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Patrick Mikalef[1,2] Hans Yngvar Torvatn[1] and Emrah Arica[1]

[1] SINTEF Digital, S. P. Andersens veg 5 7031, Trondheim, Norway
[2] Norwegian University of Science and Technology, Sem Saelands Vei 7-9 7491, Trondheim, Norway
{patrick.mikalef, hans.torvatn, emrah.arica}@sintef.no

Abstract. With the last few years seeing an increased introduction of technological innovations in factories, one of the most pressing issues is how these technologies can be deployed to optimally support the activities of professionals that are actually utilizing them. Despite heavy investments in novel technologies, there are often negative consequences for the human factor, particularly when there is a lack of alignment between the task that it is used towards and the fit in terms of human training and the needs it is targeted to fulfil. In this research we build on the Task-technology Fit theory and a sample of 182 professionals working in Norway and explore the configurations of elements that drive positive impacts when introducing digital technologies to support factory work. We analyze data through a fuzzy set qualitative comparative analysis (fsQCA) method and demonstrate that there are several different combinations of conditions that can deliver positive impacts.

Keywords: Task-technology fit, human-machine symbiosis, fsQCA

1 Introduction

While there have been substantial investments in digital technologies for manufacturing purposes over the last few years [1], a critical issue is that in many cases the technologies used to support tasks of professionals are often not used as intended, or even not adopted at all [2]. Some studies have highlighted that the intended value from investments in novel technologies is not actually realized. A sizeable number of studies suggest that the underlying cause of this is due to a miss-match between what is needed from the human side in relation to work activities and what is provided by the technology [3]. In fact, some researchers have reported that professionals working in the manufacturing industry often have trouble adopting and routinizing newly introduced technologies [4]. This leads to negative impacts on their job performance when they have to utilize such systems [5]. Nevertheless, this problem is not strictly identified in the domain of manufacturing and factory work, and has been a core concern in several other domains including the education, banking and financial sector, and even high-tech companies [6, 7]. It is surprising to see that the human factor has received only limited attention to date when taking into account the huge costs invested by companies to develop and adopt such technologies [8].

A growing body of research underscores on the importance of looking into the symbiosis between humans and machine [9, 10]. The main idea is that human cyber-physical systems should serve to improve human abilities to dynamically interact with machines, and improve human physical-, sensing- and cognitive capabilities [2]. The underlying logic of this perspective is that by optimizing human-machine cooperation organizations can realize improvements in performance and efficiency [11]. In doing so there have been a number of different approaches into examining how humans and machines can complement each other capabilities and create value, and what factors influence human intention to adopt and use technologies such as the Technology Adoption Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) [12]. Nevertheless, these models don't account for which technologies best fit which task. The theory of task-technology fit (TTF) has been a particularly prominent perspective and well-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 [13]. The TTF theory has received substantial attention within other fields such as the Information Systems domain, yet when examining the adoption of technologies to support manufacturing and factory work studies are still scarce [14]. There is a growing perspective within the broader field of technology adoption that there may be several different ways by which technological solutions can be used to support professionals work activities [15]. The underlying premise is that individuals in their work are faced with different tasks that they must complete.

The objective of this study is to adopt a TTF theoretical perspective, and examine which are those combinations of tasks, technology, and individual use practices that fit together and lead to positive impacts in the context of manufacturing and factory professionals work. We build on a recent large-scale empirical survey conducted with 182 professionals, and by applying the novel methodological approach fuzzy set qualitative comparative analysis (fsQCA) we reveal several configurations that lead to positive outcomes for job-related activities. In this way we can identify a number 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.

2 Background

To explore how technologies deployed within the manufacturing domain can contribute to positive outcomes of work performance, we develop this research on the task-technology fit theory [13]. Based on TTF theory, digital technologies will be more likely to yield a positive impact when the functionalities they deliver can fit the tasks individuals must undertake. Since its inception, the theory has been extended in several ways, with the latest studies recognizing how individuals use these technologies as well as the design and training practices surrounding adoption and diffusion, have an important role on performance of technology use [16]. Hence, the task-technology fit theory has been applied at various levels of analysis, examining effects on individuals and groups [17], as well as in many different contexts, from specific technologies [18] to effects on industries or particular professions [19]. When looking into the area of manufacturing and factory work, there has been very limited work following this approach. Despite this, recent work has recognized the importance of the human factor highlighting that there needs to be alignment between the jobs humans must perform, the digital technologies introduced to support them, and the training they receive to adopt such systems into their work [20]. To determine how these aspects jointly contribute to drive positive impacts in job performance, we follow a configurational approach in data analysis [21].

Configurational approaches have been growing in interest in the IS and technology management community over the past few years [22, 23]. Such approaches have the advantage that they enable the identification of multiple different paths, or solutions, that lead to an outcome of interest [24]. In practical terms, this means that in the case of positive impacts of digital technology use in the manufacturing and factory work context, 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. Nevertheless, in spite of the promise of such approaches, 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 factory and manufacturing workplace [25]. The bulk of research building on the task-technology fit theory has emphasized on the two main concepts (i.e. task and technology) [26], while a growing stream of research incorporates in the investigation the role of individuals and how technologies are deployed and routinized in work activities [27]. An increasing number of research is looking into the formal and informal mechanisms of adopting 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 [28].

3 Method

3.1 Data Collection

To examine the configurations of elements regarding tasks, technology, and individual use context that lead to positive impacts in the work environment, a survey instrument was developed. 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 factory and manufacturing workers amongst others. No specific areas of manufacturing were selected, and respondents covered tasks of several different functions. The scales of the questionnaire are described in section 3.2. The callers informed participants about the purpose of the study and asked respondents to answer a number of questions. 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 minutes. A total of 182 complete responses were received from the manufacturing industry. From this sample, most responses came from the age-groups 45-59 years (38%) and 30-44 years (37%). In terms of gender distribution, the largest proportion of the sample consisted of male employees (72%) while females accounted for 28% of the sample. When looking at the educational background of respondents, most of them had as a highest academic qualification a degree from high school (42.9%), while 35.67% had until 4 years in higher education (equivalent to bachelor's degree).

Table 1. Descriptive statistics of sample respondents' profile

	Sample (N=182)	Percentage (%)
Age		
Under 30	33	18%
30-44 years old	67	37%
45-59 years old	69	38%
More than 60 years old	13	7%
Highest Educational Level		
Primary school	6	3.3%
High school	78	42.9%
Higher education (less than 4 years)	65	35.7%
Higher education (more than 4 years)	33	18.1%

3.2 Measurements

Regarding 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. 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 [29]. 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. Finally, we asked respondents to indicate how often they were expected to work outside of paid work hours [30].

Concerning 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 that are commonly used by manufacturing professionals. We captured the extent to which respondents believed that digital technologies they used in the jobs were functional and reliable, user-friendly, and adaptable [31]. 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 equipment), and wearables (smart glasses, smartwatch), or augmented reality technologies [32].

In terms of individual use context, we tried to capture elements that were relevant to how individuals adopt and utilize novel digital technologies, 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 [13]. We examine the degree to which individuals 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 [33]. Finally, when it comes to examining the impacts of digital technology use in the manufacturing sector, 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 [34].

4 Analysis

To identify the configurations of task, technology, and use practice lead to lead to positive or negative work impact we employ a fuzzy-set Qualitative Comparative Analysis (fsQCA) approach. Applying such an approach is particularly relevant to the case of digital technology usage within the manufacturing 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 [35]. A first step of performing a fsQCA analysis requires that we calibrate dependent and independent variables into fuzzy or crisp sets. To calibrate continuous variables such as the ones we have utilized in the survey into fuzzy sets we followed the method proposed by Ragin [36]. 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) [37]. Based on prior empirical research 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. The results of the analysis are depicted in the table below and discussed in the final section.

Table 2. Configurations leading to high work performance

Configuration	**Positive Impacts**				
	1	2	3	4	5
Task					
Core task	●		●	●	
Reporting and documentation task		●		⊗	
Information/Coordination task		●	●		●
Leadership					●
Non-Routineness		⊗		⊗	
Technology					
Reliability		●	●	●	●
User-friendliness	●		●	●	●
Adaptability/Flexibility	●			●	
Personal computer		●		⊗	
Mobile devices			●		●

Wearables	●				
Augmented Reality	●			●	
Individual Use Context					
Colleague support			●		
Training	●			●	
Planning participation	●			●	●
Consistency	0.86	0.91	0.93	0.83	0.88
Raw Coverage	0.27	0.18	0.13	0.18	0.21
Unique Coverage	0.11	0.08	0.09	0.10	0.04
Overall Solution Consistency	0.86				
Overall Solution Coverage	0.42				

5 Discussion

This study finds that there are different combinations of technologies, features, and mechanisms to routinize depending on the task at hand. Furthermore, the results indicate that tasks that revolve around core tasks, such as those in the workstation can be improved the right combination of technologies and attributes in their design, coupled with the necessary training practices. The black circles denote a presence of a condition while the crossed-out ones an absence of it. For instance, in column 2, the solution reads as follows. When the task of the worker includes activities of reporting and documentation and information coordination and is a routine activity, then high reliability coupled with the use of a personal computer and a collegial support regime are sufficient to drive positive work performance. Likewise, other solutions show different tasks and combinations of them, pinpointing to certain activities within the work environment and how they can optimally be enhanced by means of digital technologies. What is interesting to observe also is that apart from the physical technologies themselves, there are also functional characteristics and design principles that need to be considered. In addition, the strategies applied to deploy and routinize such technologies are identified in solutions. These solutions are by no means exhaustive and can be examined on an even more granular level, nevertheless, they do illustrate a novel approach for uncovering combinations of elements around the use of technology that lead to positive outcomes. Future research can extend on this method and identify how human-machine symbiosis can be optimized.

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