A Configurational Approach to Task-Technology Fit in the Healthcare Sector

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Abstract. In spite of strong investments in digital technologies in the healthcare and medical services domain over the past couple of decades, one of the most pressing issues is that in many cases the technologies that are adopted to support the everyday tasks of professionals are often not used as intended, or even not used at all. A growing number of studies have also noted negative impacts in many circumstances when professionals such technologies them into their work tasks. This poses a major concern as investments in supporting technologies are often hindering efforts of professionals rather than enabling them. Following a task-technology fit approach we build on a sample of 445 health and medical service professionals working in Norway. This study explores the configurations of elements that lead to positive and negative impacts when using digital technologies to support work. To derive results, we utilize a fuzzy set qualitative comparative analysis (fsQCA) to showcase that there are several different configurations of tasks, technologies, and use practices that can either help produce positive impacts or create negative ones.

Keywords: Task-technology fit · fsQCA · Healthcare · Norway · Empirical

1 Introduction

In spite of heavy investments in digital technologies in the healthcare and medical services domain over the past couple of decades [1–3], one of the prevailing issues is that in many cases the technologies to support tasks of professionals are often not used as intended, or even not used at all [4]. In fact, several independent studies have documented that health and medical service professionals do not adopt newly introduced technologies, whether they are used to support core tasks [5], reporting and documenting [4], or for task coordination [6–8]. In particular when one factors in the large costs associated with developing and implementing such digital technologies in the healthcare sector, as well as their potential to significantly improve professionals work performance [9], it is a big surprise to see that there are still many professionals that chose to not adopt technologies in their work activities or report negative consequences [10]. In the last few years, a number of studies have delved into this issue, attempting to explore the reasons as to why health professionals either do not use

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supporting technologies, or to understand why they experience negative impacts from incorporating them in their work practices [11].

Despite a number of different approaches been utilized in examining such effects and their roots, a prominent perspective, that of task-technology fit, has been argued to be particularly suited in explaining how specific job-related tasks, aspects of the technology, as well as use practices coalesce to create fit, and subsequently positive impacts [12]. This theoretical framework examines alignment at the micro-level, looking into how individuals and their tasks are in fit with the used technologies. While the task-technology theory has received considerable attention in the broader IS domain, within the context of health and medical service professionals use of technology, studies have remained much sparser. Even more, the vast majority of studies applying this perspective to uncover key success factors to fit, adopt a methodological approach that does not account for the diversity of use patterns and requirements of varied tasks that professionals need to deal with in their everyday work [13]. Recent work in the field of health technology adoption, and within the more general IS domain, supports the idea that there may exist multiple different ways by which technology can produce positive impacts to employees [14]. The main rationale of such approaches is that individuals in their work are faced with different tasks that they must complete. This requires different approaches with regards to the use of technology, as well as specific adoption and diffusion practices to achieve expected outcomes.

The purpose of this study is to examine through a task-technology fit theoretical perspective, which are those combinations of tasks, technology, and individual use practices that fit together to contribute to positive impacts in the context of health and medical service professionals work. We draw on a recent large-scale empirical survey conducted with 445 professionals in the domain, and by applying the novel methodological approach fuzzy set qualitative comparative analysis (fsQCA) uncover several different configurations that lead to either positive or negative impacts. Through this way we are able to identify a series of different tasks, the aspects pertinent to technology that best fit task requirements, as well as individual use and adoption practices that facilitate optimal fit. Similarly, we highlight those that produce negative outcomes to professionals, as a means of demonstrating what should be avoided in practice. In the rest of the paper we discuss the background and related literature in the domain, introduce the method applied and the data that is analyzed, followed by the results and a discussion on their implications.

2 Background

To explore how different digital technologies can contribute to positive and negative impacts of work performance in the health and medical services sector we build on the task-technology fit theory [12]. The theory holds that digital technologies will have a higher probability of positively impact individual work performance when the capabilities they deliver can match the tasks individuals must perform. Since its inception the theory has been extended in several ways, with latest literature recognizing the fact that individual use characteristics and the design and training practices surrounding adoption play a significant role on performance impacts of technology use [15]. The task-technology fit theory has subsequently been used at various levels of analysis, examining effects on individuals and groups [16], as well as in many different contexts, from specific technologies [17] to effects on industries or particular professions [18]. Within the context of healthcare and medical services, there have been several studies that examine factors that contribute to task-technology fit, and as a consequence positive work-related impacts [19]. These studies have been increasing over the past few years seeing the growing use of digital technologies in the healthcare sector. Now, more than ever, health professionals are using digital technologies either due to governmental pressures, or to improve their work performance in a range of different tasks [7]. Yet, despite heavy investments and a strong move towards digitally-enhancing tasks of health professionals, there still many that state that such digital technologies are becoming more of an obstacle rather than an aid in improving work [20].

Configurational approaches which are grounded on the tenets of complexity theories have being growing in interest in the IS community over the past few years [21]. One of the main strengths of such approaches is that the allow for the possibility of multiple different paths, or solutions, that lead to an outcome of interest [22]. This means, that in the case of positive impacts of digital technology use in the health and medical services sector, it would be possible to detect several successful cases of using technologies to perform specific tasks, along with the individual use characteristics that describe them. The literature has documented some first studies following task-technology fit theory and configurational approaches in explaining optimal patterns for use of health and medical services technologies [23]. Nevertheless, there is still very limited research in exploring how the different aspects pertinent to task, technology, and individual use coalesce to drive fit, and as a result positive impacts in the workplace. While the bulk of research building on the task-technology fit theory has focused predominantly on the two main concepts (i.e. task and technology) [24], a growing stream of research incorporates in the investigation the role of individuals and how technologies are deployed and routinized in work activities [25]. In fact, more and more research is looking into the formal and informal mechanisms of adopting and routinizing the use of technologies in the workplace, acknowledging the fact that just as important as the technology itself to support a task are the practices through which they are embedded in work [26].

3 Method

3.1 Data Collection

To explore the configurations of elements pertinent to tasks, technology, and individual use context that lead to positive and negative impacts in the work environment, a survey instrument was developed. The survey-based approach is regarded as an appropriate method to accurately capture the use of technologies, and beliefs and attitudes of individuals in the work environment, and also specifically in the health sector [27]. According to Straub, Boudreau and Gefen [28]), the survey-based method is based suited in exploratory settings and predictive theory. To develop the respective constructs, we utilized a 5-point Likert scale, which is regarded as an appropriate method where no standard measures exist for quantifying notions such as attitudes and beliefs. To make sure that the measures were reliable and valid, a pilot study was conducted the year before the main study (i.e. in 2016) gathering responses from approximately 1000 individuals in Norway working in different sectors. This pilot study enabled us to assess the content validity of items, and to ensure that all questions were easily understood. For the main study, a representative population following the level 1 of NACE Classification Codes (Nomenclature des Activités Économiques dans la Communauté Européenne) was selected within Norway, and a list of individuals within each industry was constructed following a representative sample based on job type.

A professional data collection company was commissioned with conducting phone polls to individuals throughout Norway using a database of approximately 10.000 individuals in a variety of different industries, including those of health and medical services. The callers informed participants about the purpose of the study and asked respondents to answer a number of questions by giving an appropriate response. The data gathering process lasts roughly four months (May 2017–August 2017), and the average time for answering the questions of the survey was 23 min. A total of 445 complete responses were received from the health and medical services industry. From this sample, most responses came from the age-groups 30–44 years (34%) and 45–59 years (34%). In terms of gender distribution, the largest proportion of the sample consisted of female employees (74%) while men account for 26% of the sample. When looking at the educational background of respondents, most of them had as a highest academic qualification a degree from a university or other higher-education institution until 4 years (42.2%), while 36.6% had an educational background of over 4 years in higher education (equivalent to master's degree or Ph.D). Finally, when looking at leadership responsibilities, the vast majority of the sample stated that they did not have leadership responsibilities (74.4%), 8.8% noted that they had managerial responsibilities, 3.8% that they had personnel responsibilities, and 13.0% that they had both types of responsibilities. To examine the possibility of non-response bias in our sample, the profiles of the respondents from the mailing list were benchmarked against information about the health sector and the profiles of people employed from the central statistics bureau. Outcomes confirmed that there was no statistically significant difference between the two sub-groups and that the sample of respondents was representative of the population.

3.2 Measurements

To operationalize the different dimensions that are relevant in examining task-technology fit and individual use a number of different constructs were used to capture the greatest possible breadth of these categories of variables. All measures were based on prior empirical research and were therefore previously tested in empirical studies. In Appendix A we provide a full list of the questions asked.

When examining attributes relevant to the task itself, we utilized measures that included questions on the types of tasks in which digital technologies were used, the difficulty ad time-criticality of the task, if the level of non-routineness. The types of information we measured under the Task label followed relevant literature examining similar phenomena in IT use in the workplace [29, 30]. Specifically, we measured on a 5-point likert scale the frequency in which respondents used digital technology for core tasks, reporting and documentation tasks, and information/coordination [31]. To determine if they held positions that required leadership skills, we asked respondents to indicate if they had no leadership responsibilities, personnel, managerial, or both. For the purpose of this study, we aggregated as a dichotomous variable leadership with 1 denoting that they had at least one of personnel or managerial, or 0 if they didn't have any leadership responsibility. Finally, to assess the level of non-routineness, we asked respondents to indicate how often they were expected to work outside of paid work hours [32].

With regards to technology-related characteristics we followed a similar approach, looking at different aspects related to functionality and user-friendliness, while also incorporating specific types of devices in the questions tat are commonly used by health and medical professionals. More specifically, we captured the extent to which respondents believed that digital technologies they used in the jobs were functional and reliable, user-friendly, and flexible and adaptable [33]. Furthermore, we assessed the extent to which respondents need to use different types of devices to perform their work such as personal computers, mobile devices (e.g. smart phones, tablets and portable recording equipment), and wearables (smart glasses, smartwatch/bracelets), or augmented reality technologies [34].

In terms of individual use context, we tried to capture elements that were relevant to how individuals adopt and utilize novel digital technologies within their work place, as well as what types of support mechanisms are set up to facilitate such usage. In congruence with past empirical studies we include aspects that can affect how easily and well individuals utilize digital technology [12]. Specifically, we examine the degree tow which individual have a support network from colleagues when using digital technologies, the extent to which they have been trained to use the latest digital technologies in their organizations (e.g. courses, e-learning, self-education through reading), as well as the level to which they have been involved in the joined planning of introducing new digital technologies.

Finally, when it comes to examining the impacts of digital technology use in the healthcare and medical sector, we examine two opposing depending variables. On the one hand we capture the level to which digital technologies have a positive contribution to work performance. We operationalize this variable as the level to which the quality of work gets better, work is done fast, and the level to which the work performed relies on the use of digital technologies [35]. Since our aims is to also capture configurations that lead to decreased performance, we use separate measures to assess the negative consequences of using digital technologies. Specifically, we develop negative impacts by asking respondents to evaluate the level to which digital technologies have given them a greater workload. Have increased requirements for concentration in work, have resulted in greater time pressure, and have increased stress levels.

3.3 Measurement Model

Due to the fact that the model contains primarily formative or single-item constructs, we apply different assessment criteria to evaluate each. First-order formative constructs were assessed in terms of multicollinearity, weights and significance. Since we only had first-order constructs, these values were examined at the construct and item level respectively. All items had positive and significant association with their higher-order constructs. When examining for multicollinearity issues we looked at Variance Inflation Factor (VIF) values, with values above 3.3 being the cut-off threshold [36]. All first order variables had values below the threshold indicating an absence of multicollinearity within our data.

4 Findings

To examine what configurations of task, technology, and use practice lead to lead to positive or negative work impact we utilize a fuzzy-set Qualitative Comparative Analysis (fsQCA) approach. FsQCA is a set-theoretic method that in based on Boolean algebra (i.e. set membership) to determine how configurations of elements are linked to specific outcomes. The technique follows the principles of complexity theories and allows for the examination of interplays that develop between elements of a messy and non-linear nature [22, 37]. What makes fsQCA different from other methods of analyzing data is that it supports the notion of equifinality. In essence, equifinality means that a specific outcome (e.g. positive or negative work impacts) may be a result of different configurations of elements, and that these configurations can deviate depending on context or individual use patterns. Applying such an approach is particularly relevant to the case of digital technology usage within the health and medical services context, since depending on the type of task, and characteristics of the individual, different digital technologies and use support mechanisms may be more or less relevant in producing positive impacts. Consequently, it is important to understand what configurations of tasks, technologies, and use practices yield most positive impacts, and which most negative ones. Conducting such analyses through FsQCA enables this identification as it is oriented towards reducing elements for each configuration to the fundamentally necessary and sufficient conditions. In addition, fsQCA supports the occurrence of causal asymmetry, which in short means that for an outcome to occur, the presence and absence of a causal condition depend on how this causal condition combines with one or more other causal conditions [22].

As a first step of performing the fsQCA analyses, it is necessary that we calibrate dependent and independent variables into fuzzy or crisp sets. Positive and negative impacts are set as the dependent variables of our study, while the independent variables that are used include those that fall under the categories of task, technology, and individual use context. The only crisp set we have in this analysis in the leadership responsibilities which are coded for 1 if there are is at least the requirement to handle personnel or other managerial matter, or 0 in the absence of such requirements. Contrarily, fuzzy sets in this analysis can range anywhere on the continuous scale from 0, which denotes an absence of set membership, to 1, which indicates full set membership. To calibrate continuous variables such as the ones we have utilized in the survey into fuzzy sets we followed the method proposed by Ragin [38]. Following this procedure, the degree of set membership is based on three anchor values. These include a full set membership threshold value (fuzzy score = 0.95), a full non-membership value (fuzzy score = 0.05), and the crossover point (fuzzy score = 0.50). Since this study uses a 5-point Likert scale to measure all continuous constructs, we follow the suggestions of Ordanini, Parasuraman and Rubera [39] to calibrate them into fuzzy sets. Following these guidelines, and based on prior empirical research (Fiss, 2011; Ragin, 2009), we computed percentiles for each construct so that the upper 25 percentiles serve as the threshold for full membership; the lower 25 percentiles for full non-membership; and the 50 percentiles represent the cross-over point.

4.1 Fuzzy Set Qualitative Comparative Analyses

To extract the configurations that lead to positive and negative impacts we relied on the software fsQCA 3.0. By conducting two separate analyses, the fsQCA algorithm produces truth tables of 2^k rows, where k is the number of predictor elements, and each row indicates a unique possible combination of elements. The fsQCA software then sorts all the 445 observations into each of these rows based on their degree of membership of all the causal conditions. An outcome if this is a truth table where some rows contain several observations while others just a few or even none depending on the collected data. As part of this step it is up to the researcher to reduce the number of rows according to two rules: (1) a row must contain a minimum number of cases, this value was set to a frequency threshold of 5 cases; and (2) selected rows must achieve a minimum consistency level of 0.80. Therefore, configurations that do not fit into these rules are excluded from the analyses. In order to obtain results that explain positive and negative impacts of digital technologies, we use the method proposed by Ragin and Fiss [40]. This method identifies core conditions that are part of both parsimonious and intermediate solutions, and peripheral conditions that are not detectable in the parsimonious solution and only appear in the intermediate solution [41]. Outcomes of the fuzzy set analyses for positive and negative impacts are presented in Table 1. The black circles (●) the presence of a condition, while the crossed-out circles (⊗) indicate the absence of it. Core elements of a configuration are marked with large circles, peripheral elements with small ones, and blank spaces are an indication of a don't care situation in which the causal condition may be either present or absent.

Table 1. Configurations leading to high and low performance

Configuration	Positive Impacts					Negative Impacts			
	P1	P2	P3	P4	P5	N1	N2	N3	N4
Task									
Core task			●		●	●			●
Reporting and documentation task		●	●	●			●		
Information/Coordination task	●	●		●				●	
Leadership	●	●	⊗	⊗	⊗	●	⊗	●	⊗
Non-Routineness	●		⊗	●	⊗		●	●	
Technology									
Reliability	●	●		●	●	⊗	⊗		
User-friendliness		●	●	●	●	⊗	⊗		
Adaptability/Flexibility	●	•			●			⊗	⊗
Personal computer		●	●	●		●	●	●	
Mobile devices	●			●				●	
Wearables					●				●
Use Context									
Colleague support			●	●	•	●	⊗	•	
Training		●	●		●		•	⊗	⊗
Planning participation	●				●	⊗		⊗	⊗
Consistency	0.913	0.907	0.892	0.917	0.873	0.943	0.908	0.874	0.870
Raw Coverage	0.216	0.221	0.184	0.194	0.131	0.131	0.092	0.106	0.118
Unique Coverage	0.192	0.186	0.144	0.139	0.088	0.122	0.073	0.899	0.101
Overall Solution Consistency	0.885					0.879			
Overall Solution Coverage	0.573					0.342			

The outcomes of the analysis for positive impacts produce five different solutions. The solutions are grouped into those that are oriented for leadership-related roles (P1–P2) and non-leadership (P3–P5). Solutions P1 and P2 present some commonalities but are based on use of different technologies. P1 produces positive impacts for use of mobile devices to perform information and coordination tasks that are characterized by non-routineness. For successful use of such systems a prerequisite is that the are above all reliable and adaptable, and that employees are contributors during the planning and introduction of such technologies. In P2 the utilized technologies are personal computers for reporting and documentation tasks and information/coordination. Again, reliability is found to be a core contributor to positive impacts of digital technology use, with user-friendliness being another core-condition, and adaptability playing a lesser important role. Successful adoption of such technologies is coupled with training. Solution P3 concerns personal computer use for core tasks and reporting and documentation. This solution corresponds to employees that do not undertake leadership tasks and their work is characterized by routine practices. Positive impacts in this case result from developing user-friendly technologies and providing support within the working environment and training for use. P4 on the other had refers to non-routinized work activities that necessitate tasks of reporting and documentation and information coordination. Here the used technologies include personal computer and mobile devices, with user-friendliness and reliability being core characteristics leading to positive impacts combined with support from colleagues. Finally, P5 refers to routinized work for core tasks using wearables. Here we find that for such technologies' reliability, user-friendliness and adaptability all have t co-exist in tandem with appropriate training and involvement in the planning and introduction of such digital technologies.

When looking into negative impacts we do not make the assumption that they will be the counter-situation to positive ones, since a series of different elements may coalesce to result in a negative outcome. We negative impacts are realized when for core tasks that are performed by employed with leadership responsibilities, there is an absence of user-friendliness and reliability for tasks done on personal computers, and where the preferred method of training is through collegial support and an absence of participation during planning and introduction. Similarly, in solution N3 when it comes to tasks that require information and coordination of a non-routinized nature performed on personal computers and mobile devices, an absence of flexibility combines with a lack of training and participation in planning lead to sub-optimal outcomes. In solution N2 which corresponds to personnel that do not have leadership responsibilities and use digital technologies for non-routinized reporting and documentation tasks on personal computers, the absence of reliability and user friendliness, along with low support within work on using such technologies leads to negative impacts. Finally, solution N4 concerns core tasks conducted by employees without leadership responsibilities utilizing wearable devices. In these cases, limited flexibility combined with no training and participation in the planning yields negative impacts.

5 Discussion

This study builds on the increased digitization of work practices within the healthcare and medical services sector and attempts to explore what configurations of tasks, technologies and individual use contexts lead to positive and negative impacts. This study is motivated by the increased embeddedness of work practices with digital technologies and the large amounts invested annually in improving operations by means of such technologies. Nevertheless, the value of such technologies is often questioned, and several studies pinpoint that a lack of any significant impacts, or even negative ones, are due to the fact that there is often a mismatch between what is required, how it is assimilated in operations, and how it is leveraged to support certain tasks. Even more, there are several reports that despite investments in digital technologies in the healthcare sector, there is a denial of use that can be attributed to several reasons, but primarily due to the fact that these technologies make work practices much more arduous and stressful rather than providing any value. While there has been some work on task-technology fit in the healthcare environment, the methodologies applied to date do not allow for the exploration of the diverse profile and patterns of use [42].

Specifically, our study contributes theoretically by expanding the perspective of task-technology fit and unshackling for research methods that can explain part of the picture. The use of configurational approaches such as that of fsQCA can enable researcher to uncover different configurations of conditions that lead to positive outcomes, providing a renewed, and more individual-specific perspective on how to optimally use digital technologies to enhance work and improve productivity. The findings demonstrate that there are unique combinations of critical factors that contribute to making technology work of healthcare and medical service professionals, and that these do not only relate to the technology, but also to its fit with specific tasks, the routinization of work, as well as how organizations plan and diffuse them. This raises the question of how organizations should plan such initiatives to prepare for pre-adoption, and to facilitate continued and optimal usage. From a practical point of view, the results of this study can be used by technology managers to formulate different strategies around digital technologies in the healthcare and medical sector. In particular, our results showcase something that is often mentioned by consultants, but that is hardly applied in practice; that there needs to be a greater degree of personalization when planning and deploying digital technologies to support work, particularly in a very information-sensitive, time-critical and low fault tolerant sector such as that of the healthcare. It is also quite striking to see that there are several ways in which digital technologies can produce negative impacts to professionals. Such results should prompt professionals to understand why heir digital solutions are creating more of a burden than helping those they were intended for and creating deployment practices that work towards positive impacts.

While the results of this research shed some light on the complex relationships between tasks in the healthcare sector, digital technologies, and individual usage characteristics, they must be considered under their limitations. First, the sample of our analysis consists of employees working in Norway. It is probable that individuals that work in other countries may have slightly different configurations of factors that positive impacts since there is likely a cultural effect that could play a role. Second, while we examine positive impacts, we do not look at them specifically. It may be likely that we have a mix of positive impacts and negative ones at the same time. An interesting future direction would see where the optimal balance between the two is and how to achieve that. It is very likely that positive impacts are also accompanied by some negative and more salient ones. Third, although fsQCA allows us to examine the configurations of factors that lead to positive and negative impacts in work performance, the process through which this is done is not well explained. A complementary study suing a qualitative approach would likely reveal more insight on the stages of use of technology, where major obstacles present themselves and how they are overcome.

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