Introducing user experience in manual data collection: the effect of social influence, managerial support, and usefulness

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Abstract: Previous research has found quality issues in the data that technicians collect about the assets that they maintain and repair. Factors affecting this manual collection of data include social influence, managerial support, and the usability of the computerised maintenance management systems (CMMS). The purpose of this work is to quantitatively investigate the results of previous qualitative studies regarding the role of social influence and the user experience of a CMMS in manual data collection. A survey is developed to quantitatively study manual data collection in a maintenance organisation. The results reveal that these factors influence data collection performance. This extends existing understanding of manual data collection and calls for future research that would overcome the limitations to this study caused by the limited number of respondents. The effects of social influence and usefulness have important implications for the interaction design of data collection tools.

Keywords: manual data collection; computerised maintenance management system; CMMS; user experience; social influence; data quality.

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1 Introduction

Intelligent devices equipped with sensors provide large amounts of data. However, these data alone are not sufficient for providing services, nor for data-centric decision making (Madhikermi et al., 2016). The results from advanced data analytics rely on the quality of the data that is analysed. Even if manufacturing companies aim to automate the creation of this asset data by condition monitoring technologies, still some data remains to be collected manually. This includes operational and cost related data from service operations, such as hours spent at the site and spare parts used (Unsworth et al., 2011). If manually collected data is missing, it will affect the results of data analytics. For example, sensors can usually give exact down time of a piece of equipment, but not the reason behind down time: redundancy, maintenance, waiting for spare parts, etc. Manual data collection is error prone, however, and several data quality issues have been observed in manually collected data (Mahlamäki et al., 2016; Sandtorv et al., 1996). Ali-Marttila et al. (2018) discovered that several elements contribute to the value of maintenance services, but, often, mainly the cost dimension of maintenance services is measured. Measurement metrics should be adapted to human factors (Berges et al., 2013). It is important to include the quality of manually collected data in key performance indicators.

Digitally facilitated knowledge processes can empower production workers by leveraging their knowledge processes, decision-making skills and social interaction practices (Hannola et al., 2018).

This approach could be extended to maintenance contexts. Maintenance work has traditionally been ‘blue-collar work’, but the shift towards knowledge work has been noticed already in 1994: “Workers are expected to possess skills for data gathering, problem solving, experimentation, and information technology use” [Roth et al., (1994), p.31]. Current requirements of using modern computerised maintenance management systems (CMMS) and even mobile applications for closing work orders are emphasising this shift into more knowledge intensive work. This requires new capabilities from maintenance technicians and their supervisors.

Previous research has resulted in the awareness of several factors that affect manual data collection. Managerial pressure and technological input control have been identified as influential in manual data collection (Molina et al., 2013). Tretten and Karim (2014) and Antonovsky et al. (2016) complement discussion of technological input control with remarks and analysis on the usability of CMMS. For example, Antonovsky et al. (2016) discovered difficulties in locating information from the CMMS. Furthermore, Haegemans et al. (2019) propose that making the information system easier to use can improve the attitude of data collectors towards data collection. Baseline usability challenges relate to inconsistent user interfaces (UIs) that do not provide feedback to incorrect actions, unclear interplay between systems, and too much manual input of information, leading to unmotivated users who were unwilling to use the CMMS (Tretten and Karim, 2014).

Schraven et al. (2015) have reviewed the use of maturity models in the task of evaluating asset management implementation and they argue that shortcomings of these models remain in accounting for employee experiences. Similarly, Oja and Galliers (2011) suggest that enterprise system usage should be studied as a holistic user experience (UX). Whereas usability can be seen as the instrumental aspects of interaction, UX also covers the experiential elements of interaction and it is a consequence of the user's internal state (e.g., motivation), the characteristics of the system (e.g., usability), and the context of interaction (e.g., social setting) (Hassenzahl and Tractinsky, 2006). There is a gap in current literature on CMMS usage that has covered usability aspects (Tretten and Karim, 2014), but not UX. Whereas usability emphasises productivity related issues [effectiveness, efficiency (ISO 9241-11, 1998)], UX could support motivation for CMMS usage. In the context of manual data collection, the UX of a CMMS can include the usability, motivation, and social aspects of using the system. In this study, these aspects are combined into two constructs: usefulness and social influence. As previous work by Molina et al. (2013) has shown the importance of managers in this context, managerial support is also examined.

The goal of this study is to examine the effect on manual data collection that UX has resulting from social influence, managerial support, and usefulness. Drawing on previous studies, these three constructs are conceptualised in the context of manual data collection. The constructs and a conceptual model for understanding the effects of social influence, managerial support, and usefulness on the individual's data collection performance are then developed and validated.

The research question of this study is: *what is the effect of social influence, managerial support, and usefulness on manual data collection performance?*

To answer this question, a survey is developed and used to gather data from a maintenance organisation (N = 81). Partial least squares (PLS) modelling is used to investigate the relationships between social influence, managerial support, usefulness and manual data collection performance.

This paper delivers both theoretical and managerial contributions. Maintenance technician work is analysed in socio-technical settings, comparing the effect of managerial and social influence with the usefulness of the CMMS. This research extends previous work by Tretten and Karim (2014) and Antonovsky et al. (2016) by providing quantitative evidence of the effect of usability on manual data collection performance. Furthermore, UX aspects are included into the analysis. The effect of managerial support is analysed in a similar manner as Molina et al. (2013) studied managerial pressure, and this work is extended by also looking at the social influence of colleagues at work. The results of this study can provide a starting point for practical improvement actions, as well as serving as numerical evidence of the importance of UX. This is important in the development of CMMS beyond the instrumental as indicated in the model of UX by Hassenzahl and Tractinsky (2006). Unsworth et al. (2011) give examples of the meanings and importance technicians assign to data collection: if collecting data is only weakly related to preparing for a shutdown and not related to any other goals of a technician, it is not likely that he or she would collect high quality data. Improving the UX by giving links to meaningful goals can introduce emotion and affect in workplace systems.

2 Manual data collection

After completing practical maintenance tasks, closing work orders with accurate data of the tasks is an essential part of maintenance. Typically, this manual collection of maintenance data is conducted with a CMMS. CMMS are complex enterprise systems, and using them is mandatory for maintenance personnel despite the challenges they may have in using the system. IT adoption has been studied using the technology acceptance model (TAM) (Davis, 1989) and several following theories that have modified this model [e.g., unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003)]. TAM suggests that perceived usefulness and ease of use are antecedents to behavioural intention to use and actual use of systems (Davis, 1989). This literature has recognised the difference of mandatory and voluntary technology (e.g., Ojiako et al., 2012), and several studies have addressed the adoption and continued use of enterprise information systems (e.g., Cheng, 2018), and even initial adoption intention followed by actual rejection, demonstrating how adoption alone is not necessarily leading to continued use (Elbanna, 2010).

In the maintenance context, however, the question is not whether or not technicians adopt and continue to use the CMMS, it is also about *how* they use it. The problem with CMMS use can be that even if it is adopted and used, the quality of manually collected data is insufficient for purposes such as simulation (Mahlamäki et al., 2016) or data-centric decision making (Madhikermi et al., 2016). The requirements for data quality, such as accuracy, accessibility, relevance, completeness and timeliness, depend on the task at hand and may change over time (Strong et al., 1997). In this context, technicians should provide the data in a timely manner (timeliness) and with enough detail (accuracy and completeness). This manually collected data and its quality defects have been the subject of several previous studies (e.g., Betz, 2010; Lehtonen et al., 2012; Unsworth et al., 2011).

Tretten and Karim (2014) introduce usability as a key factor in the manual collection of maintenance data and identify several usability improvement areas in the CMMS used by their case organisation. Whereas usability concerns the ability to carry out a task successfully, UX looks at the individual's entire interaction with the system, and the thoughts and feelings resulting from such interaction (Tullis and Albert, 2013). Measuring UX can be a synonym to measuring usability (e.g., Sauro and Lewis, 2012) or it can include usability measures and measures of emotions, with techniques such as eye-tracking and heart rate monitoring (e.g., Tullis and Albert, 2013).

Haegemans et al. (2018) hypothesised that social pressure would have an effect on data collectors' intention to enter data correctly, but their study did not support this. The researchers proposed that this could be a consequence of not differentiating between managers and co-workers. Eckhardt et al. (2009) compared the social influence of different workplace referents, e.g., colleagues and superiors, in technology adaption. A similar division of co-worker types into peer influence and superior influence was made by Brown et al. (2010) in their study of collaboration technologies and IT adoption. Following their example, this study also differentiates between the influence of management and colleagues.

In this study, the focus is on the practical aspects of UX: usability and utility, as well as the contextual aspects in the form of social influence and managerial support. These constructs are presented in the following.

2.1 Social influence

Social influence is a part of several IT adoption models, such as the UTAUT (Venkatesh et al., 2003). Vannoy and Palvia (2010) have developed a model of technology adoption, suggesting social computing aspects as antecedent to social influence, and augmenters of usefulness and ease of use. In these studies, social influence is defined as the degree to which a person perceives that important others expect the use of the system (Venkatesh et al., 2003). However, knowing why the data is needed and what it is to be used for is related to collecting high quality data (Lee and Strong, 2003). Haegemans et al. (2017) took this one step further and showed that it is not enough to *know why* the data is needed, the data collectors should also know *why it is important*. The present study continues by adding the social perspective: it is proposed that it is important to know why the data is needed and *by whom*. This is the social aspect of utility: the benefits to others of collected data. It is assumed that this aspect is especially important when the question is also about the quality of collected data, not simply of adopting and using the system. The first hypothesis of this study thus becomes:

Hypothesis 1 Social influence will be positively related to the collection of high-quality data.

2.2 Managerial support

The importance of management commitment to data quality has been supported by several studies (e.g., Lin et al., 2006; Tayi and Ballou, 1998; Tee et al., 2007). Management structures not promoting the accuracy, completeness and timeliness of data collection, as well as specifying appropriate data quality levels can negatively affect the quality of manually collected data (Lin et al., 2006; Tayi and Ballou, 1998).

Managers' own leadership styles have a moderating effect on their IT adoption intention and knowledge sharing intention (Tseng, 2017). The aim of this study is to examine whether the effect also applies on their team's knowledge sharing in the form of manually collected data. Therefore, Molina et al. (2013) are followed in focusing on performance instead of intention, and looking at the managerial role from the technician's point of view. However, Molina et al. (2013) look at management role from the viewpoint of managerial pressure: the fear of punitive actions. Their study demonstrated that managerial pressure is effective in improving manual data collection performance for those data collectors who are only extrinsically motivated; the effect is opposite for those intrinsically motivated. Murphy (2009) sees the managerial role as a supportive one, and taking the same point of view the second hypothesis of this study is formulated as follows:

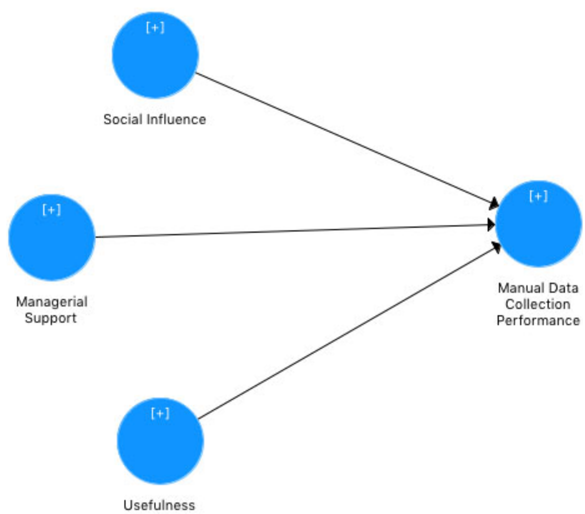
Hypothesis 2 Managerial support will be positively related to the collection of high-quality data.

2.3 Usefulness

Frustrating experiences with computers at the workplace have been reported to waste over 40% of users' time on the computer (Lazar et al., 2006). A recent study has addressed UX of enterprise systems in the adoption phase (Hwang, 2014). However, UX evolves over time from initial orientation to incorporation to identification (Karapanos et al., 2009). The focus of this study is on the incorporation phase: forming of functional dependency through usability and utility, the pragmatic aspects of UX (Roto and Rautava, 2008). Hassenzahl (2004) differentiates between the goodness and the beauty of a product, the former relating to satisfaction with the product and the latter to hedonic qualities of stimulation and identification. As Karapanos et al. (2009) relate beauty to the social meanings that the product communicates about its owner, the hedonic aspects are seen as less relevant in an organisational context in this study where users do not own the product nor have other options available. Therefore, this study focuses on the pragmatic aspects of UX in CMMS use.

In the context of this study, the goal of a maintenance technician is to close work orders with accurate information after completing a maintenance task. Usability addresses the fluency of this task. ISO 9241-11 (1998) standard defines usability as the effectiveness (ability to complete a task), efficiency (completing the task with reasonable time and effort), and satisfaction (acceptability and comfort) of achieving a specific goal in a specific context by specific users. In addition to effectiveness, efficiency, and satisfaction, Nielsen (1993) defines usability with attributes learnability (system being easy to learn), memorability (user being able to return to the system without having to learn everything again), and errors (low error rate and easy recovery from errors), in addition to efficiency and satisfaction.

Figure 1 The research model and hypothesised relations between constructs (see online version for colours)



Utility is another pragmatic aspect of UX (Roto and Rautava, 2008). Lack of direct benefits from providing good quality maintenance data is one of the reasons behind poor maintenance documentation (Betz, 2010). CMMS are used on various levels of organisations: operators, maintenance personnel, maintenance planners, maintenance managers, accountants, and senior management (Labib, 2004). One common challenge with such large, collaborative systems is that data collectors who must put in effort to collect high quality data are not the same people who use the data and thus benefit from data input (Grudin, 1988). If maintenance technicians do not have easy access to the data that they provide it becomes more difficult for them to see the benefits of providing the data.

Nielsen (1993) has presented usefulness as the usability and utility of the system. In this study, *usefulness* includes the usability of the system and its utility, i.e., benefits of using the system for the data collector. This leads to the third hypothesis:

Hypothesis 3 Usefulness will be positively related to the collection of high-quality data.

The hypotheses are summarised in Figure 1, which depicts the conceptual model of the effects of social influence, managerial support, and usefulness on manual data collection performance.

3 Methods and data

This study takes a quantitative approach to confirm the findings from previous qualitative studies (Tretten and Karim, 2014; Mahlamäki and Nieminen, 2019) that were presented in previous section. The research process consisted of a literature review that was combined with our own previous case studies to form hypotheses for this study. The hypotheses were tested empirically with a field survey of CMMS users. The survey data was then analysed using PLS approach.

3.1 Questionnaire design

This work started with a literature review and experiences from previous case studies (Mahlamäki and Nieminen, 2019). An initial pool of 35 items was drawn from this previous research. These items represented the three factors: social influence (Vannoy and Palvia, 2010; Lee and Strong, 2003; Haegemans et al., 2017), managerial support (Molina et al., 2013; Murphy, 2009), and usefulness (Betz, 2010; Tretten and Karim, 2014), as well as the dependent variable manual data collection performance. All items were measured on a five-point Likert scale: from 1 (‘strongly disagree’) to 5 (‘strongly agree’). Multiple items were used for each construct, as suggested by Tullis and Albert (2013).

Previously validated measurement items were used wherever possible to help ensure the validity of the measures, and to compare the results with previous studies (Bradburn et al., 2004). An established test, Brooke’s (1996) ten-item system usability scale (SUS), was administered along with the survey. SUS is a quick and easy survey tool to assess the usability of a product or service. It includes ten items that are rated on a five-point Likert scale (0–4). The items are summed and multipied by 2.5 to get a single score on a scale of 1–100. The result is a measure of how easy the system is to use. The original version of the scale with positive and negative items was used. However, the same Likert scale (1–5) that was used for all other items was also used for the SUS items. In the analysis phase, the scale of negative items was reversed and the mean of the SUS items was used as ‘SUS usability’ that was part of the usefulness construct. For the SUS score presented in Subsection 4.2, the scale of 1–5 was transformed to 0–4 and then the score was calculated as explained above.

The questionnaire was pre-tested to make sure that the terminology is correct, questions are clear and the questionnaire is not too long. For this pre-test, a colleague who was familiar with the company and research context was involved, in addition to the main contact at the company, and two managers and supervisors who had previously worked in a technician position and were thus in the target population. The filling of a printed survey was also observed and the questions discussed with two persons who had previously worked as technicians. The questionnaire was modified according to the feedback received from the pre-test.

3.1.1 Data collection performance

In this study, data collection performance is the dependent variable and it refers to the self-reported performance of maintenance technicians in closing work orders with good quality data. The items used by Molina et al. (2013) were modified to match the context of the case company and used for measuring the accuracy and completeness dimensions of data quality. These items were:

1 “I close work orders with accurate and correct information” (ACCURATE).

2 “I close work orders with useful additional information” (ADDITIONAL).

For the timeliness dimension, the following items were used:

3 “I close work orders immediately after finishing the task” (TIMELINESS).

4 “I keep maintenance supervisor updated on my task progress” (PROGRESSUPDATE).

5 “I let maintenance supervisor know immediately if there are delays with my maintenance task” (DELAY).

6 “I let maintenance supervisor know immediately if my maintenance task is done ahead of time”(FASTER).

3.1.2 Independent variables

For managerial support, the items used by Molina et al. (2013) were modified to a more supportive tone:

1 “If the level of my work order closing is below agreed level, my supervisor instructs me of correct way of working” (CORRECTION).

2 “My supervisor gives feedback if there are deficiencies in the work orders that I’ve closed or if I don’t keep him updated on my progress with the maintenance task” (FEEDBACK).

3 “Maintenance supervisor lets me know if there are mistakes in the work orders that I have closed” (MISTAKES).

Usefulness was measured with items

1 “I need the information that I fill in the CMMS in my work” (NEEDDATA).

2 “With the CMMS I can get things done faster” (EFFICIENCY).

3 “I use the information others have filled in the CMMS in my work” (NEEDOTHERSDATA).

4 SUS usability (mean of the SUS items) (SUS).

Eckhardt et al. (2009) found colleagues in the same department to have most influence on IT adoption, for both adopters and non-adopters. Therefore, this research concentrates on colleagues when measuring social influence. Social influence was measured with items

1 “People whose opinion I value expect me to close work orders without delay” (VALUEOPINION).

2 “I have seen other people benefit from sharing information on task progress with their supervisors or colleagues” (BENEFIT).

3 “I know who needs information from closed work orders” (DATAUSERAWARE).

4 “I know what the information from closed work orders is used for” (DATAUSAGEAWARE).

3.2 Data collection

The survey was conducted online in a three-week period within one maintenance organisation. An invitation to fill in the survey was sent to all 245 technicians working in the company at the time. 81 responses were received (33% response rate). This response rate is similar to previous surveys conducted internally by the organisation. The response rate compares favourably with similar surveys: Molina et al. (2013) report a 20% response rate. In this survey, all questions were compulsory and, therefore, no responses had to be excluded because of incomplete answers. There were no other reasons for excluding responses, either.

3.3 Case company

The case company provides services with their asset fleet. The maintenance organisation employs 245 maintenance technicians whose task is to keep the fleet in operating condition. The maintenance staffs works in three shifts. The company uses a CMMS for keeping maintenance records. The CMMS is a large enterprise system provided by an outside vendor and it had been in use for four years at the time of research. The same CMMS is widely used within the industry. However, work orders are printed, signed and stamped by the technicians, and data is inputted in the system afterwards. In addition, each unit of the fleet is monitored with individual logging system running on a tablet. The logging system is also used for recording maintenance requests by the operating staff. It is synchronised with the CMMS once equipment is at home base. The logging system had been in use for seven years at the time of research.

3.4 Sample characteristics

The sample consisted of 81 technicians. Their average age was 42 and they had worked on average 20 years in the company and 14 years in their current position, which was either technician (60) or team leader (21). All but seven had vocational education (one did not answer, one middle school, and five high school). Fourteen mentioned a high school diploma in addition to a vocational degree. Gender was not recorded as there were only a few female technicians working for the company at the time of research.

4 Results

4.1 Instrument validation

PLS approach was chosen to evaluate the reliability and validity of the measures in this study. PLS approach aims at maximising the explained variance of the dependent variable in a causal model and it works effectively also with smaller sample sizes (Hair et al., 2011). SmartPLS (https://www.smartpls.com) software was used for the analysis. The reliability of the constructs performance, managerial support, usefulness and social influence was calculated on the sample. The loadings, composite reliability (CR) and average value extracted (AVE) are presented in Table 1. Individual item reliabilities are evaluated with the outer loadings of the items and they are all above the 0.6 threshold recommended by Bagozzi and Yi (1988). CR values indicate internal consistency and they were all higher than the recommended 0.70 (Hair et al., 2011). Convergent validity is measured by AVE that should be higher than 0.50 (Hair et al., 2011). This criterion is met as can be seen in Table 1. Table 1 also presents t statistics that were obtained in a bootstrap with 5,000 samples, all above 1.96 at the 0.05 level.

Table 1 Loadings, CR, average variance extracted, t values and variance inflation factors (VIFs)

Construct/indicator	*Loading*	*Composite reliability, average variance extracted*	*t value $p < 0.05$*	*Variance inflation factor*
Performance				
• Additional	0.734	CR: 0.87, AVE: 0.52	12.2	1.63
• AllData	0.724		10.9	1.76
• Delay	0.732		8.34	2.44
• Faster	0.648		6.04	2.02
• ProgressUpdate	0.786		9.14	3.23
• Timeliness	0.681		7.51	1.54
Social influence			5.23	
• Benefit	0.681	CR: 0.84, AVE: 0.57	7.43	1.64
• DataUsageAware	0.766		13.2	1.80
• DataUserAware	0.803		16.4	1.90
• ValueOpinion	0.756		11.5	1.71
Managerial support				
• Correction	0.825	CR: 0.87, AVE: 0.69	2.36	24.2
• Feedback	0.803		16.3	1.62
• Mistakes	0.866		10.4	1.57
Usefulness			2.11	
• Efficiency	0.790	CR: 0.88, AVE: 0.66	11.6	1.76
• NeedData	0.867		19.5	2.52
• NeedOthersData	0.855		13.7	2.46
• SUS	0.715		8.49	1.53

Managerial support can be seen as a type of social influence. To make sure that the scale for managerial support is not measuring the same thing as the scale for social influence, discriminant validity of these constructs is evaluated with Forner-Lacker criterion as well as by comparing all indicators' loadings with their cross loadings (Hair et al., 2011). All correlations between constructs were smaller than the square roots of the AVEs, thus fulfilling the Forner-Lacker criterion (see Table 2). In addition, all indicator loadings were higher than their cross loadings, providing support for discriminant validity.

Multicollinearity was examined by each indicators VIFs, all of which were below 5 (see Table 1) and thus meeting the criterion proposed by Hair et al. (2011).

Table 2 Square root of AVE (diagonal) and correlations between constructs

	Performance	*Social influence*	*Managerial support*	*Usefulness*
Performance	0.719			
Social influence	0.693	0.753		
Managerial support	0.543	0.558	0.832	
Usefulness	0.447	0.379	0.207	0.809

4.2 System usability scale

SUS score for the CMMS was 61 with a standard deviation of 18.1. According to the percentile ranks presented by Sauro and Lewis (2012), this is between 29% and 44% percentile ranks, an equivalent of a grade 'D'. Sauro and Lewis (2012) also give benchmarks for different interface types, and for enterprise software applications the mean SUS score is 67.6 with a standard deviation of 9.2. Users who have more experience with a system tend to rate it higher on SUS than users with less experience (Tullis and Albert, 2013). In this study, all respondents used the system in their daily work and it is thus expected that the score was higher than it would have been for novice users.

4.3 PLS analysis

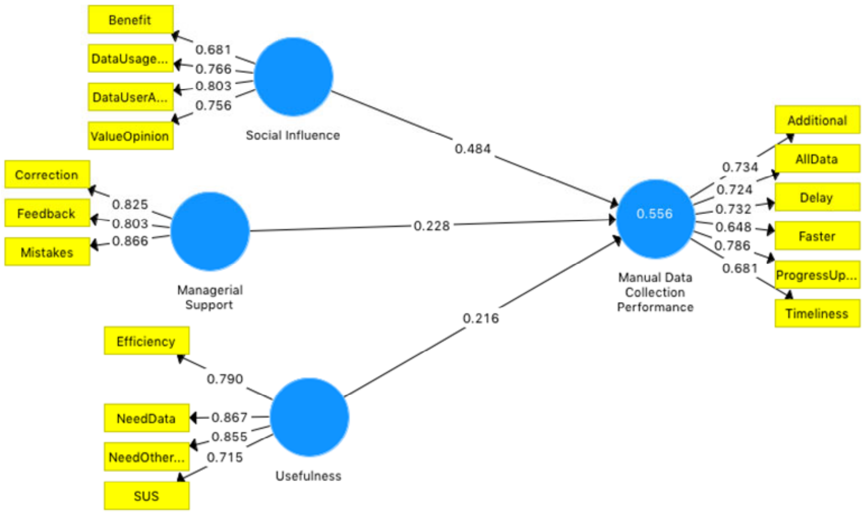
PLS approach was used for path analysis of the proposed model. Calculation for the analysis including loadings and path coefficients (β) was done using the PLS algorithm in SmartPLS. The results are shown in Figure 2. The explained variance (R^2) of the dependent variables was examined, because PLS does not assess overall model fit. The model explained a considerable portion of the variance for Manual data collection performance ($R^2 = 0.56$). The explained variance in the model well exceeds the level of 0.10 for a construct to be relevant in a model (Falk and Miller, 1992). The Stone-Geisser test also suggested a satisfactory fit ($Q^2 = 0.24$) (Hair et al., 2011).

Figure 2 depicts the path model resulting from PLS analysis. The path coefficient β for each construct and the loadings for the indicators are shown in the figure. It shows support for all three hypotheses. R squared for manual data collection is 0.556, shown in the circle representing the dependent variable.

The first hypothesis was "social influence will be positively related to the collection of high-quality data." A positive effect was found of social influence on the performance in manual data collection ($\beta = 0.484$, $t = 5.53$, $p < 0.01$) and Hypothesis 1 was thus supported.

The second hypothesis was "managerial support will be positively related to the collection of high-quality data." There was a positive effect of managerial support on good performance in manual data collection ($\beta = 0.228$, $t = 2.55$, $p < 0.05$). Hypothesis 2 was thus supported.

Figure 2 Path model with path coefficients and loadings shown in the arrows (see online version for colours)



The third hypothesis, "usefulness will be positively related to the collection of high-quality data." combined usability of the CMMS and benefits of entered data to data collector. Usefulness had a positive effect on manual data collection performance ($\beta = 0.216$, $t = 2.2$ $p < 0.05$). Hypothesis 3 was also supported.

All three, social influence, managerial support, and usefulness, were found to be statistically significant determinants of performance in manual data collection. Together, they explained 55.6% of the total variance. The relative strength of their explanatory power was different, though. Social influence was a much stronger predictor of manual data collection performance as compared to managerial support and usefulness.

5 Discussion

5.1 Research synthesis

The impact of social influence, managerial support, and usefulness on manual data collection performance was examined in this study. These factors contribute to UX and they appear in the three hypotheses. These hypotheses were supported by the results, which show that social influence has the strongest impact on manual data collection performance. This motivational factor has not been addressed by the previous studies of manual data collection. The impact of social influence has been studied in relation to technology adaption (e.g., Eckhardt et al., 2009; Vannoy and Palvia, 2010), but the results of this study show its impact in the context of manual data collection. Vannoy and Palvia (2010) state that IT adoption literature's focus on usefulness and ease of use may not fully explain technology adoption when it comes to social computing. This study extends this idea to manual data collection conducted with IT tools, and examines how social influence affects data collection. Social influence proved to be a significant factor in the success of manual data collection, aligned with previous studies of social influence on technology adoption (Brown et al., 2010; Eckhardt et al., 2009) with the extension of including the knowledge of who needs the collected data. Those technicians who wanted to share information with their colleagues were also reporting best performance. These technicians were also most likely to know who needs the data that they are collecting and what it is used for. Haegemans et al. (2018) did not find support for their hypotheses of social pressure having an effect on data collectors' intention to enter data correctly and proposed that this could be a consequence of not differentiating between managers and co-workers. In this study, this distinction was made. However, this study did not differentiate between peer pressure and willingness to help friends and colleagues in achieving their work goals. Furthermore, managerial support could also be seen as social influence. This raises questions about hierarchy and its relation to social influence. If the supervisor is also a team member, are results different than with a more distant manager? These themes would be an interesting starting point for future research.

The results of this study confirm many of the findings of the earlier studies indicating that managerial support has an effect on manual data collection performance (Lin et al., 2006; Murphy, 2009; Tayi and Ballou, 1998). Molina et al. (2013) did not find support for their hypotheses of managerial pressure and disciplinary action being positively related to the collection of high-quality data. The viewpoint of this study to the role of managers is broader than the items used by Molina et al. (2013) to measure managerial pressure with emphasis on control and punitive actions. According to contemporary characterisations of managerial role, it extends beyond control and even punitive actions to support and coaching (e.g., Ellinger et al., 2003). The items developed by Molina et al. (2013) were used as a starting point for defining the items used in this study, modifying them to fit the supportive managerial role. This changes the managerial role from push to pull: instead of creating fear of punitive actions, the manager or supervisor motivates technicians to collect high quality data. Even if the measures of managerial support were similar to the ones Molina et al. (2013) used to measure managerial pressure, self-concordance was not measured in a similar manner as they did, and, therefore, these results are not directly comparable with theirs.

Automated collection of asset data is the most efficient and least error prone. However, it has been observed by the authors that there is data that needs to be collected manually and automating this 'last mile' of data collection is not in the foreseeable future. As the manual data collection is conducted with a CMMS, also usability has been identified as an important factor in this context (Antonovsky et al., 2016; Tretten and Karim, 2014). To extend these previous observations, this study has quantitatively measured usability, utility, and their effect on data collection performance. This has been achieved by combining an established usability scale [SUS (Brooke, 1996)] with efficiency of the CMMS (ISO 9241-11, 1998) and own benefit of collected data (Grudin, 1988).

The initial goal for this study was to measure more UX aspects than basic usability factors. This has been done by measuring the usefulness of the CMMS for the data collector. Furthermore, measures of social influence and managerial support were included, covering some important aspects of the use environment and thus affecting UX. However, Hassenzahl and Tractinsky (2006) provide a wider view of UX as they include emotional aspects and aesthetics into their model of UX. Similarly, Karapanos et al. (2009) include emotional attachment in the identification phase of experiences, including personal and social issues. In this study, it is assumed that in the enterprise environment, more emphasis would be on the usefulness of the tool, i.e., its usability and utility.

Whereas the results of this study support the importance of these factors, it does not mean that beauty and emotions would not have an effect on manual data collection and, therefore, a following study concentrating on these factors would be welcomed.

5.2 Managerial implications

Managers influence the motivation of data collectors, both by setting an example with their own attitudes towards data quality and by supporting the motivation by explaining the meaning and importance of high-quality data. This can be achieved in the introduction of data collection practices and tools as well as by continuous feedback of the quality and utilisation of collected data. A requirement for successful managerial support is managers' own awareness of the role of collected data in own operations as well as the organisation outside own unit. Importance of high-quality data can be communicated with concrete examples of who is benefiting from collected data and how they use it. For example, long operation and maintenance contracts with a set price based on historical data about maintenance costs and spare part usage will cause problems if only a portion of actual maintenance time and effort has been reported in a CMMS (Mahlamäki et al., 2016). On one hand, the results of this study indicate that social influence might cause employees to develop workarounds to deal with enterprise systems that have deficiencies in their usability. On the other hand, replacing a system that has issues with its usefulness with a better system might not improve data collection performance if data collectors are not aware of who is using the data they collect and for what purpose.

It is, however, the managers' responsibility to make sure that the tools used have an adequate level of usefulness (usability and utility) for data collectors. The tools and practices should not result in excess physical or cognitive effort from data collectors. For example, walking back and forth between a desktop computer and the maintained unit should be avoided, as well as UIs that require the data collector to memorise which fields need to be filled in. The benefits of collected data should overweigh the effort needed in data collection. Any data collection 'just in case' should be avoided and the manager should be able to explain the need for every collected datum. Ideally, this should also be visible in the CMMS. Usability improvements of the CMMS can begin with a usability walk through or usability testing. However, the results of this study indicate that investing time and effort in improving the usefulness of the CMMS might not improve the performance in manual data collection remarkably if data collectors lack motivation for collecting data. Usefulness could be seen more as a hygiene factor: something that causes problems if it is not present, but that will not alone increase motivation.

The results of this study have important implications for the design of UIs for maintenance data collection. From system development point of view, it is important to see the effect on data collection performance from social influence. Implementing social features and making the data collector's role visible in the CMMS would be likely to improve the quality of manually collected data. Possible ways to do this include adding a link from data collector to data user. For example, showing how many times a certain work order detail has been read or giving the data user a possibility to 'like' a piece of additional information. This would give data collectors social feedback and knowledge that the data they are collecting is helping someone do their work.

5.3 Limitations of the study

The sample of this study is from a single company and the sample size was rather small. Therefore, future research is suggested with larger samples from various industries to increase the generalisability of the results. Furthermore, adding data from various industries would likely add data with various CMMS. This would allow comparing the performance of data collectors who are using systems with varying levels of usefulness.

Performance was measured by asking the data collectors to evaluate themselves as data collectors. This gives their experience of how they are performing. Data collector's own assessment of their data collection performance may be biased. However, the survey was anonymous, and, therefore, the respondents had no reason to exaggerate their performance. It was also underlined that the survey is conducted by independent researchers and individual answers would not be revealed to the company in question. Using supervisors' evaluation or measuring data quality from the CMMS might give different answers. However, connecting supervisors' evaluations or data quality metrics to survey responses would compromise the anonymity of survey responses and that could have an effect on the responses and overall willingness to participate in the survey.

Non-response error is a potential limitation of surveys. The option of using both paper and online versions of the survey was considered. It was chosen to go with only the online version, as previous studies have shown that giving multiple answering options will actually lower the response rate (Dillman et al., 2014). However, in the interviews it was discovered that there were technicians who were not in favour of digitalisation. One of them commented: 'paper prints will never be replaced'. It is possible that these people would also not answer an online survey and this would bring bias toward the acceptance of digitalisation among respondents.

Furthermore, there were two free text fields at the end of the questionnaire (for further comments regarding manual data gathering and for comments to researchers) and 32 respondents added comments after filling in the survey. The comments were both positive and negative towards new mobile tools, emphasising their usability (eight responses), and the challenging working environment that can make it difficult to use and carry mobile devices. It was also pointed out that smart phones are too small for reading instructions and five comments could be categorised as showing negative attitudes towards the introduction of new tools.

With 40% of respondents giving additional comments to the survey, there are two conclusions that can be drawn: on the one hand, this is an important topic and the technicians want to be involved in the development of their work. On the other hand, it can be that the people who did not respond are those people who are not so interested in their work and their opinions and attitudes might differ significantly from the responses received in this study. A similarly high response rate (55.6%) to an open-ended survey question was observed by Antonovsky et al. (2016).

6 Conclusions

Servitisation of the manufacturing industry makes manually collected data very valuable. Cost efficient provision of long industrial service contracts requires manually collected data of previous maintenance service tasks. This study has described the effect of social influence, managerial support, and usefulness on manual data collection performance.

The results of this study give quantitative evidence of the importance of each of these factors.

Social influence was the strongest predictor of manual data collection performance of the three factors measured in this study. The results indicate that social influence in the form of expectations from colleagues as well as providing data to be used by colleagues can increase performance in collecting high quality data. Managers can give direct support to manual data collection, but they can also play an important role in exploiting the benefits of the other two factors, usefulness and social influence. This can be addressed already at the development or acquisition phase of CMMS. By emphasising the UX of the CMMS for data collectors through the inclusion of social aspects and the fluency of data collection practices, organisations can improve the quality of manually collected data. Managers can also make social influence more explicit by explaining the importance of manually collected data to its users or even have data users come and meet data collectors face-to-face.

Given the importance of manually collected data in service provision, more research is needed to advance this important line of study. In this study, UX is addressed through usability, utility and social aspects. Future research could, however, extend into other aspects of UX, such as the temporal or the hedonic and aesthetic aspects. Future work could compare UX and performance before and after the introduction of a new system to find out how changing the system affects the results. Comparing systems of various levels of usability would reveal whether the relative standing of predicting factors change if the system ranks very high or very low on usability. This study has provided quantitative evidence of the effect of UX on manual data collection performance and thus serves as an important contribution to research on both UX and manual data collection.

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