample size. However, data saturation was reached, since no new topics regarding implemented technologies at work emerged by increasing in the number of interview transcripts in the analysis [35]. Furthermore, a recent systematic review on minimum sample size for data saturation in qualitative research concluded that 9 – 17 interviews were found to be sufficient to reach data saturation, which was met in this study [46]. Nevertheless, text mining is known for the analysis of comprehensive data sets that are too large to be analysed manually [36]. A few technologies could not be sufficiently related to sentiments because they were rarely mentioned in the transcripts used. Increasing the number of interviews could have provided further insights regarding the health professionals' sentiments towards technologies at work. However, regarding the mentioned data saturation, it is not granted that more interviews would allow other technologies to be linked to sentiments. Another limitation lies in the data pre-processing. Data pre-processing of unstructured German text data is limited to the available software packages. The authors of the spacyr package used for the lemmatisation reported an accuracy of 73% for this process, which led to words that have not been or incorrectly lemmatised [30]. These errors had to be corrected manually and will differ from other data sources. Moreover, the SentiWS does not allow automatic detection of sentences with negation. Although this was considered in our data pre-processing [34], it bears the risk of not having identified all negated statements as such. Also, the SentiWS does not include all sentiments of German language but is being updated continuously [33]. However, with regard to comparable lexicons, the SentiWS showed better performance in terms of identifying sentiments [47]. Some of the questions from the interview guide were negatively phrased, in particular, those focussing on Computer Anxiety. Albeit the determinant elaborates the anxiety towards technology usage, negative formulated questions might have influenced the interviewees' tendency. Furthermore, it cannot be excluded that a sampling bias is present. The convenience sampling approach could have introduced some bias that people who are already sensitised to the topic and are interested in expressing their views are more likely to participate. The slight tendency to make negative statements about technologies and the identification of positive and negative properties, however, suggests that no extreme opinions were represented in this sample.

Conclusions

This project has highlighted that behind a positive or negative attitude towards technologies, there can be a tension between desired added value and experienced disadvantages. Nurses, physicians and psychologists in psychiatric hospitals mentioned a limited number of technologies at work, with the computer, documentation in the electronic health record and communication via email being the most discussed technologies. The results indicate that the current technologies do not meet the health professionals' expectations. Future research should focus on implementation studies including health professionals' sentiments to identify important factors for a successful implementation. Health professionals should be involved early in the development process, and research should support psychiatric hospitals in this process from development to evaluation of digital solutions at work.

Declarations

Ethics approval and consent to participate

The Swiss ethical board of the Canton of Bern confirmed that the study was not subject to the Swiss Federal Act on research involving human beings (Req-2020-00179). The study was conducted in accordance with the Declaration of Helsinki. Participants received written information before the start of the study about the contents, the aim and the voluntary nature of their participation and gave their written informed consent. The data were anonymised during the data preparation process to ensure anonymity of the participants.

Consent for publication

Not applicable

Availability of data and materials

The datasets generated and/or analyzed during the current study are not publicly available due to potentially patient identifiable information as part of data. Anonymized data supporting the findings of this study are available from the corresponding author Christoph Golz, christoph.golz@bfh.ch. The script file and interview guide are available as supplement.

Competing interests

The authors report no conflict of interest. The authors alone are responsible for the content and writing of the paper.

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Authors' contributions

S.A, S.H., S.Z and C.G developed the interview guide. C.G. conducted the interviews. S.A., C.H., and C.G. analysed the data. S.H. and S.Z. supervised the findings of the work. C.G. drafted the manuscript and designed the figures. All authors discussed the results and commented on the manuscript.

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Multimedia Appendix A

Determinants of the TAM	Nr.	Questions
Computer Self-Efficacy	1	What do you think of when you hear 'digital technologies'?
Experience	2	Describe a typical working day.
Experience	3	For which activities do you use digital technologies?
Experience	4	How do you experience the impact of digital technologies on your everyday work?
Job Relevance	5	What role do digital technologies play in your work?
Output Quality / Result Demonstrability /	6	From your point of view, what are the 3 most stressful digital technologies you use?
	6.1	Why do you experience the [technology] as stressful?
	6.2	How does the [technology] influence your performance?
Output Quality / Result Demonstrability	7	From your point of view, what are the 3 most supporting technologies you use?
	7.1	Why do you experience the [technology] as supporting?
	7.2	How does the [technology] influence your performance?
Experience	8	What digital technology has been implemented recently and how did you experience this implementation?
Experience	9	Tell about a sense of achievement in working with digital technologies.
Computer Self-Efficacy	10	How do you assess your competence in dealing with digital technologies in your workplace?
Perceived ease of use	11	Can you tell me how you rate the reliability of the digital technologies provided in your workplace?
Computer Anxiety	12	How do you experience the overload caused by digital technologies in your work?
Computer Anxiety	13	To what extent are you concerned about exposing your privacy using digital technologies?
Management / Organizational support	14	Do you sometimes have to work with the digital technologies in your free time?
Management / Organizational support	15	Describe how you can separate your private life from your work due to digital technologies.
Management / Organizational support	16	How do you experience the change in your role due to digital technologies?
Management / Organizational support	17	To what extent are you interrupted in your work by digital technologies?
Objective Usability	18	Give an example of how you deal with the demands on you with regard to digital technologies.
Design characteristics	19	How do you feel about the possibility of another person being able to monitor all your performance through a digital technology?
User participation	20	What digital technologies would you like to have to better manage your work?

Multimedia Appendix B

Path to the R script file:

https://github.com/ChristophBFH/text_mining_10.1186-s12913-022-08823-4/blob/f77d4b51a5823dbc3c84e249b325d5dd5be5ec51/Supplementary_A.R

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CHAPTER 5

Content Validation of a Questionnaire to Measure Digital Competence of Nurses in Clinical Practice

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Abstract

Clinical practice nurses need adequate digital competence to use technologies appropriately at work. Questionnaires measuring clinical practice nurses' digital competence lack content validity because they miss attitude as part of the underlying definition of digital competence. The aim of the current study was to identify items for an item pool of a questionnaire to measure clinical practice nurses' digital competence and to evaluate the content validity. A normative Delphi study was conducted, and the Content Validity Index on item and scale level was calculated. In each round, 21 to 24 panelists (medical informatic specialists, nurse informatics specialists, digital managers, and researchers) were asked to rate the items on a 4-point Likert scale ranging from not relevant to very relevant. Within three rounds, the panelists reached high consensus and rated 26 items of the initial 37 items as relevant. The average Content Validity Index of 0.95 (SD = 0.07) demonstrates that the item pool showed high content validity. The final item pool included items to measure the knowledge, skills, and attitude. The items included represent the international recommendations of core competences for clinical nursing. Future research should conduct psychometric testing for construct validity and internal consistency of the generated item pool.

Keywords

Clinical practice nurse, digital competence, delphi study

Introduction

Nurses globally are increasingly affected by digitalization, such as the everyday use of electronic health records, on each working day [1-3]. The digitalization of healthcare has brought numerous possibilities for utilizing digital technologies at work in nursing [4]. On one hand, these possibilities impact nursing interventions, such as the use of telehealth to reduce emergency admission for patients with chronic diseases [5]. On the other hand, they are used to enhance administrative processes such as the implementation of electronic health records [6].

According to the Technology Acceptance Model [7], the extent to which technologies are perceived as helpful and useful is determined by the 'Perceived Ease of Use' and the 'Technology Self-Efficacy'. 'Technology Self-Efficacy' is the perceived degree to which an individual thinks he or she has the ability to interact with a specific technology [7], also known as digital competence [8]. Insufficient digital competence of health professionals has shown to be associated with a higher stress level induced by technology at work [8], which in turn can lead to higher burnout symptoms or lower job satisfaction among health professionals [9]. Thus, nurses need adequate digital competence [1] to use technologies appropriately and stay healthy at work. This has been acknowledged internationally, and the American Association of Colleges of Nursing described "Informatics and Healthcare Technologies" as part of the core competencies for nursing education [10]. These core competencies describe the ability to identify suitable technologies and to use them accordingly. However, these competencies differ across the specific nursing roles, such as nurse managers, nurse informatics specialist, or nurses in clinical practice [4]. Whereas nurse managers play a central role when it comes to strategic decisions regarding implementation of technology and allocation of financial resources, nurses in clinical practice use technology to control patients' health state, to secure patient related information, and for interprofessional communication. Nurses in clinical practice use digital technologies for care planning and clinical reasoning, among other patient-related tasks [11].

Even if the technology-related tasks differ across nursing roles, the predominantly underlying definition of digital competence is the same. It is comprised of knowledge and skills as its denominators [4]. However, competence [12] not only comprises knowledge and skills but also attitude. For digital competence, attitude describes the feelings towards technology or the way of behaving when interacting with technology at work [13]. The missing inclusion of attitude in studies about the digital competence of nurses is problematic insofar as a positive attitude towards and good experience with technology are known to be crucial aspects for successful implementation and usage of technologies [13-15]. For example, using the electronic health record means that nurses should know what happens to the data entered and what can be done with it (knowledge), and that they can open and close the program, edit the content, and communicate within the program (skills). Also, they are not reluctant to use the program for information exchange (attitude).

To improve the digital competence of nurses in clinical practice at work, nurse managers and those responsible for nurse training and further education need information about the nursing staffs' current digital competence level. A recent scoping review about the assessment of nursing digital competence summarizes fourteen questionnaires between 2009 and 2019. The majority of questionnaires have included more than 50 items, and this hampers their usability due to time requirements [4]. This is especially important for nurses in clinical practice as they have time constraints and often experience a heavy workload [16].

In total, 10 questionnaires were found to only focus on the topic knowledge and skills4. The other four identified questionnaires to measure nurses' digital competence from the scoping review. These included topic knowledge, skills, and attitude [4]. One of the four questionnaires was specifically developed for entry-level nursing students [17]. The other three questionnaires are based on the Self-Assessment of Nursing Informatics Competencies Scale (SANICS). SANICS is based on a specific curriculum for Wireless Informatics for Safe and Evidence-based Advanced Practice Nurse Care and thus focuses additionally on questions about the usage of wireless devices at work [18]. The focus may not be equally relevant for all nurses in clinical practice because digital maturity in healthcare differs internationally, and thus wireless devices are not regularly implemented [19, 20]. Furthermore, SANICS was developed for nursing students, and thus it also includes research and presentation skills [18] which do not reflect the top 10 core competency areas of clinical nursing from the Technology Informatics Guiding Education Reform (TIGER) [11]. Therefore, a new brief questionnaire to measure nurses' digital competence in clinical practice is needed to overcome these drawbacks.

The Guidelines in Scale Development by DeVellis [21] is often used in scale development. This includes the following 8 steps: (1) Determine clearly what we want to measure, (2) generate an item pool, (3) determine the format of measurement, (4) have initial item pool reviewed by professionals with knowledge in the field, (5) consider inclusion of validation items, (6) administer items to a development sample, (7) evaluate the items, and (8) optimize scale length. The first four steps lead to an initial item pool that is rated as relevant by professionals with knowledge in the field, and this allows one to elaborate for content validity [21]. Therefore, the aim of this study was to identify relevant items for an item pool to measure clinical practice nurses' digital competence comprising the dimensions knowledge, skills and attitude and to evaluate the items' content validity.

Materials & methods

To reach the goals, we used a qualitative-quantitative approach by conducting a normative Delphi study to reach the content validity of the initial item pool [22]. The normative Delphi technique is a structured and iterative process with a series of surveys (rounds) in which individuals with knowledge in the respective field rate proposed theory-based items for their thematic relevance in order to reach a consensus about the relevant items which describe the theoretical construct [23].

Preparatory steps before the Delphi study

To prepare the Delphi study, the first three steps by DeVellis [21] were processed. For a description of the construct 'digital competence' as well as the identification of the initial item pool, we conducted a literature search to identify relevant literature which hasn't been included in two recently published reviews [4,13]. The focus was on the identification of questionnaires for nursing digital competence 4 and the definition of health professionals' digital competence [13]. The keywords were based on both of the identified reviews: "skills, competency, literacy, knowledge, attitude, expertise, ability, know-how" AND "Healthcare Informatic Technology, computer, Information Computer Technology, informatics, medical technology" AND "nurs*, health professional, health care". For the literature search, the databases Web of Science, MEDLINE, CINAHL, PubMed, and Google Scholar were used. Only articles in German and English were included. Articles about scale development or articles discussing definitions of digital competence for nurses or health professionals were included. Articles which only cited a definition of digital competence in healthcare or only used a questionnaire to measure nurses' digital competence were excluded after screening the respective references. In this study, we used the following description of nurses' digital competence for the development of the item pool: (1) A person must "have underlining knowledge, functional skills, and appropriate social behavior (e.g., attitude) to be effective at work" [12]. Thus, the digital competence of nurses in clinical practice is comprised of knowledge, skills, and attitude [13]. (2) Even though a brief questionnaire was aimed at the first item pool, a large amount of items were expected to minimize the bias of missing out in order to reflect the full construct [21]. The research group developed 37 items based on the findings from the literature search and organized the items into the three categories (knowledge, skills, and attitude) in MS Excel with 9 items for knowledge, 9 items for skills, and 19 items for attitude. More items for attitude were included because it was seen to be difficult to measure this with items, and therefore a sufficient number of items are important for the item pool [21]. The items were formulated in a more general way in order not to develop a questionnaire that would be too time-consuming for a nurse in daily practice. Furthermore, the items were positively phrased, because negatively phrased items were found to be less reliable [24], as well as a combination of both negatively and positively phrased items [25]. For example, instead of asking for specific skills and/or situations, such as "restarting the computer", the research group developed an item that subsumes this case and comparable cases for error management with technology: "I know how to manage errors of digital technology. (3) For the measuring format, a 5-point Likert scales was chosen because it is the most common item format for measuring opinions, beliefs, and attitudes [21].

Review of the item pool

Study sample

Sampling was conducted by contacting relevant international associations by email. These included the Canadian Nursing Informatics Association, AMIA's

Nursing Informatics Working Group, and Schweizerische Interessengruppe Pflegeinformatik. The associations were asked to forward the invitation to their members for the participation of their networks by snowball sampling. The email included information about the study's aim and the invitation to participate in all rounds. Furthermore, potential panelists of the research group's network were contacted directly and invited to participate with the same invitation email. When a participant dropped out in one round, we tried to find a replacement by contacting the associations and research group's network again. Although participants in Delphi studies are often referred to as experts, it is recommended to refrain from labelling the participants as experts because having knowledge in a specific field does not imply having expertise [26]. Thus, the inclusion criteria for the panelists were as follows: a completed training program as medical or nurse informatics specialist, a digital manager working in a health organization, or a researcher with expertise in the field (e.g., publications in the field). This was to ensure that different perspectives from research and practice were represented [26].

Data collection

The Delphi survey was distributed using the online survey UmfrageOnline® (enuvo GmbH, Pfäffikon, Schwyz, Switzerland). The Delphi comprised as many rounds as needed to reduce the variance of the opinions so that they became more homogeneous [27]. In the rounds, the panelists were asked to rate each item on a 4-point Likert scale (1 = not relevant, 2 = somewhat relevant, 3 = quite relevant, 4 = very relevant) as proposed by Polit and Beck [22]. The panelists could also add comments as free text to suggest changes in the phrasing of the respective items or to suggest additional relevant topics as items for the upcoming rounds. After each round, the panelists received an online report on the results of the previous round regarding the item's relevance and the research team's decisions from the free text data. The panelists could thus reproduce the decisions to exclude an item or to add new items.

Data analysis

To quantify the panelists' consensus that all relevant questions would be asked to measure nurses' digital competence in clinical practice, an analysis for the content validity was conducted with the software R (R Studio, Boston, Massachusetts, United States of America) [28]. Content validity describes the item sampling adequacy, which means that high content validity exists if the item pool reflects the defined construct [21]. In the current study, this is clinical practice nurses' digital competence. In each round, an item content validity index (I-CVI) score was calculated that evaluated the relevance of each item [22]. The I-CVI is computed as the number of panelists giving a rating quite relevant or very relevant in the rounds divided by the total number of panelists [22]. A decision in favor of an item was made with a threshold of the I-CVI greater than 0.80. This means that the item would be excluded in the case of a CVI below 0.8. In addition, the average scale-level content validity index (S-CVI/Ave) was computed for the last round. This is the average of all I-CVI. For acceptable content validity, a S-CVI/Ave of 0.90 or higher is expected [22]. The free text was clustered thematically and discussed in the research group until a consensus was reached on how to rephrase an item or if the suggestions resulted in an additional item.

Ethical considerations

This study is not covered by the Swiss Human Research Act. Accordingly, there is no approval from the responsible authority. Before the start of the study, the panelists received written information about the contents, the aim of the study, and the voluntary nature of their participation. They gave their informed consent by confirmation via survey link. The data were anonymized during the data preparation process, and it did not allow tracing back to the panelists. The panelists had the option to stop their participation without giving a reason.

Results

Overall, three rounds of this Delphi study were conducted between May 2020 and January 2021 in order to reach the requirements for a content valid item pool to measure nurses' digital competence in clinical practice.

The mean age of the panelists in all rounds was 45.5 (SD = 9.6), and the majority were male (n=17, 59%). The majority of the panelists were from Switzerland (n = 15, 51.7%), followed by Germany (n = 6; 20.7%), Netherlands (n = 3; 10.3%), United Kingdom (n = 3; 10.3%), Austria (n = 1; 3.4%), and Italy (n = 1; 3.4%). Regarding their profession, the majority of the panelists were nurse informatics specialists (n = 16; 55.2%), followed by digital managers (n = 8; 27.6%), researchers (n = 3; 10.3%), and medical informatics (n = 2; 6.9%).

The number of items in the Delphi study per round are summarized in Figure 1.

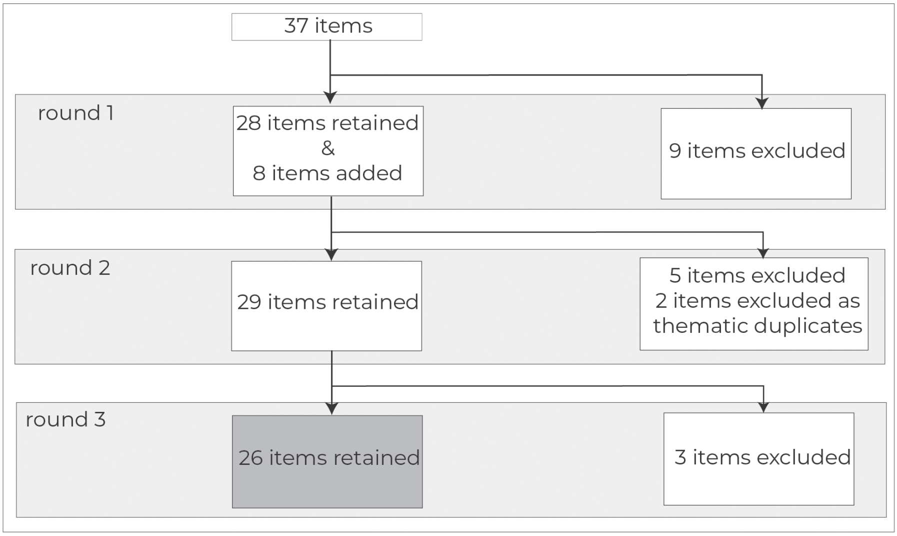

Figure 1: Number of items per round for the Delphi study

Round 1

The first round took place in May – June 2020 with 24 panelists. In the first round, the I-CVI of the 37 items (knowledge = 9, skills = 9, attitude = 19) ranged between 0.33 and 1.00, showing a high variance regarding the rated relevance across the initial items. Overall, 9 out of the 37 initial items (knowledge n= 4, skills n= 2, attitude n= 3) had an I-CVI below 0.8 and were therefore excluded from the second round (Table 1). The main comment of the panelists on items with a I-CVI below 0.8 was that these items were not relevant for nurses in clinical practice. For instance, the item "I am familiar with the digital technology activities in the world" was rated as not relevant because it was formulated too broadly, and the familiarity with digital technology at the workplace was seen as sufficient for nurses' clinical work. The item "I know how to manage errors of digital technology" was also rated as not relevant because the panelists expected that nurses in clinical practice contact IT-support if errors with digital technologies occur at the workplace. The panelists provided 8 additional items which were rephrased to meet the items' structure, and these were added in round two. They included items such as "I am aware that patients themselves are increasingly using digital technologies to manage their symptoms" or "I am able to reach conclusions based upon information gathered on digital technologies".

Table 1: List of excluded items with the I-CVI below 0.8 in all three rounds

Items	I-CVI
Knowledge (n=9)	
I am confident in providing a definition of digital technology.	0.44
I am familiar with the digital technology activities in my country.	0.67
I am familiar with the digital technology activities in the world.	0.33
I am familiar with the current limitations of digital technologies.	0.71
I am aware that digital technologies can only assist me in the decision-making process.	0.39
It is clear to me why standardized comparable data are needed in the nursing profession.	0.72
I am aware that only a standardized nursing language offers the basis for evidence-based nursing development.	0.11
I am familiar with the digital technology activities employed by my organization.	0.71
I am familiar with the latest possibilities offered by digital technology at my workplace.	0.71
Skills (n=3)	
I know how to manage errors of digital technology.	0.59
I can support my team in the application of digital technologies.	0.75
I feel confident in advising my patients on the use of digital technologies to support their recovery.	0.65
Attitude (n=5)	
Innovation in digital technology should be a priority of the decision makers.	0.57
I would like to support the development of useful digital technology.	0.71
I would find new digital technologies easy for me.	0.57
Digital technologies promote the involvement of patients in documentation and treatment.	0.76
I use digital technology even if it is not mandatory.	0.67

Round 2

Round two was conducted during August – September 2020 with 21 panelists. Overall, 6 panelists from the first round dropped out (dropout rate = 25%), and 3 new panelists were added to the sample. In the second round, the I-CVI of the 36 items (knowledge n= 12, skills n= 8, attitude n= 16) ranged between 0.11 and 1.00. In total, 5 (knowledge n= 3, skills n= 1, attitude n= 1) out of the 36 items had an I-CVI below 0.8 and were therefore excluded from the third round. All 5 excluded items were added for round two based on the panelists' comments from round one. The panelists comments on the items with I-CVI below 0.8 were that they were too specific and more relevant for nurse informatics specialists. "The awareness that standardized comparable data are needed in the nursing profession" is an example of an item with I-CVI below 0.8. The panelists' comments in round two resulted in a revision of 5 items in the skills topic for uniformity of the wording as follows: "I feel confident about using digital technology to [...]". Five further comments concerned the similarity of three items focusing on "ethical", "privacy" and "confidentiality". The research group decided to reduce the three items to one item in favor of the topic "confidentiality", as proposed by the panelists. It is argued that "confidentiality" refers to the duty of anyone entrusted with health information to keep that information private, which is understood as ethical handling of electronical health information.

Round 3

Round three took place during December 2020 – January 2021 with 21 panelists. After the second round, 2 panelists dropped out (dropout rate = 9.5%), and they were replaced by 2 new panelists. The questionnaire for the third round was comprised of 29 items (knowledge = 6, skills = 8, attitude = 15). The I-CVI ranged between 0.67 and 1.00, showing a lower variance across the rated items than in the rounds before. Overall, 3 out of the 29 items had an I-CVI below 0.8 and were therefore excluded (Table 2). The S-CVI/Ave for the list of the final 26 items (knowledge = 4, skills = 8, attitude = 14) was 0.95 (SD = 0.07).

Table 2: Final list of items with the I-CVI

Items	I-CVI
Knowledge (n=4)	
In general, I would rate my knowledge of digital technology as satisfactory.	1.00
I am familiar with digital technologies at my workplace.	0.95
I am familiar with the current laws and regulations pertaining to the protection and exchange of medical data (e.g., data protection, informed consent, and confidentiality) at my workplace.	0.86
Patients use digital technologies to manage their symptoms themselves.	0.81
Skills (n=8)	
I feel confident in dealing with confidentiality issues relating to digital technology at my workplace.	1.00
I feel confident about using digital technology to share information.	1.00
I feel confident about using digital technology to obtain data and information on clinical care.	1.00
I am able to reach conclusions based on information acquired through digital technologies.	1.00
I feel confident about using digital technology to communicate.	0.90
I feel confident about the secure management of health data using digital technology.	0.90
I feel confident about using digital technology to find relevant information.	0.86
I feel confident about using digital technology.	0.81
Attitude (n=14)	
Digital technologies will make my day-to-day work easier.	1.00
I have an open attitude towards digital technology-related innovations at my workplace.	1.00
Digital technology fits well with the way I like to work.	1.00
I enjoy using digital technology at my workplace.	1.00
I encourage others to use digital technology in their professional practices.	1.00
I am willing to improve my ability to use digital technology through further training.	1.00
I believe that digital technology provides numerous benefits in terms of quality of care.	1.00
I believe that digital technology improves clinical care.	1.00
I believe that digital technology improves patient outcomes.	1.00
I believe that digital technology is beneficial for my patients.	1.00
I believe that digital technology is beneficial for health professionals.	1.00
I like to use digital technology at work.	0.90
I am keen to use new digital technologies in my future professional practices.	0.86
I believe that digital technology is relevant for my future profession.	0.81

Discussion

The current study focused on the identification of a content valid item pool as the basis for a future questionnaire measuring the digital competence of nurses in clinical practice. It is comprised of the dimensions knowledge, skills, and attitude. The Delphi study resulted in 26 items (knowledge = 4, skills = 8, attitude = 14) derived from a 37-item pool with an acceptable S-CVI/Ave score above 0.9. We included proportionally more items (n=19) on the topic attitude than on the other topics in order to have the expert panel evaluate their relevance, and the expert panel rated 14 out of them as relevant. This underlines the importance of attitude as one topic of digital competence.

The excluded items show the expert panels' consensus that nurses in clinical practice are not expected to solve problems with digital technologies themselves but to have them solved by the IT-support. The panelists rated topics such as being familiar with the current limitations of digital technology or the ability to manage errors of digital technology as not relevant for clinical practice nurses. The low relevance for managing errors or solving problems with digital technology by nurses in clinical practice goes in line with the international recommendations of core competences for clinical nursing [11, 29].

The expert panel also rated the relevance of the items about the nurses' familiarity of available digital technologies in the world or supporting the development of useful digital technology as low. Hence, nurses working in clinical practice are not expected to have a comprehensive overview of potential available digital solutions or to support in the development of digitalization processes at work according to the panelists. This might be a problematic estimation across all nursing generations, since generation z nurses (e.g., digital natives), in particular, have a more comprehensive knowledge about the possibilities of technology and expect active usage of technology at work [30]. Thus, they could contribute to finding innovative solutions at work. However, with this focus, technological innovation is limited to top down, as nurses in clinical practice are not expected to engage with it. For the item pool, this could mean that future adaptions of it might be necessary to meet the ongoing changing role of nurses in clinical practice influenced by disruptive change and new abilities of younger generations within the field of technology usage at work.

The current 26 items, which were rated as relevant, present an item pool and not a final version of the questionnaire to assess digital competence. The next steps in the guidelines describe the process for conducting a factor analysis on this draft 26 item pool and testing it for internal consistency. The findings of these tests could result in item reduction and may lead to a brief valid and reliable questionnaire which can be used to assess digital competence.

Compared with other questionnaires measuring nurses' digital competence, the items in this questionnaire have a more general wording, which means that the items are not formulated to match specific skills but rather to an overarching topic. Whereas SANICS asks specifically for the ability to navigate the operating system Windows, for example [18], the present questionnaire broadly elaborates the ability to use digital technology. On one hand, SANICS is thus limited to the evaluation of technologies using a specific operating system. On the other hand, specific mentioning of an operating system implies that nurses know the corresponding operating system for each device they use. In the course of increasing change with regard to software and hardware in healthcare [1, 2], a more general formulation of the items seems more timeless. Further comparison of the present questionnaire with other available questionnaires measuring nurses' digital competence should be conducted by evaluating concurrent and criterion validity in future research.

Strengths and Limitations

One strength of the study is the multistep Delphi study to achieve satisfactory content validity by involving different professions with knowledge in the field. Within the multistep procedure, the panelists can think about the topics' relevance for several rounds and reassess their initial ratings [31]. The controlled feedback process between the research group and panelists made both the researchers' and panelists' decisions traceable [31].

There are also limitations to be considered. We cannot exclude potential sampling bias of the panelists in this study since no evaluation of the panelists' underlying understanding of digital competence preceded, and we conducted a convenience sampling. Nonetheless, the panelists rated items from knowledge and skills as not relevant, indicating that all panelists found the items relevant, which described the nurses' attitude towards technology at work. Yet, it may be that other panelists would have rated differently. Furthermore, the study only allows us to interpret the content validity. For a questionnaire to be used in future research and practice, further validation for construct validity, concurrent validity, criterion validity, and internal consistency is needed.

Conclusions

This Delphi study led to a content valid item pool as a basis for the development of a brief questionnaire for clinical practice nurses' digital competence. Further psychometric testing is needed before it can be applied. The study contributes to the discussion about the definition of nurses' digital competence by indicating that the nurses' attitude is seen as relevant in the context of digital competence.

Acknowledgments

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CHAPTER 6

Psychometric validation of the Digital Competence Questionnaire for Nurses

This chapter was submitted as: Golz, C., Hahn, S., Zwakhalen, S.M.G., *Psychometric validation of the Digital Competence Questionnaire for Nurses.* Nursing Open, submitted.

Abstract

Aim: To evaluate the construct validity and internal consistency of the Digital Competence Questionnaire for Clinical Practice Nurses.

Design: A cross-sectional study was conducted with a sample of English-speaking clinical practice nurses.

Methods: 26 items from an initial item pool, developed in a previously conducted Delphi Study, were included. Exploratory factor analysis for construct validity with "oblimin" rotation and a two-factor solution, as well as an internal consistency test using Cronbach's alpha, was conducted.

Results: Data were obtained from 185 clinical practice nurses. The final questionnaire consisted of 12 items allocated to two factors: knowledge & skills (n = 6) and attitude (n = 6). The factor 'attitude' explained 33% of the variance and the factor 'knowledge & skills' 24%, resulting in a cumulative explanation of the variance of 57% by both factors. The internal consistency of the total scale and per factor was satisfactory.

Conclusion: The Digital Competence Questionnaire for clinical practice nurses is valid and has acceptable internal consistency. Future validation of psychometric parameters, such as test-retest reliability, discriminative validity, and sensitivity to changes in the questionnaire, is needed to allow a conclusion on the goodness of fit.

Implications for the profession: Researchers can use the questionnaire to evaluate digital competence among clinical practice nurses and use the mean score as a primary outcome for intervention studies. Nurse managers may assess the level of digital competence at entry of clinical practice nurses to identify their needs.

Contribution: Clinical practice nurses were invited to fill out the online survey.

Impact

- What problem did the study address? No questionnaire on digital competence among clinical practice nurses has yet been developed to measure knowledge, skills, and attitude in a timely manner.
- What were the main findings? The Digital Competence Questionnaire for clinical practice nurses is valid and internal consistent.
- Where and on whom will the research have an impact? Research and clinical practice for measuring digital competence among clinical practice nurses.

Keywords

digital competence, digital literacy, nurse, cross sectional study, questionnaire, assessment, digital technology, psychometric validation, construct validity, internal consistency

Funding details

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Introduction

Digital competence is the degree to which an individual thinks he or she has the ability to interact with technology [1]. It comprises the theoretical understanding of how a technology can be used (knowledge), the ability to use the technology (skills), and the feelings towards technology or the way of behaving when interacting with technology (attitudes) [2, 3] (Figure 1).

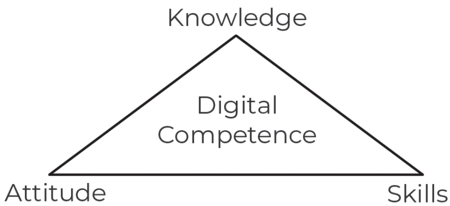

Figure 1: Framework of digital competence

In times of digital progress in the health sector, it is becoming increasingly important for clinical practice nurses to have sufficient digital competence, since it has been found to be an inhibitor of technology-related stress at work [4]. The so-called technostress can lead to higher burnout symptoms or lower job satisfaction among nurses [5], which in turn are associated with increased intention to leave the organization [6]. Clinical practice nurses spend most of their workday providing direct care to patients as face-to-face interactions in all kinds of settings within the health sector. They interact with technology, for example, by entering the information in the electronic health record and should be able to securely manage and transfer these data [7].

Digital competence can be measured by using self-reported questionnaires. A scoping review from 2021 summarized fourteen questionnaires to measure nurses' digital competence [2]. The majority of these questionnaires focus on undergraduate or graduate students, nurse leaders, or nurses informaticists, and six of them were developed for nurses in clinical practice [2]. One of those is the TIGER-Based Assessment of Nursing Informatics Competencies (TANIC), with 85 items consisting of computer skills, information knowledge, and clinical information management [8]. Shortcomings of the available questionnaires measuring digital competence of clinical practice nurses include their sole focus on knowledge and skills [2] and neglect of individuals' attitudes at part of the digital competence definition [3]. A positive attitude towards technology at work in healthcare is associated with successful implementation and usage of technology at work [3]. For example, it is known that technical issues and low reliability of implemented electronic health records leads to negative experiences among nurses with technology and consequently worsening of their attitudes towards using technology at work [9].

The majority of the questionnaires summarized in the review of Kleib, Chauvette [2] such as the TANICS are lengthy and have more than 50 items and thus require a lot of the participants' time to fill them out. In recent years, the response rate in surveys has fallen sharply, and the forecast indicates a further decline [10]. Whereas in the 70's the response rate in surveys was high with approximately 75%, it is now usual to reach approximately 30%. The projected response rate for 2035 is expected to be near 20% [10]. There are different approaches to increase the response rate, such as the combination of different survey methods (e.g. phone, e-mail and mail), but also the inclusion of the minimum questions needed to cover the questioned topics [11]. Thus, in order not to burden nurses more than they are already through their work and still obtain adequate responses, research should aim to minimise the time needed to fill out questionnaires by obtaining their ability to measure the construct [2].

Hence, a new brief questionnaire is needed to measure digital competence among nurses in clinical practice, paying attention to knowledge, skills, and attitudes. For this purpose, in a previous study, a Delphi Study was conducted, resulting in an initial item pool with 26 items with high content validity (average Content Validity Index = 0.95) [12]. The aim of this study was, therefore, to evaluate the construct validity and internal consistency of the Digital Competence Questionnaire for clinical practice nurses (DCQ).

Methods

The development of the DCQ for clinical practice nurses was based on the Guidelines in Scale Development by DeVellis [13]. This includes the following eight steps: (1) Determine clearly what we want to measure, (2) generate an item pool, (3) determine the format of measurement, (4) have initial item pool reviewed by professionals with knowledge in the field, (5) consider inclusion of validation items, (6) distribute the survey, (7) perform item reduction, and (8) perform psychometric analysis of the reduced questionnaire. As preparation for the psychometric validation, an initial item pool with 26 items (knowledge n = 4, skills n = 8, attitude n = 14) was generated in the first five steps [12]. In this paper, we focus on the remaining three steps as described by DeVellis [13]: (6) survey distribution, (7) item reduction, and (8) psychometric analysis of the reduced questionnaire.

Survey Distribution

Study sample

To test the construct validity and internal consistency of a questionnaire, 5–10 participants per item (question) of a scale are recommended [13]. Therefore, we aimed for a sample size between 130 and 260 participants based on the initial item pool with 26 items. A combination of convenience and snowball sampling with English speaking clinical practice nurses was conducted internationally to complete an online survey.

Data collection

A cross-sectional study was conducted using the online survey tool SurveyMonkey® between January and March 2022. Emails with information about the study's aim, inclusion criteria, data protection, and the survey link were sent directly to clinical practice nurses were reached from the researchers' network by email and asked to forward the invitation to their colleagues. Private social media groups for clinical practice nurses on Facebook and Reddit were contacted and asked to forward the invitation for participation to their members. The study information along with the survey link was posted in private social media groups. Participation was voluntary.

Instrument

The instrument included questions on individual characteristics (age, country, and profession) and items related to digital competence. Only the question on profession was a mandatory question and was designed to exclude participants from the analysis who did not belong to the sample. The 26 initial items on the DCQ for clinical practice nurses from the Delphi Study [12] were scored on a five-point Likert-Scale from 1 ("fully disagree") to 5 ("fully agree"), with a high score indicating high self-perceived digital competence. The five-point Likert-Scale format was chosen because it is the most common item format for measuring opinions, beliefs, and attitudes [13].

Item Reduction and Psychometric Analysis

Data analysis

Data analysis was conducted using the statistical software R [14] and the package 'psych'. Missing data was handled by listwise deletion if at least one item was missing from the 26 items on digital competence. The analysis comprised a descriptive analysis (mean, median and standard deviation, minimum, maximum, skewness, kurtosis) and an exploratory factor analysis (EFA) for construct validity and an internal consistency test using Cronbach's alpha with satisfactory values >0.7 [15]. Skew and kurtosis are known to have a relevant impact on the EFA results with skewness ≥ ±2 and kurtosis ≥ ±7 [15]. The assumptions for an EFA are item correlations above 0.3, a significant Bartlett's test of sphericity, and Kaiser-Meyer-Olkin values ≥0.7 for the included items and all items combined [15]. If an item did not meet one of the criteria, it was excluded from the next steps, and all assumptions were re-evaluated. For the EFA the rotation method "oblimin" was used, as the included items were correlated [15]. We chose the number of factors on the basis of a scree plot and parallel analysis. The parallel analysis compares the random eigenvalues with the eigenvalues from the dataset. The number of factors is defined as the number of eigenvalues from the dataset exceeding the random eigenvalues. A factor should comprise at least three items [15]. Cases with missing values for one item of the scale were excluded.

Ethical considerations

The local Swiss ethical board confirmed that the study was not subject to the Swiss Federal Act on research involving human beings (Req-2020-00179).

Participants received written information before the start of the study about its contents and aim as well as the voluntary nature of their participation and gave their informed consent by completing the first survey page. The data collection was anonymous.

Results

Of the 197 individuals who responded to the online survey in March – April 2022, 6 reported having another function in nursing, such as nurse managers (n = 4) and nurse informaticists (n = 2), and were excluded from further analysis. Overall, 191 English-speaking clinical practice nurses participated in the study. Of these, 185 completed the questionnaire, resulting in inclusion of 93.9% of cases (Figure 2).

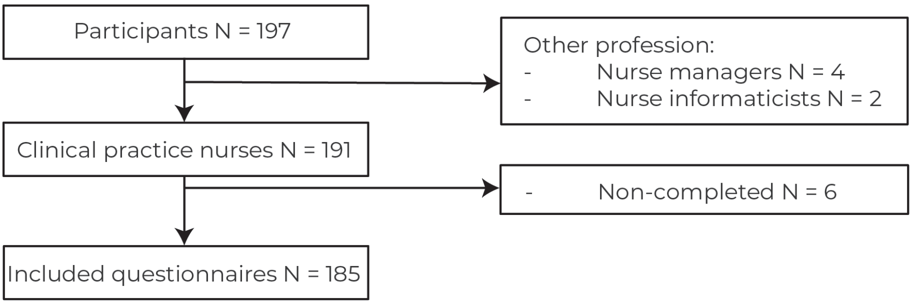

Figure 2: Flowchart detailing the number of included participants in the analysis.

The mean age was 38.40 years (SD = 9.42). The majority were from United States of America (n= 39, 21%), followed by United Kingdom (n = 33, 18%), Australia (n = 25, 14%), Switzerland (n = 22, 12%), Canada (n = 17, 9%), Ghana (n = 12, 6%), Indonesia (n = 10, 5%) and other countries (n = 27, 15%). Most of the respondents were female (n = 134, 72%) and had a bachelor's (n = 81, 44%) or master's degree (n= 72, 39%) in nursing.

Table 1 summarizes the descriptive results of the 26 items. The median of the items ranged between 2 and 5, with high scores indicating a ceiling effect. Skew and kurtosis were not found to be above the cut-offs with < ±2 for skewness and < ±7 for kurtosis. On average, the participants took 6 minutes to complete the 26-item questionnaire.

Table 1: Descriptions of the items

Nr.	Topic	Item	Mean	SD	Median	Min	Max	Skew	kurtosis
1	Knowledge	I am familiar with the digital technologies at my workplace.	4.34	0.76	4	1	5	-1.53	4.16
2	Knowledge	In general, I would rate my knowledge of digital technology as satisfactory.	4.23	0.76	4	2	5	-0.62	-0.34
3	Knowledge	I am familiar with the current laws and regulations pertaining to the protection and exchange of medical data (e.g., data protection, informed consent, and confidentiality) at my workplace.	3.96	0.92	4	1	5	-0.77	0.62
4	Knowledge	Patients use digital technologies to manage their symptoms themselves.	2.56	1.23	2	1	5	0.61	-0.56
5	Skills	I feel confident in dealing with confidentiality issues relating to digital technology at my workplace.	4.12	0.87	4	1	5	-0.58	-0.45
6	Skills	I feel confident about using digital technology to find relevant information.	4.44	0.69	5	3	5	-0.82	-0.56
7	Skills	I feel confident about using digital technology to share information.	4.24	0.77	4	2	5	-0.65	-0.41
8	Skills	I feel confident about using digital technology to communicate.	4.48	0.81	5	2	5	-1.63	2.07
9	Skills	I feel confident about the secure management of health data using digital technology.	3.91	1.08	4	1	5	-0.64	-0.51
10	Skills	I feel confident about using digital technology.	4.34	0.81	5	2	5	-0.93	-0.1
11	Skills	I feel confident about using digital technology to obtain data and information on clinical care.	4.44	0.62	5	3	5	-0.64	-0.57
12	Skills	I am able to reach conclusions based on information acquired through digital technologies.	4.23	0.77	4	2	5	-0.56	-0.67
13	Attitude	I am keen to use new digital technologies in my future professional practices.	4.46	0.74	5	3	5	-0.96	-0.56
14	Attitude	Digital technologies will make my day-to-day work easier.	4.21	0.85	4	1	5	-0.84	0.42
15	Attitude	I have an open attitude towards digital technology-related innovations at my workplace.	4.29	0.83	4	2	5	-0.98	0.22

Table 1: Continued

Nr.	Topic	Item	Mean	SD	Median	Min	Max	Skew	kurtosis
16	Attitude	Digital technology fits well with the way I like to work.	4.21	0.87	4	2	5	-0.66	-0.78
17	Attitude	I enjoy using digital technology at my workplace.	4.20	0.87	4	2	5	-0.59	-0.94
18	Attitude	I encourage others to use digital technology in their professional practices.	4.26	0.82	4	2	5	-0.92	0.19
19	Attitude	I like to use digital technology at work.	4.25	0.88	5	2	5	-0.74	-0.72
20	Attitude	I am willing to improve my ability to use digital technology through further training.	4.39	0.76	5	2	5	-0.92	-0.17
21	Attitude	I believe that digital technology provides numerous benefits in terms of quality of care.	4.23	0.83	4	2	5	-0.79	-0.22
22	Attitude	I believe that digital technology improves clinical care.	4.26	0.81	4	2	5	-0.68	-0.64
23	Attitude	I believe that digital technology improves patient outcomes.	4.15	0.82	4	2	5	-0.56	-0.58
24	Attitude	I believe that digital technology is beneficial for my patients.	4.15	0.76	4	2	5	-0.61	-0.02
25	Attitude	I believe that digital technology is beneficial for health professionals.	4.37	0.76	5	2	5	-0.95	0.13
26	Attitude	I believe that digital technology is relevant for my future profession.	4.59	0.62	5	2	5	-1.52	2.36

Construct validity

Item 4 “Patients use digital technologies to manage their symptoms themselves” was excluded from subsequent steps due to an overall low correlation below the threshold of 0.3 (r = -0.22 to -0.26). The Bartlett’s test for sphericity ($\chi 2$ (24) = 118.22, $p<0.001$) with the remaining 25 items was significant and the KMO measure of sampling adequacy showed acceptable values above 0.7 (KMO = 0.83). The scree plot and parallel analysis proposed a three-factor solution. However, when conducting the EFA, the third factor only comprised two items. Thus, we proceeded with a two-factor solution. Items 2, 7, 10, 13, 14, 15, 18, 20, 22, 25, and 26 were excluded stepwise from the analysis due to high cross-loadings above 0.4. Items 3 and 9 were excluded due to low factor loadings <0.4. The Bartlett’s test and the KMO measure were re-evaluated for each iteration. The remaining item pool consisted of 12 items. The loadings per factor from the EFA with the 12 items are summarized in table 2. For loadings above 0.4 the numbers are marked in bold. Factor 1 (Attitude) explained 33% of the variance and factor 2 (Knowledge & Skills) 24%, resulting in a cumulative explanation of the variance of 57% by both factors.

Internal consistency

All included items reached the conventional threshold of 0.7 for Cronbach’s alpha, indicating sufficient internal consistency for the questionnaire with 0.91 (CI95% 0.90–0.93). Exclusion of additional items would result in a lower Cronbach’s alpha. Thus, the highest value was reached with the remaining 12 items. Both factors also reached the desirable threshold with 0.81 (CI95% 0.79–0.82) (factor 1 attitude, n = 6 items) and 0.91 (CI95% 0.90–0.93) (factor 2 knowledge and skills, n = 6 items).

Table 2: EFA loadings

	Attitude	Knowledge & Skills
	Explained variance 33%	**Explained variance 24%**
Label	Factor 1	Factor 2
Digital technology fits well with the way I like to work.	**0.75**	-0.06
I enjoy using digital technology at my workplace.	**0.82**	0.01
I like to use digital technology at work.	**0.69**	0.08
I believe that digital technology provides numerous benefits in terms of quality of care.	**0.91**	-0.08
I believe that digital technology improves patient outcomes.	**0.72**	0.11
I believe that digital technology is beneficial for my patients.	**0.89**	-0.03
I am familiar with the digital technologies at my workplace.	0.11	**0.51**
I feel confident about using digital technology to find relevant information.	-0.07	**0.84**
I feel confident about using digital technology to communicate.	-0.03	**0.99**
I feel confident about using digital technology to obtain data and information on clinical care.	-0.1	**0.71**
I am able to reach conclusions based on information acquired through digital technologies.	0.12	**0.40**
I feel confident in dealing with confidentiality issues relating to digital technology at my workplace.	0.18	**0.45**

Discussion

This article demonstrates the construct validity and internal consistency of the 12-item digital competence questionnaire for clinical practice nurses. The factors explain a sufficient proportion of the variance, since it meets the average percentage of explained variance in behavioral science of approximately 57% [16]. The reduction from the initial 26 items with a high content validity index to a 12-item questionnaire indicates that not all 26 items are needed to explain a satisfactory variation of the latent variables [13]. This is confirmed by the high internal consistency of both factors included.

Additional items would not have led to a higher explanation of variation and therefore can be considered redundant. The internal consistency of the factor knowledge and skills was above 0.9, which may be regarded as undesirable. Such a high value may indicate that the items within a factor measure the same phenomenon and are therefore unlikely to be a valid measure of the construct. As the values of the factors cluster around this threshold of 0.9 and are below 0.95, we do consider the value acceptable [17].

Both factors fit the underlying theory of digital competence. Factor attitude (n = 6 items) assesses the participants' attitude and Factor knowledge and skills (n = 6 items) captures the knowledge and skills. Based on the gathered data, it was not possible to distinguish between knowledge and skills, although in theory they are two different entities of the concept 'digital competence' [18]. This finding is contradictory to other studies evaluating a questionnaire for undergraduate nursing students, which identified separate factors for knowledge in informatics and informatics skills [2]. One reason might be that the initial item pool from the Delphi Study included small numbers of items concerning knowledge (n = 4) and skills (n = 8). A factor should comprise at least three variables [15], and with a starting point of four items for knowledge, this might have impeded the identification of knowledge as a separate factor. As a result, the individual factors knowledge and skills were aggregated into one factor. From a theoretical perspective this is not a problem, as knowledge and skills are related and explain a part of competence [18]. Furthermore, whereas attitude is a subjective feeling, belief or opinion, knowledge and skills have in common that they can be objectified and assessed by asking to describe, for example, available information systems (knowledge) or asking to save a file (skills) [8]. This commonality may make them more susceptible to loading on the same factor, as knowledge and skills ask for something factual and attitude involves a cognitive process considering other factors such as beliefs, feelings, and behavioral intentions toward technology. Nonetheless, since knowledge and skills are aggregated into one factor, a low score in the developed questionnaire does not allow determination of whether it is due to a shortage of knowledge or skills. The reasons for a low value in the factor knowledge and skills can be concluded based on the individual item scores. For a more in-depth examination of the identified low values and to identify the exact need for action, one may use existing comprehensive scales [2]. For example, the TANIC allows elaboration of whether the clinical practice nurse needs support with updating data and information or with communicating electronically with others, such as colleagues [8].

The included items in the questionnaire were found to be relevant and sufficient by international panelists. They had overall 37 items to rate and the possibility to add further important items but ended with a 26-item pool [12]. Overall, the aim of having a short questionnaire for measuring the digital competence of clinical practice nurses was reached. The development targeted for a short questionnaire, which measures digital competence and not in addition for a multidimensional questionnaire that allows an interpretation per dimension. Also, a unidimensional questionnaire would have been a possible solution. Thus, apart from a possibly lower explained variance, the questionnaire does not have a loss in capturing digital competence.

The DCQ for clinical practice nurses can be filled out in less than six minutes. Regarding the number of items in questionnaires measuring the digital competence of nurses, our questionnaire is shorter [2] without loss of validity and reliability. For example, the reliability of other scales such as TANIC or the Canadian Nurse Informatics Competency Assessment Scale for measuring nursing informatics competence ranges between 0.81 and 0.99 [2]. Regarding validity, for some scales, only content validity was elaborated, or no validation was reported [2]. For the Canadian Nurse Informatics Competency Assessment Scale, an exploratory factor analysis was also conducted, resulting in a scale with 21 items allocated into four factors, where a distinction could be made between knowledge and skills [19]. This comparison indicates that our DCQ could be further improved to be able to differentiate between knowledge and skills without losing the necessary brevity of the scale. In particular, the shortness of our DCQ can be an advantage as it is less time-consuming for clinical practice nurses, who are already burdened by a lack of time at work.

Strengths and limitations

The development of this digital competence questionnaire called the DCQ was based on the eight steps by DeVellis [13], which lays the basis for the development of a theoretical sound and applicable questionnaire. Furthermore, it facilitates traceability of the process. We adhered to clear guidance in terms of decisions to be made based on the respective cut-off values, which has been mentioned as often missing in publications on factor analyses for scale development [13]. Factor analysis is known as a robust method for identifying items that are performing better than others [13]. To increase the robustness of the method, we applied “oblimin” for rotation and used Spearman correlation due to the non-normal distribution of the data [15]. The planned minimum sample size was reached. However, the sampling method could have led to a sampling bias since technology-savvy clinical practice nurses might to be more active on social media platforms. This could be one reason for the high ratings of self-perceived digital competence. Nevertheless, other studies also found high self-reported digital competence among nurses [5, 20, 21], which might be an indication that the sample is adequate for nursing. Furthermore, the mean age of 38 years for the participants does not indicate that only the digital natives of Generation Z have filled out the survey. In comparison with the mean age of 43 years for the nursing population in the United Kingdom, for example, the age difference seems small [22]. Other studies show that older age is associated with lower digital competence among nurses [5, 21]. In this respect, the scale needs to be validated to see if it can differentiate between age groups. Despite the potential limitation through the recruitment on social media platforms, social media as a recruitment tool in gaining increasing interest and is shown to be a cost-effective solution to reaching a suitable sample of the target population [23]. In our case, the use of social media recruitment expanded our reach of English-speaking participants.

Another reason for the high ratings of digital competence could be the self-perceived overestimation of incompetent individuals [24]. The phenomenon is known as the Dunning-Kruger effect and describes individuals’ unawareness of their own levels of competence. In particular, lower performing individuals were shown to overestimate their knowledge and skills [25], which may apply to clinical practice nurses from countries with less digitalized health sectors. To avoid the problem of measurability, adjuvant objective tests are recommended, such as multiple-choice tests on, e.g., word processing [25].

The DCQ for clinical practice nurses still needs further psychometric testing. The current study misses, for example, information about reliability aspects like intra- and interrater reliability or test-retest reliability [13] as well as the sensitivity to change. Sensitivity to change is the ability of the questionnaire to identify true differences between two measurements because of an intervention. This is especially informative when monitoring an intervention to improve the digital competences among nursing staff. Furthermore, other aspects of validity such as discriminative validity to evaluate the questionnaire's ability to discriminate between groups, such as technology-savvy vs. less technology-savvy clinical practice nurses, is needed.

Discussion

We developed a short digital competences questionnaire for clinical practice nurses and added the dimension attitude to the underlying competence construct. The short questionnaire can be used by researchers and practice to elaborate clinical practice nurses' digital competence. Researchers could use the mean score as a primary outcome for intervention studies. Nurse managers may assess the level of digital competence at entry of new clinical practice nurses or of those already employed to identify needs. If needs are identified, in-depth evaluation of the exact need for action is needed. Future psychometric validation of the DCQ for clinical practice nurses is needed to allow a conclusion on the goodness of fit. Further development of the questionnaire to differentiate between knowledge and skills without losing the advantage of brevity is needed.

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CHAPTER 7

General Discussion

The overall aim of this thesis was to investigate the impact on health professionals of technology in the workplace, through an analysis of the extent of technostress and its influencing factors across health professional groups and settings.

Main findings

- Technostress among health professionals is moderate and differs between professional groups, settings, age and negatively influences long-term consequences.

This thesis shows that the health professionals reported a moderate perceived technostress. The technostress experienced among the health professionals differed between settings and professional groups (Chapters 2 & 3). Health professionals working in acute care or psychiatric hospitals reported significantly higher technostress than professionals working in long-term care and outpatient settings (Chapter 2). Technostress was found to have relevant long-term consequences. The highest association of technostress was found with burnout symptoms. Technostress was further associated with the presence of headaches. Also, the health professionals' intention to leave their profession or their organization was found to be associated with technostress. Moreover, the presence of technostress was associated with job satisfaction, general health status, quality of sleep and the workability (Chapter 3). Regarding the individual characteristics of the health professionals, digital competence was found to be associated with age, meaning that older health professionals reported lower digital competence (Chapter 3).

- Digital competence and social, organizational and management support are relevant inhibitors of technostress.

The results revealed that social support and digital competence are relevant inhibitors of technostress (Chapter 2 & 3). Health professionals with higher technostress showed lower digital competence. Physicians and nurses showed higher technostress and lower digital competence than other health professionals. It was only possible to identify that the social support received by the health professional was as an inhibitor through using the underlying conceptual model. The conceptual model included other potential stress-reducing factors from the model of causes and consequences of work-related stress besides those already included in the technostress model. The text mining analysis underlined the relevance of support for the health professionals from the organizational and management perspective. For unreliable technology, health professionals missed having help from IT services. Regarding management support, the managers failed to perform the task of involving health professionals early in the development and implementation of the technology (Chapter 4).

- Attitude is an essential core element of digital competence.

The health professionals' attitude towards technology was found to be a core element of their digital competence. Items to measure attitude were internationally rated to be very relevant as part of digital competence (Chapter 5). The validation of the Digital Competence Questionnaire for nurses in clinical practice proved that attitude, together with knowledge and skills, explains a sufficient variance of the construct of digital competence (Chapter 6). Negative sentiments outweighed negative attitudes among health professionals. Overall, health professionals saw the benefits of technology at work but reported that they could not take full advantage of them because of barriers such as non-availability, non-reliability, or low usability (Chapter 4).

Figure 1 summarizes the relationships identified from Chapters 2 – 4 between individual characteristics, influencing factors (risks for work-related stress and technostress creators), job resources and technostress inhibitors, stress reaction (technostress), and long-term consequences. The dashed line in Figure 1 was not a subject of the studies reported in this thesis into technostress in the healthcare setting. No conclusion on causality can be drawn from the arrows, since the results are solely based on cross-sectional studies.

Now, let us bring back Dora, Marc and Alice, who were introduced at the beginning of this thesis. Their case stories give examples of causes of stress, stress reactions and consequences of technostress among health professionals, based on the findings of this thesis. Each of them is found in Figure 1 with different influencing factors, resources, and outcomes. As I described in the introduction, they experience different technostress creators. Dora is the oldest of them. Her age has a negative association with digital competence.

She experiences technostress that is primarily triggered by the feeling of lacking competence. Her technostress inhibitor is the social and technical support given by her colleague Marc. Marc's technostress inhibitor is his digital competence. His quantitative demands are higher, since he must achieve his tasks as a registered nurse and help others in the team with technical problems. Marc feels that he is not being sufficient rewarded by his superiors for his commitment. Alice experiences several technostress creators, and the inhibitors are not enough to reduce her technostress. She lacks the inhibitor of being involved in the development and implementation of the technology. Her technostress is thus negatively associated with her job satisfaction.

Methodological considerations

Below is a reflection on the appropriateness of the methodologies applied, and the internal and external validity of the resulting findings are discussed. To do this, a critical reflection on the internal and external validity of the findings is performed.

Validity of the findings

Internal validity is achieved when the study design, conduct and analysis allow valid answers with minimal bias [1]. The bias can only be minimized, since bias can be identified in all study designs [2]. In this thesis, the internal validity is established through different triangulations, such as methodological, data and theoretical triangulation [3]. Further, several potential biases and how they were minimized are discussed.

First, I performed methodological triangulation by combining different study designs [3]. The thesis comprises quantitative studies with a cross-sectional design (Chapters 2 & 3) and a text mining analysis based on qualitative interview data (Chapter 4). In the cross-sectional studies, associations based on the underlying model were tested with (hierarchical) multiple linear regression models (Chapters 2 & 3). The findings from the cross-sectional studies were enriched with the sentiment analyses of single interview transcripts to gain an in-depth insight into the attitude of health professionals towards technologies in healthcare that had already been implemented (Chapter 4).

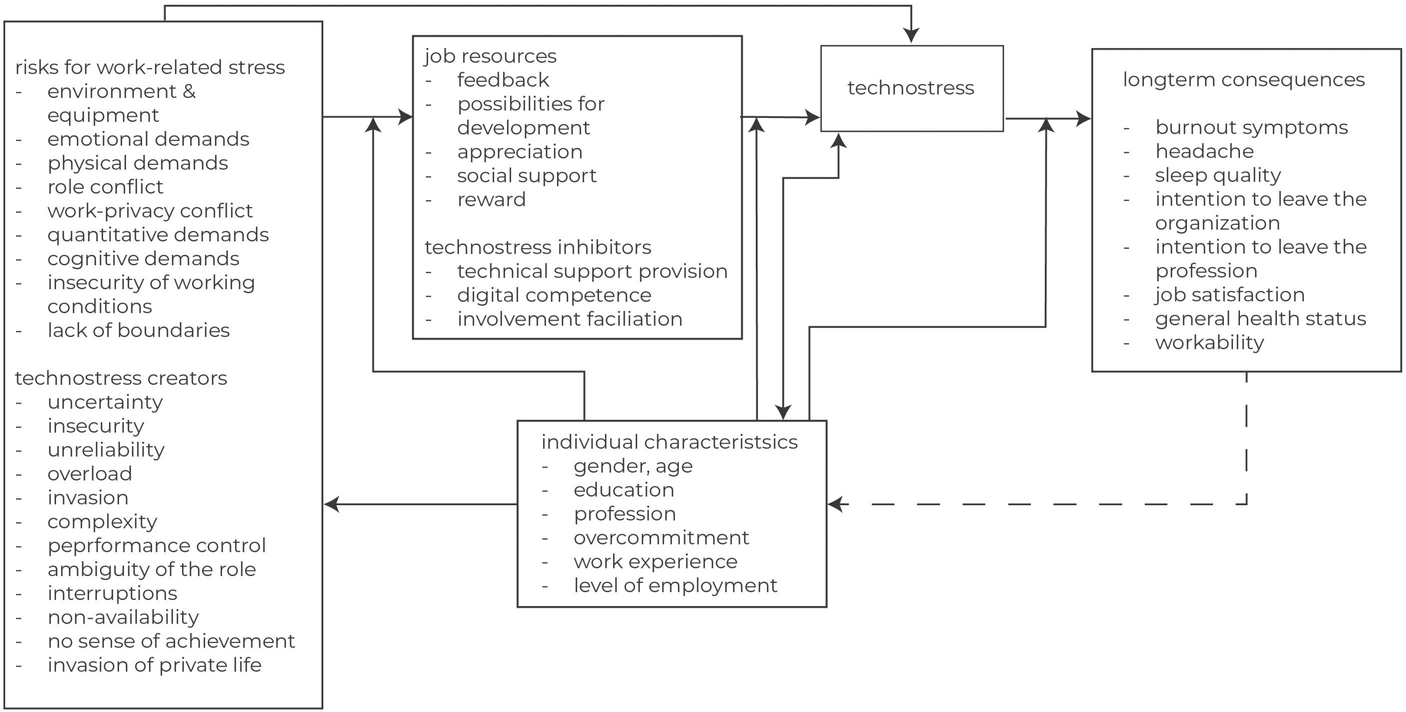

Figure 1: Summary of the findings, integrated into the underlying conceptual model of the causes of stress, stress reactions and consequences of technostress among health professionals

The sentiment analysis revealed a discrepancy between the expected and the real usability of these technologies that could not have been distinguished just by measuring attitude in a cross-sectional study as part of the digital competence questionnaire. The in-depth insight was possible with the qualitative data collection approach that was based on a semi-structured interview guide. The participants talked for approximately three quarters of an hour specifically about their attitude towards technologies that had already been implemented, and this gave a more comprehensive perspective than would have been obtained by having a few items about attitude included in a questionnaire. Thus, the findings from the text mining study highlighted the relevance of the health professionals' attitude, which resulted in the development of the studies described in Chapter 5 and 6 in relation to the Digital Competence Questionnaire. Therefore, the methodological triangulation led to an enrichment of information on the topic and guided further steps in this thesis. However, cross-sectional designs have shortcomings, which are discussed in the paragraph about limitations.

Second, data triangulation was done by collecting data from multiple health organizations from the same and different settings, as well as from different groups of health professionals [3]. Data triangulation from different sources increases the chance of obtaining a more comprehensive insight into a phenomenon and of discovering similarities and differences between the data sources included, such as the participating health organizations or professional groups. The hierarchical model that was calculated showed that the organizational level had no relevant contribution to the explained variance. Thus, the data triangulation from the different sources in the same setting led to a more comprehensive insight into the topic. In this thesis data triangulation was the foundation for the comparison of settings and health professional groups (Chapters 2 & 3). The differences identified in the settings and health professional groups are the first internationally available findings to indicate that health professionals' technostress and digital competences differ. As the health professional groups were found to be relevant predictors of technostress and digital competence, a narrow perspective, for example one that only looked at nurses, would have been inappropriate as it would not have shown that there are occupational characteristics that lead to this difference. Furthermore, the data triangulation of the different settings (Chapter 2) served as a decision point for choosing the setting for further focused work. In this thesis, the focus on psychiatric hospitals was pursued since the psychiatric setting was ranked second after clinics in respect of the extent of perceived technostress among health professionals (Chapter 2), despite the expected lower digitalization level when compared to clinics. Furthermore, although there is a lack of research overall into technostress in the healthcare sector, the vast majority of available publications focus on the clinical setting [4]. However, another type of data triangulation would have added value to the thesis: the inclusion of indicators from patients such as quality of care. This may be of importance insofar as a negative association between technostress and quality of care has been found among childcare workers [5]. This might also be true for health professionals, since nurses' burnout was associated with rationing of nursing care [6], which has an influence of the quality of care. However, there were three reasons for not including patients' outcomes: 1) The questionnaires were already long in order to cover the underlying model (Chapters 2 & 3), and the underlying model does not address patient indicators. 2) Further items would not have been reasonable, since longer surveys tend to have lower response rates. 3) For the secondary data analysis (Chapter 2), the questionnaire was already predetermined and tailored to a specific research question that did not look at the perspective of patients [7]. Nevertheless, these reasons do not diminish the problem of the lack of inclusion of patient outcomes. The relevance of elaborating on patient outcomes with work-related stress among health professionals has already been shown, as, for example, nurses' burnout compromises productivity and patient outcomes [8]. The exclusion of patient outcomes in the context of work-related stress could be a shortcoming of the underlying model. In healthcare, managers should focus on the quadruple aims of reducing the cost of the services, improving the experience of health professionals, improving the experience of patients and achieving better outcomes [9]. In the underlying model, only the health professionals' experience and the outcomes for the health professionals in terms of long-term consequences are covered. One reason for this shortcoming in the thesis could be that the merged models were developed generically across sectors and are thus intended to be valid for industry as well as healthcare. Consequently, appropriate models would be needed to enable this quadruple perspective for healthcare.

Third, “theoretical triangulation is the use of multiple theories or hypotheses when examining a phenomenon” [3, p.254]. Theoretical triangulation allows a more comprehensive perspective and analysis of the phenomenon. In this thesis the underlying conceptual model is based on the merger of two models: the model of the causes and consequences of work-related stress of Russell and Maître [10] and the technostress model of Ragu-Nathan and Tarafdar [11]. Because of the comprehensiveness of the model, the validation of the underlying model for healthcare was divided into multiple studies with separate hypotheses. Two of the studies conducted (Chapters 2 & 3) were assigned to parts of the underlying conceptual model. As indicated in Figure 1, nearly all the expected relations were evaluated. The combination of the models described above generated the new knowledge that, besides the known technostress inhibitors, social support and possibilities for development are negatively associated with technostress. Those inhibitors were not described by Ragu-Nathan and Tarafdar [11] in their technostress model. Thus, the theoretical triangulation laid a crucial foundation for this thesis, which now contributes to the discussion on adding technostress and its inhibitors to occupational stress research.

Fourth, I minimized measurement bias by using internationally well-established questionnaires [2], such as the Copenhagen Psychosocial Questionnaire (COPSOQ) for measuring influencing factors and long-term consequences [12]. Measurement bias occurs if the questionnaires used are not assessed for validity and reliability [2]. The COPSOQ has a long history in international research on work-related stress, and is available in 18 languages [12]. Although none of the scales used in this thesis were specifically developed for the healthcare sector, they had already been used and psychometrically tested in the healthcare sector, with satisfactory validity and reliability [13-15].

Fifth, all the quantitative studies are based on self-reports by health professionals. There are various methods available to measure stress at work, such as self-reporting, observations, or physiological indicators [16]. Each of the methods has its advantages and its disadvantages. Self-reports could be subject to potential biases such as social desirability or negative affectivity [16, 17]. Even more important, however, seems to be the possible response bias in occupational stress research, as it has been found that a high level of work-related stress increases non-response in surveys [18]. Thus, it could be that health professionals with high work-related stress did not participate in the survey, limiting the validity of the findings. Minimizing this bias would have required several approaches that I did not control for [18]: (a) the buy-in of supervisors, who motivate participation and act as facilitators to emphasize the study's relevance; and (b) possible incentives to encourage participation. Nevertheless, self-report data has also been found to overestimate measurements of work-related stress, whereas observational data may underestimate the real work-related stress [16]. This difference has also been found for the COPSOQ questionnaire with health professionals [14]. Another possibility would have been the measurement of physiological indicators such as glucocorticoid cortisol, adrenaline and noradrenaline, and blood pressure [16]. Although regarded as more objective than the other approaches, this method has its disadvantages, in particular regarding reliability. For example, cortisol has a latency of 10-30 after an event and already has a peak in its value in the morning, meaning that there are additional differences between individuals [16]. Thus, for comparative values, samples must be taken at the same time, taking into account possible events prior to the measurement. Furthermore, physiological indicators may not be specific to work-related stress, as they also respond to other experiences like discomfort, pain, and other (non-work related) events such as an unsatisfying marriage [19]. Consequently, other methods like psychological indicators are "no optimal substitute for self-report" [16, p.250]. In this case, the self-report method seems to be adequate because, although it relies on only one source, the scales used for it have proven to be valid internationally and across sectors. However, self-reports of own competences are particularly prone to be overestimated by individuals with low competences [20], which might result in an overestimation of the results of the thesis for digital competence. Maderick and Zhang [21], for example, found that teachers with low digital competence overestimated their knowledge and skills, and this may also apply to health professionals. Here the thesis leaves us with ambiguity about the extent to which this is true for the results of the thesis. A supplementary observation or examination of knowledge and skills, which are easier to capture than behavior, would have been useful for comparison to verify the self-reported digital competence.

This leads us to a further discussion of the limitations of the thesis. Several limitations regarding internal validity need to be considered, as internal validity can be compromised by different biases [1]. The results of the quantitative studies are based on a cross-sectional design, which does not allow causal conclusions to be drawn. In cross-sectional studies, the predictor and the outcome are assessed at the same time and therefore alternative reasons for the findings should be ruled out [22]. One strategy to achieve this is to assess all possible information that could contribute to the explanation of the findings [23]. Although this strategy was followed by applying multiple linear regressions based on a comprehensive conceptual model, the reported explained variances of the regression models indicate that additional information is missing. Furthermore, the data collection used for the studies could be subject to sampling bias, since convenience and snowball sampling methods were used. A recent review on sampling bias in technostress research concluded that it was mostly individuals with a good education from rich populations who were included in studies on technostress at work [24]. This thesis included health professionals working in Switzerland, which is known to be a rich country. However, the education of the health professionals ranged from no degree to doctorate, and it was possible to show that the educational level is a relevant predictor of technostress.

External validity describes the generalizability of a study, answering the question of whether the findings can be applied to a broader context [1]. In this thesis, all health professional groups were included (Chapters 2, 3 & 4) which reflects the reality in health organizations that a particular application of technology, such as electronic health records, influences the daily work and interactions of all health professionals. However, the association between technostress and digital competence, as well as the association between technostress and its long-term consequences, are findings limited to psychiatric hospitals in this thesis (Chapters 3 & 4), which does not allow a generalization of the findings to the healthcare sector. Furthermore, two of the studies were specifically focused on nurses, limiting the generalizability to other health professions of the questionnaire that was developed (Chapters 5 & 6). The thesis fails to report on the level of digitalization of the organizations included and the frequency of the health professionals' interaction with technology, and these have been found to be relevant predictors of technostress and digital competence [13]. Lastly, the Digital Competence Questionnaire that was developed for nurses in clinical practice needs further psychometric testing to prove its validity, including discriminative and convergence validity, and its reliability, including intra- and inter-rater reliability and test–retest reliability [25].

Theoretical reflections

The question now is: Who is to blame for the technostress among health professionals that has been identified? Is it the health professionals, who lack digital competence and are reluctant about using technology, or is it the technology, which fails to meet the basic requirements, such as usability and reliability? The answer is that it is both. However, technology as a product of human ingenuity cannot be directly to blame; rather, the blame lies with those responsible for the development, implementation, and maintenance of the technology. Moreover, the view of technostress as a negative consequence of technology seems to be a one-sided one.

Technostress: distress and eustress

In this thesis I used the definition of technostress as "a reflection of one's discomposure, fear, tenseness and anxiety when one is learning and using computer technology" [26, p.3004]. In line with that, the underlying model of the thesis treated technostress from a solely negative perspective, and this was found to be the dominant research perspective on technostress [27, 28]. This could have led to an overinterpretation of the negative effects of technology [27, 28]. Tarafdar and Cooper [27] highlighted the idea that technostress should be discussed in the context of distress and eustress. The differentiation between distress and eustress in stress research is nothing new. It was introduced in 1974 by Selye [29], who acknowledged that there are different types of response to stress. By approaching stress with this understanding, the stress reaction depends on the individual's interpretation of the situation [30]. In the past decades there has been a discussion about "moving away from a disease and dysfunction model [of stress to] focus on positive attributes of people and organisations" [31, p.3]. This movement is also found in technostress research, where researchers have developed models that distinguish between techno-distress and techno-eustress [27, 28]. In their understanding, techno-eustress describes the positive stress that individuals experience in a reaction that appraises technology as a challenge and motivation and not as a threat [27, 28]. Techno-eustress is found, for example, if an individual sees the use of technology as an opportunity for the improvement of their competence and work life. Techno-eustress in healthcare is influenced by perceived usefulness, involvement facilitation, and technical support [32]. These are in turn inhibitors of techno-distress, and were also measured in this thesis and found to have a negative association with technostress.

Framing technostress as part of an overarching model of occupational stress

In the methodological considerations I discussed the added value for the thesis arising from the theoretical triangulation resulting from the combination of the model of causes and consequences of work-related stress of Russell and Maître [10] and the technostress model of Ragu-Nathan and Tarafdar [11]. This also leads to theoretical considerations. The results of the thesis indicate that the models complement each other in a useful way that leads to the identification of social support as a technostress inhibitor. Thus, how one is embedded in a social environment and how one is helped with technostress in this environment also plays a role in technostress. The timeliness of this finding is evidenced by recent research that has explicitly examined the role of social support in technostress and has proved that it has a significant influence on reducing technostress in general [33]. The authors divide social support into emotional support and instrumental support, with both being inhibitors of technostress, which fits the results of the thesis and the conceptual model [33]. Whereas instrumental support is task-related, enabling one to use the technology as intended, emotional support provides understanding of one's problems and encourages one to tackle challenges, such as learning to use a new type of technology [33].

Research on work-related stress is targeted on reducing work-related stress and improving working conditions. In this context, the influence of technology should not be considered in isolation from that of other factors, such as quality of leadership or conflict between work and private life [7]. Merging the two models leads to some thematic overlaps, such as the overlap between “conflict between work and private life” and the technostress creator “invasion of private life.” On the one hand, shift work and substituting or rescheduling shifts at short notice causes conflict [7]. On the other hand, such requests for substituting or rescheduling are only possible via technologies through which one can be reached, such as a telephone [34]. These overlaps are not a problem at first, but in principle only what is necessary should be added to the questionnaire. Thus, for future research, the overlaps would have to be checked statistically for redundancy.

The influence of individual characteristics and attitude on technostress

Health professionals experience technostress, and this can result in long-term consequences such as burnout symptoms (Chapters 2 & 3). However, the results of the thesis show that not only they, but also those who contribute to their own technostress and that of others, are affected. Individual characteristics such as gender, age, and education play a vital role in the experience of technostress. They are also associated with digital competence, as one relevant inhibitor of technostress. Furthermore, it seems that the role health professionals play in the blame game depends on the professional group and the setting. In particular, the mental health setting was found to be slower in advancing in digital transformation because of attitudinal barriers such as lack of engagement and concerns about worsening the therapeutic relationship [35-39]. Such attitudes are shaped by personal socialization and are in a state of transformative change through personal experiences with technology. If technologies are perceived to be reliable and to give added value to the work, people will experience their use to be enjoyable, which positively influences their attitude [40].

At this point we take a look at the Technology Acceptance Model (TAM3) of Venkatesh and Bala [40]. When developing the interview guide for the text mining study, it was noticed that there is a thematical overlap between TAM3 and the conceptual model of the thesis. TAM3 is an internationally known model and describes the influence of attitude on the behavioral intention to use a technology [40]. It describes some of the same influencing factors and inhibitors as the technostress model, such as individual characteristics, social influence, and facilitating conditions like organizational support. Furthermore, several items from the Digital Competence Questionnaire for nurses in clinical practice, such as perceived job relevance, overlap with TAM3. In TAM3 the job relevance is the degree to which one thinks the technology is relevant for the job [40]. In the Digital Competence Questionnaire, the nurse is asked to rate the relevance of the technology for his or her job with a focus on patient outcomes and quality of care (Chapter 6). In conclusion, it is evident that attitude is included in this thesis, as it seems to be the decision point in favor of or against the use of an application of technology, and lays the basis for innovation readiness in organizations [41]. Attitude as a moderator of innovation readiness within a health organization takes on even greater weight when considering the power structures in health organizations. In healthcare, physicians play a core role in the digital transformation process, since their opinion is highly relevant for the management [42]. Thus, physicians' commitment to change is crucial. However, other professional groups, such as nurses, also contribute to a sustainable digital transformation. Possibly due to their reduced voice at management level, nurses find workarounds to deal with inadequate technology [43]. If they have no choice about whether to implement it or not, they show their resistance through the inappropriate use of the implemented technology [44].

Involvement of health professionals in decision making processes

Health professionals need to be involved, be it in management decisions [45], in the schedule planning [7, 46] or in the development and implementation of technologies [47]. Regarding technology development, health professionals are often involved in the process too late, and this hampers the usability of the technologies [48]. In this thesis, the lack of early involvement was demonstrated by the fact that technology that had already been implemented did not meet the expectations of the health professionals (Chapter 4). The literature on co-creation approaches suggests that early involvement in technology development and implementation has a beneficial effect on health professionals' experience, which in turn positively influences their attitudes toward technology [47]. In addition to participation in development and implementation, involvement in measures to promote inhibitors and to reduce technostress creators seems relevant; this would include increasing the health professionals' digital competence or establishing a functioning IT support system.

This is where the management strategy of Total Quality Management (TQM) comes into play. TQM in health organizations is aimed at enhancing outcomes and improving the efficiency of delivered services, and is of growing interest in health organizations [45]. It has been described as the cooperative management of organizations along with the employees [49]. One barrier to successful TQM is a lack of commitment and involvement of health professionals [45]. Thus, the same shortcomings of inadequate involvement are as evident for TQM as they are in the development and implementation of technology. Also, within TQM, technology plays an essential role, as it can be used to facilitate information and the analysis of gathered data [49]. For example, the data gathered in electronic health records can be used by an algorithm to predict the need for action by patients [50]. The expected added value of technology in TQM can only be achieved if the data are entered correctly with an appropriate digital competence and if there is a willingness to use the technology accordingly and an intention to learn from the data entered, for quality improvement. Thus, when it comes to change, it always comes down to attitude, with a negative attitude emerging more quickly than a positive one, and an already existing negative attitude being difficult to revise [51].

Implications and Recommendations

The above-described major findings and methodological and theoretical considerations have several implications and lead to recommendations for future research and healthcare practice. While the implications arise from the importance of the findings, the recommendations provide propositions for specific actions.

Future research

For future research the following recommendations derived from the implications are proposed: (1) differentiation between techno-eustress and -distress, (2) co-creation of measures to reduce techno-distress and increase techno-eustress, (3) further psychometric testing of the Digital Competence Questionnaire for nurses in clinical practice developed in this thesis, and (4) inclusion of indicators for quality of care in future research on technostress.

Differentiation between techno-eustress and -distress

Although this thesis gave a first insight into technostress, it followed the dominant negative perspective on the issue. A future approach looking at the positives and negatives of technology at work seems conducive to knowledge dissemination, as raising awareness among health professionals about positive reactions to technology can contribute to changing their attitudes. The dominant focus in technostress research on the negative effects (techno-distress) limits the validity of the conclusions, through giving too much weight to the negative perspective. Future research on technostress in healthcare should focus on the influencing factors of techno-eustress and -distress for a more holistic perspective. Comparisons of individual, organizational and environmental characteristics that promote either techno-eustress or -distress may provide knowledge about target-oriented measures. This requires existing models to be used as a basis [27, 32] and suitable measurements, in particular for techno-eustress, to be developed, since this has not yet been covered adequately [27].

Co-created measures to reduce techno-distress and increase techno-eustress

In this thesis an insight into the extent of technostress experienced and its inhibitors, such as digital competence among health professionals, was gained (Chapter 2 & 3). This knowledge lays the foundation for the development of measures. With the availability of suitable measurements (to measure techno-eustress and techno-distress), intervention studies are needed to elaborate effective methods to enhance health professionals' digital competence, reduce techno-distress, and, respectively, increase techno-eustress. The thesis underlines the importance of involving health professionals in the early stages of the development and implementation of new technologies (Chapter 4). The co-creation of measures, such as educational programs or new technologies, allows health professionals to have positive experiences, which may positively influence their attitude towards technology. It may also enhance the chance of the sustainable implementation of technology. For successful co-creation, researchers, along with the health organization involved, should establish a "favourable value co-creation environment" for which the credibility is key to real involvement [52, p.397]. For this purpose, available guidelines such as the Co-creation Impact Compass, can be used to provide tools for researchers to apply co-creation in research projects [53].

Further psychometric testing of the Digital Competence Questionnaire for nurses in clinical practice

Because there was no suitable questionnaire available to measure the digital competence of health professionals for this thesis, the Digital Competence Questionnaire for nurses in clinical practice was developed and tested for construct validity using exploratory factor analysis and internal consistency (Chapters 5 & 6). The questionnaire needs further psychometric testing, such as test–retest reliability and construct validity using confirmatory factor analysis. Other available questionnaires can be used to control for criterion and concurrent validity.

Inclusion of indicators for quality of care in future research on technostress

As described in the methodological considerations, the indicators for patient outcomes such as quality of care were not integrated in this thesis. There is the possibility that technostress will cause rationing of care and decrease quality of care, as the health professionals might spend more time with the technology. On the other hand, a lack of digital competences could lead to incorrect documentation and thus also to a loss of quality of care.

Healthcare practice

The implications and the corresponding recommendations for healthcare practice stem from the identified and discussed inhibitors of technostress, and concern (1) the establishment of a new role for team support, (2) the involvement of health professionals in development and implementation, and (3) the adaptation of technical support to the needs of health professionals.

Establishment of a new role for team support

The thesis highlights that support within a team is an important inhibitor of technostress (Chapters 3 & 4). Team members with better digital skills are asked for support by colleagues with fewer digital skills. Older health professionals should acknowledge that their younger colleagues may have higher digital competences, and should use them as a source for learning [54]. Younger health professionals take on an implicit team support role that is additional to their actual work. Leaders should show appreciation of these employees by officially assigning them this role and allocating time resources to them. The role implies the development of a role description, the designation as an independent function or additional function, and an appropriate remuneration if the job is to be attractive, especially in times of scarce personnel resources. The Digital Competence Questionnaire for nurses in clinical practice could be used as a basis to identify the members of a team who have better digital competences. The team would also know who to contact with technical questions if suitable team support for technical questions was identified. By establishing a new role, the managers would also promote development opportunities among their employees.

Involvement of health professionals in development and implementation

The identified lack of involvement has implications for health professionals and managers (Chapter 4). The management should involve health professionals in the early stages of the development and implementation of technologies at work. This goes in line with the co-creation described in the research implications, as the involvement of health professionals should be carried through from beginning to end. For health professionals, this means gaining knowledge in informatics to engage in dialogue with developers. In particular, experts among health professionals with appropriate qualifications in informatics are needed as a connecting link between the parties involved [55]. For the management this means the creation of a co-creation culture that allows health professionals to be truly involved in the process. For this purpose, best practice models with clear guidance on how to proceed can be used. For example, Dugstad and Eide [56] present a process for successful digital transformation through co-creation. It has five steps, beginning with pre-implementation preparations and ending with service transformation and quality management.

Adaptation of technical support to the needs of health professionals

This thesis shows that technical support is important for managing unreliable technology and answering questions in the daily routine (Chapter 4). The current technical support in health organizations may not be sufficient to meet the needs of a 24/7 working week and to contribute to technology-related decisions with the management [57].

Conclusion

Technology is part of everyday life in the healthcare sector. We are only in the early stages of its possibilities. This allows us to create good conditions for health professionals to allow them to experience this digital transformation as something positive, as a challenge. The underlying model of this thesis reflects the complexity of the reciprocal interaction of the different influencing factors for technostress in healthcare. The thesis illustrates that any technology is only a product that is aimed at supporting health professionals with their work but often misses this target. The overall negative attitude towards technology that has already been implemented may be a hint that improving health professionals' attitudes is crucial as a basis for a sustainable digital transformation in healthcare.

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SUMMARY

Digital transformation in healthcare has its challenges in providing the promised added value for health professionals. This thesis is about the blame game between health professionals and technology. The overall focus of the thesis is the impact of technology in the workplace on health professionals, and the aim is to demonstrate that attitude is as important as knowledge and skills for explaining digital competence.

Chapter 1 is the general introduction of the thesis. After explaining the main concepts for the thesis, the challenges of digitalization in healthcare are described. Health professionals may experience technostress when interacting with technology at work. Technostress is a negative reaction to the interaction with technology at work. One inhibitor is the digital competence of the health professional. However, research on digital competence has predominantly focused only on knowledge and skills, neglecting the importance of attitude towards technology. Overall, research about the influencing factors, inhibitors, and consequences of technostress in healthcare is scarce. Furthermore, there is no theoretical foundation that would allow us to obtain comprehensive insights into the relevance of technostress and its inhibitors in the context of occupational stress research.

In **Chapter 2** the prevalence of technostress among health professionals, and its influencing factors, are described. For this, secondary analysis was conducted utilizing cross-sectional data from the study, “Work-related stress among health professionals in Switzerland”, which included 8’112 health professionals from 163 health organizations in Switzerland. The results showed that the health professionals experienced moderate technostress and that the technostress differed between settings and health professions. Regarding the settings, technostress was highest in acute care, with psychiatric settings coming second. In the comparison between the professional groups, technostress was highest among physicians, with nurses in second place. The results of the modelling showed that whether higher technostress was experienced depended strongly on the professional groups. Furthermore, social support was found to be an inhibitor of technostress. This study provided a first insight into technostress among different groups of health professionals across different settings.

Chapter 3 presents the association between digital competence and technostress, considering individual characteristics and the association between technostress and its long-term consequences for health professionals in psychiatric hospitals. The data were collected using a cross-sectional design from 493 health professionals in three Swiss psychiatric hospitals. The health professionals rated their technostress as moderate and their digital competence as high. Digital competence was found to be significantly associated with technostress. Among the individual characteristics, age and profession were significantly associated with both digital competence and technostress. Technostress was found to be a relevant predictor of several long-term consequences such as burnout symptoms, job satisfaction, intention to leave the profession or organization, general health status, quality of sleep, headaches, and workability. Based on this study it was concluded that further digitalization in psychiatric hospitals may have an increasing impact on the technostress experienced. To counter technostress, enhanced digital competence will be needed, as this is an inhibitor of technostress. This will allow health professionals to cope with technostress sustainably and, thus, lower the risk of adverse long-term consequences.

Chapter 4 deals with the identification of the technologies implemented in psychiatric hospitals and the description of the health professionals' attitude towards these implemented technologies. Text mining analysis of semi-structured interviews with 20 nurses, physicians and psychologists was conducted. The analysis comprised word frequency and sentiment analyses to identify the attitude from the interview transcripts. The results showed that health professionals mainly referred to computers, emails, phones and electronic health records when asked about the technologies they used. Of all the words that expressed a sentiment, 73% were positive. The technologies discussed were associated with positive and negative sentiments. However, among all the sentences that described technology in the workplace, 69.4% expressed negative sentiments. The conclusion from Chapter 4 is that the health professionals mentioned a limited number of technologies at work and that their sentiments towards the technologies were mostly negative.

In **Chapter 5**, the identification of items for an item pool for a questionnaire to measure the digital competence of clinical practice nurses, and the evaluation of the content validity, are described. For this, a normative Delphi study was conducted with a panel comprised of nurse informatics specialists, digital managers, researchers, and medical informaticists. From their ratings, the Content Validity Index, on an item and scale level, was calculated. Within three rounds, the panelists reached high consensus and rated 26 of the initial 37 items as relevant. The average Content Validity Index demonstrated the item pool to be highly content valid. The final item pool included items to measure knowledge (n = 4), skills (n = 8), and attitude (n = 14). Future research should conduct psychometric testing of the construct validity and internal consistency of the item pool that was generated.

In **Chapter 6**, the evaluation of the construct validity and internal consistency of the newly developed Digital Competence Questionnaire for clinical practice nurses is presented. The data were collected in a cross-sectional study with a sample of 185 English-speaking clinical practice nurses. The 26 items from the initial item pool described in Chapter 5 were included. The final questionnaire was developed using exploratory factor analysis and comprised 12 items allocated to two factors with a cumulative explanation of 57% of the variance: knowledge & skills (n = 6) and attitude (n = 6). Internal consistency of the total scale and for each factor was satisfactory. The findings showed that the Digital Competence Questionnaire for clinical practice nurses is a valid questionnaire in terms of construct validity and has acceptable internal consistency. Future psychometric validation, such as test–retest reliability, discriminative validity, and sensitivity to change of the questionnaire, are needed.

Chapter 7 is the general discussion of the findings. The findings from Chapters 2 – 6 are summarized, and this is followed by certain methodological and theoretical considerations. The methodological considerations discuss the internal and external validity of the findings, based on the various triangulations and further indicators. In the theoretical considerations there is a discussion of whether the health professionals or the technology are indeed to blame for technostress, as the title suggests. Furthermore, the models included, the influencing factors and the inhibitors of technostress are discussed. The chapter closes with implications and recommendations for research and practice.

Chapter 8 presents the scientific and societal impact of the thesis. It presents what has already been achieved, and the anticipated impact. The thesis will have short-term and long-term impacts on various aspects in research as well as in society. Regarding society, the impact on developers of technology, health organizations, health professionals, health professionals' educators, policy makers and patients is described.

SAMENVATTING

De digitale transformatie in de gezondheidszorg gaat gepaard met uitdagingen om zorgprofessionals de beloofde toegevoegde waarde te bieden. Dit proefschrift gaat over het spanningsveld tussen zorgprofessionals en technologie. De focus ligt op de impact van technologie op de werkplek van zorgprofessionals en het doel is om aan te tonen dat attitude even belangrijk is als kennis en vaardigheden om de digitale competentie te verklaren.

Hoofdstuk 1 omvat de algemene inleiding van het proefschrift. Na uitleg van de belangrijkste concepten van dit proefschrift worden de uitdagingen van digitalisering in de gezondheidszorg beschreven. Zorgprofessionals kunnen technostress , een negatieve reactie, ervaren bij de interactie met technologie op het werk. De digitale competentie van de zorgprofessional is een remmende factor voor technostress. Onderzoek naar digitale competentie is echter voornamelijk gericht op kennis en vaardigheden en wordt het belang van de houding tegenover technologie verwaarloosd. Er is weinig onderzoek gedaan naar de beïnvloedende en remmende factoren noch naar de gevolgen van technostress in de gezondheidszorg. Er is bovendien geen theoretische basis die ons in staat stelt uitgebreide inzichten te verkrijgen in de relevantie van technostress en de remmende factoren ervan in de context van onderzoek naar werkstress.

In **hoofdstuk 2** wordt de prevalentie van technostress bij zorgprofessionals en de beïnvloedende factoren beschreven. Hiervoor is een secundaire analyse uitgevoerd op cross-sectioneel verkregen gegevens van de studie ‘Werkgerelateerde stress bij zorgprofessionals in Zwitserland’, waaraan 8.112 zorgprofessionals uit 163 zorgorganisaties in Zwitserland deelnamen. De resultaten toonden aan dat de zorgprofessionals matige technostress ervoeren en dat technostress verschilde tussen instelling en zorgberoepen. Met betrekking tot de instellingen was technostress het hoogst in de acute zorg gevolgd door de psychiatrische instellingen. Bij de vergelijking tussen de beroepsgroepen was technostress het hoogst bij artsen, met verpleegkundigen op de tweede plaats. De resultaten toonden aan dat het ervaren van hogere technostress sterk afhing van type beroepsgroep. Verder bleek sociale steun een remmende factor van technostress te zijn. Deze studie bood een eerste inzicht in technostress bij verschillende groepen zorgprofessionals in verschillende settings.

Hoofdstuk 3 beschrijft de associatie tussen digitale competentie en technostress , en de invloed van individuelle kenmerken hierop. Daarnaast wordt de associatie tussen technostress en de langetermijngevolgen voor zorgverleners in psychiatrische ziekenhuizen beschreven. De gegevens werden verzameld via een cross-sectionele studie bij 493 zorgverleners uit drie Zwitserse psychiatrische ziekenhuizen. De zorgprofessionals beoordeelden hun technostress als matig en hun digitale competentie als hoog. Digitale competentie bleek significant samen te hangen met technostress. Van de individuele kenmerken waren leeftijd en beroep significant geassocieerd met zowel digitale competentie als technostress. Technostress bleek een relevante voorspeller te zijn van verschillende langetermijngevolgen zoals symptomen van een burn-out, tevredenheid met het werk, de intentie om het beroep of de organisatie te verlaten, de algemene gezondheidstoestand, de kwaliteit van slaap, hoofdpijn en werkvermogen. Op basis van deze studie werd geconcludeerd dat verdere digitalisering in psychiatrische ziekenhuizen een toenemende impact kan hebben op de ervaren technostress. Om technostress tegen te gaan zullen meer digitale vaardigheden nodig zijn, aangezien dit technostress vermindert. Dit zal zorgverleners in staat stellen om duurzaam met technostress om te gaan en zo het risico op nadelige langetermijngevolgen terug te dringen.

S

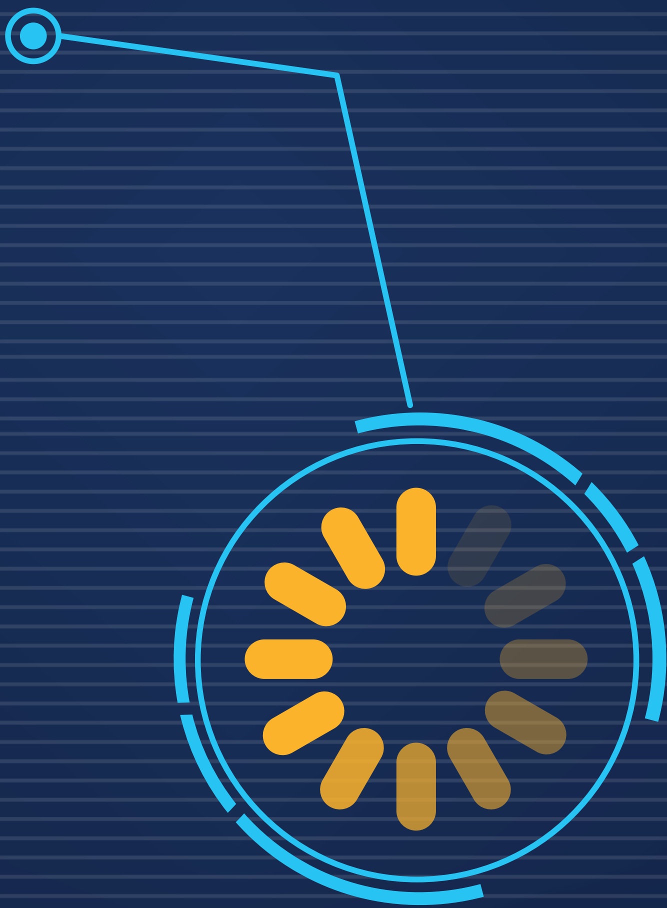
Hoofdstuk 4 behandelt de identificatie van de technologieën die in psychiatrische ziekenhuizen worden toegepast en beschrijft de houding van zorgprofessionals tegenover deze toegepaste technologieën. Er werd een tekstanalyse van semi-gestructureerde interviews met 20 verpleegkundigen, artsen en psychologen uitgevoerd. De analyse bestond uit woordfrequentie- en sentimentanalyses om de houding uit de interviewtranscripties bloot te leggen. Uit de resultaten bleek dat zorgprofessionals voornamelijk verwezen naar computers, e-mails, telefoons en elektronische patiëntendossiers wanneer er gevraagd werd naar de technologieën die zij gebruikten. Van alle woorden waarmee een sentiment werd uitgedrukt, was 73% positief. De besproken technologieën werden geassocieerd met positieve en negatieve gevoelens. Echter, van alle zinnen waarin technologie op de werkplek werd beschreven, was 69,4% negatief. De conclusie van hoofdstuk 4 is dat de zorgprofessionals een beperkt aantal technologieën op het werk noemden en dat hun sentimenten ten aanzien van de technologieën meestal negatief waren.

In **hoofdstuk 5** volgt een beschrijving van de identificatie van variabelen (items) voor samenstelling van een vragenlijst (item-pool) om de digitale competentie van klinische praktijkverpleegkundigen te meten en wordt de evaluatie van de inhoudsvaliditeit beschreven. Hiervoor werd een normatieve Delphi-studie uitgevoerd met een panel bestaande uit verpleegkundige en medisch informatici, managers digitalisering en onderzoekers. Uit hun beoordelingen werd de index van de inhoudsvaliditeit berekend op item- en schaalniveau. Binnen drie rondes bereikten de panelleden een hoge mate van consensus en beoordeelden zij 26 van de oorspronkelijke 37 items als relevant. De gemiddelde index van de Inhoudsvaliditeit toonde aan dat de item-pool een hoge inhoudsvaliditeit had. De uiteindelijke item-pool bevatte items om kennis (n = 4), vaardigheden (n = 8) en houding (n = 14) te meten. Toekomstig onderzoek zou psychometrische tests van de constructvaliditeit en de interne consistentie van de gegenereerde item-pool uit moeten uitvoeren.

In **hoofdstuk 6**, wordt de evaluatie van de constructvaliditeit en interne consistentie van de nieuw ontwikkelde 'Digitale Competentie Vragenlijst' voor klinische praktijkverpleegkundigen gepresenteerd. De gegevens werden verzameld in een cross-sectionele studie met 185 steekproefsgewijs genomen Engelstalige klinische praktijkverpleegkundigen. De 26 items uit de initiële item-pool die beschreven werd in hoofdstuk 5 werden erin opgenomen. De uiteindelijke vragenlijst werd ontwikkeld met behulp van exploratieve factoranalyse en bestond uit 12 items die waren toegewezen aan twee factoren met een cumulatieve verklaring van 57% van de variantie: kennis & vaardigheden (n = 6) en houding (n = 6). De interne consistentie van de totale schaal en van elke factor was bevredigend. De bevindingen toonden aan dat de Digitale Competentie Vragenlijst voor klinisch praktijkverpleegkundigen een valide vragenlijst is in termen van constructvaliditeit en een acceptabele interne consistentie heeft. Toekomstige psychometrische validatie, zoals test-hertestbetrouwbaarheid, discriminatoire validiteit en gevoeligheid voor verandering van de vragenlijst, is noodzakelijk.

Hoofdstuk 7 geeft de algemene bespreking van de bevindingen weer. De bevindingen uit de hoofdstukken 2 - 6 worden samengevat, waarna enkele methodologische en theoretische overwegingen volgen. In de methodologische overwegingen wordt de interne en externe validiteit van de bevindingen besproken op basis van de verschillende triangulaties en verdere indicatoren. In de theoretische beschouwingen wordt besproken of de zorgprofessionals zelf of juist de technologie verantwoordelijk zijn voor technostress, zoals de titel suggereert. Verder worden de opgenomen modellen, de beïnvloedende factoren en de remmende factoren van technostress besproken. Het hoofdstuk sluit af met implicaties en aanbevelingen voor onderzoek en praktijk.

In **hoofdstuk 8** wordt de wetenschappelijke en maatschappelijke impact van het proefschrift gepresenteerd. Het laat zien wat reeds bereikt is, en wat de verwachte impact is. Het proefschrift zal op korte en lange termijn gevolgen hebben voor verschillende aspecten in wetenschappelijk onderzoek en in de maatschappij. Wat de maatschappij betreft wordt de impact op ontwikkelaars van technologie, zorgorganisaties, zorgprofessionals, opleiders van zorgprofessionals, beleidsmakers en patiënten beschreven.



IMPACT

In the introduction to this thesis, the case stories of Dora, Marc, and Alice are presented. These describe how and why health professionals can experience stress when working with technology. This so-called technostress can lead to health problems and a lower commitment to the job for health professionals. Dora, Marc, and Alice have in common that they experience technostress to some extent. They all show other dominating technostress creators that originate from their individual characteristics, such as, for Dora, age and gender or the technology itself, or, for Marc, having to work with unreliable technology. Alice feels less satisfied with her job because of the technostress she experiences, and shows a lower commitment to the job. In this thesis we mainly focused on the experience of health professionals. Their responses highlighted the role they play in this blame game between health professionals and technology. The extent of technostress depends on where you work and what your job is, since, in particular, physicians and nurses in clinics and secondly in psychiatric hospitals showed higher technostress. Up to now, little has been known about technostress and its inhibitors, such as digital competence, in the healthcare setting. The thesis addressed this knowledge gap by giving an overview of the extent of technostress and digital competence, embedded in a comprehensive framework. Although the technostress measured was moderate, we may expect it to increase along with the ongoing digital transformation of healthcare. Thus, this topic will gain in relevance for science and society in the coming years, as digital health is often mentioned as the solution for the future for delivering high quality and sustainable care.

Scientific impact

This thesis generates new knowledge about the extent, association, and further influencing factors of technostress and digital competence among health professionals. Until now, no comparison across health professional groups and settings for this topic was available. The thesis also contributes to the discussion in stress research, showing that technostress should be incorporated in future research and also that positive reactions (techno-eustress) are of concern. Although this thesis focused solely on the distress of technology use, the underlying model allowed a complex phenomenon with reciprocal influences to be investigated, indicating several inhibitors of technostress. Our findings show that digital competence is an inhibitor of technostress, as is social support, and this gives guidance about suitable measures to reduce technostress. Furthermore, we developed and validated a 12-item Digital Competence Questionnaire for nurses in clinical practice, which is available in English and is free to use. The questionnaire is added to this publication as an additional file. Researchers can use the questionnaire and address the implications for further research mentioned in the relevant chapter. The questionnaire is already attracting international interest. Another research group from Turkey has meanwhile shown interest and requested permission to translate and psychometrically test the questionnaire.

One important scientific impact is achieved through the dissemination of the findings. The R scripts developed in this thesis are being used in a Master's degree program in nursing to teach the preparation and analysis of data in the statistics program R. All the articles were submitted to open access journals, with two having been published and one having been accepted and being available as pre-print. The chosen journals are focused either on informatics in healthcare or on health professionals. The published articles have already been cited multiple times. Furthermore, Chapters 2 and 3 were presented at three different international conferences with different audiences: (1) European Conference on Mental Health in 2021, (2) 3Länderkongress Psychiatrie in 2022 and (3) European Doctoral Conference in Nursing Science in 2019. The publication of Chapters 2 and 3 led to a request for the author to be a keynote speaker at a nursing-specific conference in Germany "5. Clusterkonferenz Zukunft der Pflege" in 2022. The keynote speech was followed by an interview, which is presented on the website of the German Federal Ministry of Education and Research. All peer-reviewed publications and the pre-print were distributed via ResearchGate and linked on social media platforms, and are available on the repository of the Bern University of Applied Sciences. For nurses and the interested public, a blog post about sustainable digitalization in healthcare is available. Managers of the participating health organizations were offered a presentation of their results. Some managers decided to proceed with this topic, and workshops were organized to discuss their digitalization strategy and define the next steps, which resulted in follow-up project ideas on fair and participatory shift planning with new technology and integrated care models with technology such as a database and interface for interprofessional information exchange. Furthermore, the developed R script for the text mining analysis is freely available as an additional file to the pre-print, which will allow other researchers to use the full script or parts of it for comparable research questions and to retrace the analysis process. All publications and the most relevant findings are presented and available on the author's private website at christophgolz.ch.

Societal impact

Society depends on a well-functioning health system. With the increase in digital solutions in everyday life, there are also expectations regarding the level of digitalization in the healthcare system. Patients want more autonomy and to be empowered to manage their own health. Technology has a key role in making this possible. To meet patients' expectations, health providers should have the necessary technologies, along with digitally competent health professionals. These competences go beyond the use of technology, as patients need to be shown which suitable solutions exist and to be guided in their use.

The thesis shows that it is not very easy to implement a new technology in healthcare because of reciprocal influences and consequences. The different preconditions of health professionals, and the development of technologies that bypass the health professionals' needs, lead to a discrepancy between the possible added value and the experienced reality. The thesis serves as a basis for players from society to raise awareness of technostress and digital competence, and to establish measures to intervene in healthcare. The players may be developers in health technology companies, managers of health organizations, health professionals, health professionals' educators, or policy makers. All these play a role in the development, implementation, and maintenance of technology at work in healthcare.

Developers are responsible for prototyping soft- and hardware, and managers for the digitalization strategy of their organization as well as the decision in favor for or against a particular technology. Raising awareness is intended to make them realize the consequences of their previous actions for health professionals. As described in the section on quadruple aims, managers should also focus on the experience of health professionals, besides lower costs, improved patient experience and better outcomes [1]. As the thesis shows, health professionals struggle with the unreliability of technologies that are implemented (Chapter 4). Furthermore, health professionals want to be involved in a co-creation process, and to cooperate actively in the development and implementation of technology. Developers and managers could contribute to positive experiences with technology among health professionals if they involved health professionals in the development and implementation phase.

For health professionals, this thesis supports a better understanding of the technostress they themselves experience at work. They can see that in this thesis they are heard and taken seriously. Health professionals should understand that their opinion is crucial in the digital transformation of the healthcare system. Nurses can use the questionnaire developed in this thesis to gain insight into their digital competence. The different perspectives in this thesis show that, although they are the ones affected by technostress, they can also play a part in reducing it and in improving digital competence. As described earlier, health professionals are not aware of how they will be influenced by the ongoing digital transformation. Thus, this thesis contributes to preparing health professionals for the future, through raising awareness. The awareness-raising can already begin in education to achieve a uniform starting position for health professionals regarding digital competence. The thesis provides evidence that higher levels of education lead to higher levels of technostress. On the one hand, this may be due to the associated professions. On the other hand, there seem to be higher expectations of digital competences for physicians and nurses at tertiary level, which are currently not being met. This is a challenge that health education organizations need to meet. Various measures are already being implemented for this purpose. In modules of the Master's degree program in nursing on knowledge transfer, research management and seminars on the Master's thesis, the thesis can serve as a basis for explaining scientific dissemination and for preparing and analyzing data in the statistics program R. Additionally, topics for Master's degree theses are suggested. Furthermore, involvement in the development and implementation of technologies requires technological knowledge and, if necessary, an expanded vocabulary to talk with developers and medical and nursing informaticists. For this, there are the first approaches towards cooperation, with a study program already on the curriculum in medical informatics that can match medical informaticists and nurses. In the first phase, module assignments for medical informatics students are now supervised by me.

For policy makers, the thesis underlines international recommendations to improve health professionals' digital competence, along with technologies tailored to health professionals' needs. The Digital Skills for Health Professionals Committee of the European Health Parliament recommends offering better incentives for health organizations and investment in the improvement of health professionals' training [2]. Regarding the generational differences in digital competences, policy makers are asked to involve technology-savvy young people in the transfer of those recommendations into practice [3]. At the national level, policy efforts are in their infancy. Only last year, a motion was submitted in Switzerland by Ettlin [4] to drive forward the digital transformation in healthcare. In exchanges with health politicians at public events, I was able to explain the relevance of the topic. The topic is gaining widespread interest in society. Even during the writing of this thesis, conferences on the topic of digitalization in healthcare and the impact on health professionals were organized by employers' associations, and I was invited to these to speak alongside health politicians.

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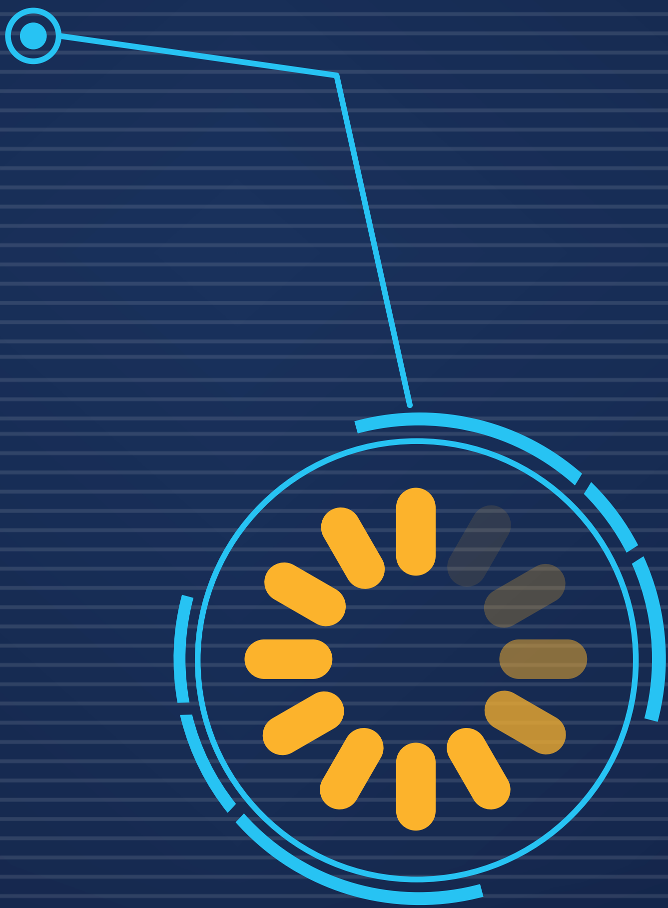

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ABOUT THE AUTHOR

Christoph Golz was born in June 1990, in Ravensburg, Germany. He started his professional career as a registered nurse on a geriatric ward in a regional hospital (2012 – 2014). During his time as a he was already involved in the evidence-based improvement and standardization of work in his team. He soon realised that his educational level was not sufficient for more comprehensive and sustainable change in practice and started with the Master of Science in Nursing at the Bern University of Applied Sciences. Along his education, he started part-time as a research assistant in the division of Applied Research and Development in Nursing BFH (2015 – 2017). After his graduation, he worked full-time as a research associate in the same division and began his PhD in the European Doctoral Program in Nursing Science (2018), organised by the University of Maastricht, the University of Graz and the Bern University of Applied Sciences. He was supervised by Prof. Dr. Sandra M.G. Zwakhalen (Maastricht University) and Prof. Dr. Sabine Hahn (Bern University of Applied Sciences). Alongside his PhD studies, Christoph was project coordinator of the national project "Strategy to counter staff shortage among health professions" and played a key role in the development of the Swiss association "Competence Network Health Workforce", which aims at improving job retention of health professionals by developing sustainable working conditions. He has further training in research management and data science. In addition to his research activities, Christoph is a co-founder of ProfessionUP Ltd. (2018), a company that develops digital training programmes for health professionals. In 2019 he received the award for the best oral presentation at the European Doctoral Conference in Nursing Science in Graz, Austria.

Since 2018, Christoph has hold management positions as head of Support (2018 – 2021) and Head of Innovation Field Healthcare – Personnel Development in the Nursing Research Department (2021 – today) at the Bern University of Applied Sciences.

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LIVING LAB IN AGEING AND LONG-TERM CARE

Living Lab in Ageing and Long-Term Care

This thesis is part of the Living Lab in Ageing and Long-Term Care, a formal and structural multidisciplinary network consisting of Maastricht University, nine long-term care organizations (MeanderGroep Zuid-Limburg, Sevagram, Envida, Cicero Zorggroep, Zuyderland, Vivantes, De Zorggroep, Land van Horne & Proteion), Intermediate Vocational Training Institutes Gilde and VISTA college and Zuyd University of Applied Sciences, all located in the southern part of the Netherlands. In the Living Lab we aim to improve quality of care and life for older people and quality of work for staff employed in long-term care via a structural multidisciplinary collaboration between research, policy, education and practice. Practitioners (such as nurses, physicians, psychologists, physio- and occupational therapists), work together with managers, researchers, students, teachers and older people themselves to develop and test innovations in long-term care.

Academische Werkplaats Ouderenzorg Limburg

Dit proefschrift is onderdeel van de Academische Werkplaats Ouderenzorg Limburg, een structureel, multidisciplinair samenwerkingsverband tussen de Universiteit Maastricht, negen zorgorganisaties (MeanderGroep Zuid-Limburg, Sevagram, Envida, Cicero Zorggroep, Zuyderland, Vivantes, De Zorggroep, Land van Horne & Proteion), Gilde Zorgcollege, VISTA college en Zuyd Hogeschool. In de werkplaats draait het om het verbeteren van de kwaliteit van leven en zorg voor ouderen en de kwaliteit van werk voor iedereen die in de ouderenzorg werkt. Zorgverleners (zoals verpleegkundigen, verzorgenden, artsen, psychologen, fysio- en ergotherapeuten), beleidsmakers, onderzoekers, studenten en ouderen zelf wisselen kennis en ervaring uit. Daarnaast evalueren we vernieuwingen in de dagelijkse zorg. Praktijk, beleid, onderzoek en onderwijs gaan hierbij hand in hand.

PhD-theses Living Lab in Ageing and Long-Term Care / Proefschriften Academische Werplaats Ouderenzorg Limburg

Christoph Golz. Technostress among health professionals: The blame game between health professionals and technology. 2023

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Ruth Vogel. Nurses in the Lead: empowering community nurse leaders to implement evidence into practice. 2022

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Theresa Thoma-Lürken. Innovating long-term care for older people. Development and evaluation of a decision support app for formal caregivers in community-based dementia care. 2018

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Donja Mijnarends. Sarcopenia: a rising geriatric giant. Health and economic outcomes of community-dwelling older adults with sarcopenia. 2016

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Judith Meijers. Awareness of malnutrition in health care, the Dutch perspective. 2009

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Monique Du Moulin. Urinary incontinence in primary care, diagnosis and interventions. 2008

Anna Huizing. Towards restraint free care for psychogeriatric nursing home residents. 2008

Pascalle Van Bilsen. Care for the elderly, an exploration of perceived needs, demands and service use. 2008

Rixt Zijlstra. Managing concerns about falls. Fear of falling and avoidance of activity in older people. 2007

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