

Department of Computer Science

Impact of User Experience on the Quality of Manually Collected Maintenance Data

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Efficient industrial maintenance operations require data of completed maintenance tasks. Usually, these data are reported in a computerized maintenance management system (CMMS). The starting point of the research was a practical problem in the industry: the quality of manually collected maintenance data was insufficient for analysis purposes. Current approaches in the study of manual data collection have neglected to account for the role of user experience in the form of social influence and usefulness of the CMMS. This study informs our theoretical understanding of manual data collection by introducing a focus on user experience hitherto lacking and informs our empirical understanding of CMMS use.

The goal of this study is to describe and analyze the manual data collection performed by maintenance technicians in industrial maintenance. The main research question of the thesis is: What factors influence manual data collection and the quality of collected data? This question is addressed with a multiple case study of three industrial maintenance providers. The study advances from explorative and descriptive case studies aiming to understand the context to specific studies investigating defined factors in detail. A total of 52 semi-structured interviews were conducted, in addition to observations of maintenance tasks and contextual inquiries of CMMS use. Research data included interview transcripts, conceptual inquiry notes and example work orders from CMMS. Finally, a survey was conducted in one maintenance organization and analyzed by partial least squares path modeling.

This study describes the elements of maintenance data that provide value and the quality issues that are currently present in manually collected maintenance data. The factors affecting manual data collection are classified under technology, organization and people factors and criteria for each factor applied to CMMS context is defined. The thesis shows that sites with good quality data and sites that have more challenges with data quality differ in the effectiveness of the CMMS, management support, competence development, work descriptions, competences of data collectors, and own benefit of inputted information. Finally, the thesis shows the effect of user experience in manual data collection with a focus on social influence, managerial support and usefulness.

The significance of this study is that it informs our theoretical understanding of manual data collection by introducing a focus on user experience of CMMS hitherto lacking and informs our empirical understanding of data collection as a part of maintenance technician work. Managerial implications of the study include making social influence visible in the user interface of CMMS and building motivation for manual data collection through data collection practices that make data usage visible for the data collector.

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Tekijä

Katrine Mahlamäki

Väitöskirjan nimi

Käyttäjäkokemuksen vaikutus manuaalisesti kerätyn tiedon laatuun

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Tehtävien teollisten huoltopalveluiden tuottamiseksi tarvitaan tietoa suoritetuista huoltotoimenpiteistä. Yleensä nämä tiedot kirjataan huollon tietojärjestelmiin (CMMS). Tämän tutkimuksen lähtöpiste oli käytännön ongelma teollisuudessa: manuaalisesti kerätyn huoltotiedon laatu ei ollut riittävä analyysejä varten. Nykyiset lähtökohdat manuaalisen tiedonkeruun tutkimukseen eivät ole huomioineet käyttäjäkokemuksen roolia sosiaalisen vaikutuksen ja hyödyllisyyden muodossa. Tämä tutkimus lisää teoreettista ymmärrystä manuaalisesta tiedonkeruusta käyttäjäkokemuksesta lähtien, sekä lisää empiiristä ymmärrystä CMMS-järjestelmien käytöstä.

Tutkimuksen tavoitteena on kuvata ja analysoida manuaalista tiedonkeruuta teollisissa huoltopalveluissa. Päättökysymyksenä on: Mitkä tekijät vaikuttavat manuaaliseen tiedonkeruuseen sekä kerätyn tiedon laatuun? Kysymyksen vastataan kolmella teollisilla huoltopalvelulla tarjoavan yrityksen tapaustutkimuksella. Tutkimus etenee kuvaavista tapaustutkimuksista, joiden tarkoituksena on ymmärtää tiedonkeruun konteksti tarkempiin tutkimuksiin, joissa tutkitaan yksityiskohtaisesti tiettyjä tekijöitä. Tutkimuksessa tehtiin 52 haastattelua sekä havainnoitiin huoltotoimenpiteitä ja seurattiin CMMS-järjestelmän käyttöä. Tutkimusaineistoon kuuluu haastattelujen litterointeja, muistiinpanoja havainnoinneista sekä esimerkkietietoja CMMS-järjestelmistä. Lopuksi tehtiin kysely yhdessä huolto-organisaatiossa ja analysoitiin sen tuloksia PLS-menetelmällä.

Tämä tutkimus kuvaa huoltotiedon arvoa luovia elementtejä sekä laatuongelmia, joita manuaalisesti kerättyssä huoltotiedossa tällä hetkellä esiintyy. Manuaaliseen tiedonkeruuseen vaikuttavat tekijät luokitellaan teknisiin, organisatorisiin ja ihmistekijöihin, sekä luodaan kriteerit kullekin tekijälle CMMS-käytön yhteydessä. Tämä työ näyttää, että kohteet, joissa tuotetaan hyvälaatuista tietoa eroavat kohteista, joilla on haasteita tiedon laadun kanssa CMMS-järjestelmien vaikuttavuuden, johdon tuen, osaamisen kehittämisen, työkuvausten, tiedonkerääjien osaamisen sekä heidän itse kerätystä tiedosta saamansa hyödyn suhteen. Lopuksi osoitetaan käyttäjäkokemuksen vaikutus manuaaliseen tiedonkeruuseen keskittyen erityisesti sosiaalisen vaikutukseen, johdon tukeen sekä hyödyllisyyteen.

Tutkimuksen merkittävyys tulee käyttäjäkokemusnäkökulman tuomisesta manuaalisen tiedonkeruun teoreettiseen ymmärtämiseen, mikä on tähän asti puuttunut. Lisäksi työ lisää ymmärrystä manuaalisesta tiedonkeruusta osana huoltotyötä. Tutkimuksen päätelmät käytäntöön näkyvät sosiaalisen vaikutuksen tuomisena näkyväksi CMMS-järjestelmien käyttöliittymissä sekä motivaation kasvattamisessa manuaaliseen tiedonkeruuseen tekemällä tiedon käyttö näkyväksi sen kerääjälle.

Avainsanat Käyttäjäkokemus, manuaalinen tiedonkeruu, CMMS, tiedon laatu**ISBN (painettu)** 978-952-64-0278-9**ISBN (pdf)** 978-952-64-0279-6**ISSN (painettu)** 1799-4934**ISSN (pdf)** 1799-4942**Julkaisupaikka** Helsinki**Painopaikka** Helsinki**Vuosi** 2021**Sivumäärä** 145**urn** <http://urn.fi/URN:ISBN:978-952-64-0279-6>

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The years of this research have been filled with great discussions with people from both academia and the industry.

I would like to thank my supervisor, prof. Marko Nieminen for providing the support and push when needed. I thank my pre-examiners, prof. Ramin Karim and prof. Timo Kärri for their constructive comments and encouraging feedback. I would also like to thank prof. Jayantha Prasanna Liyanage for acting as my opponent.

I have worked with many great colleagues throughout the years. Planning, conducting, and disseminating research with them has been very fruitful, and this dissertation is a proof of that. I thank my colleagues and co-authors for the discussions and working together that made this research possible.

The strong industry focus of this study wouldn't have been possible without the collaboration with people from the industry who have helped me to get data from their companies and opened their doors for our visits to see the daily maintenance activities. I would like to express my gratitude to the case company representatives for their help and participation in the study.

Finally, I wish to thank my family and friends for all the support during this research. I'm happy to be able to answer the question "Mom, have you written the dissertation yet?" with "Yes. It's done."

Helsinki, 6 November 2020

Katrine Mahlamäki

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List of Abbreviations

B2B	Business-to-Business
CMMS	Computerized Maintenance Management System
ERP	Enterprise Resource Planning
HCI	Human-Computer Interaction
IBI	Installed Base Information
IS	Information Systems
ISO	International Organization for Standardization
IT	Information Technology
PC	Personal Computer
PDA	Personal Digital Assistant
PLS	Partial Least Squares
SUS	System Usability Scale
TAM	Technology Acceptance Model
TENK	Tutkimuseettinen neuvottelukunta (Finnish Advisory Board on Research Integrity)
TOP	Technology-Organization-People
UI	User Interface
UTAUT	Unified Theory of Acceptance and Use of Technology
UX	User Experience

List of Publications

This doctoral dissertation consists of a summary and of the following publications which are referred to in the text by their Roman numerals

I. Mahlamäki, Katrine; Borgman, Jukka; Rämänen, Jussi; Tuovinen, Joonas; Finne, Max; Perminova-Harikoski, Olga; Tiihonen, Juha and Öhman, Mikael. 2016. Elements of installed base information value. In ICE/IEEE International Technology Management Conference, Trondheim, Norway, June 13-15, 2016, IEEE. <https://doi.org/10.1109/ICE/ITMC39735.2016.9026129>

II. Mahlamäki, Katrine; Niemi, Arto; Jokinen, Juuso and Borgman, Jukka. 2016. Importance of maintenance data quality in extended warranty simulation. International Journal of COMADEM, volume 19, issue 1, pages 3-10. ISSN 13637681.

III. Mahlamäki, Katrine and Rämänen, Jussi. 2015. Factors Influencing the Quality of Manually Acquired Asset Data. In Amadi-Echendu, Joe; Hoohlo, Changela and Mathew, Joseph. (eds.). 9th WCEAM Research Papers. Volume 1 Proceedings of 2014 World Congress on Engineering Asset Management, Pretoria, South Africa, October 28-31, 2014. Springer. Lecture Notes in Mechanical Engineering. Pages 273-284. ISBN 978-3-319-15536-4.

IV. Mahlamäki, Katrine and Nieminen, Marko. 2020. Analysis of Manual Data Collection in Maintenance Context. Emerald. Journal of Quality in Maintenance Engineering, Vol. 26 No. 1, pp. 104-119. ISSN 1355-2511. <https://doi.org/10.1108/JQME-12-2017-0091>.

V. Mahlamäki, Katrine and Nieminen, Marko (in press). Introducing User Experience in Manual Data Collection: The Effect of Social Influence, Managerial Support, and Usefulness. Accepted for publication in the Journal of Strategic Engineering Asset Management in the year 2019.

Author's Contribution

All publications of this dissertation are based on research conducted in research projects TuPaSu, FutIS, and S4fleet. The research design, data collection, data analysis and model construction have been discussed with the project teams of these research projects, and partly also conducted by several researchers working together. The contribution of the author of this thesis is detailed as follows.

Publication I: Elements of installed base information value

The author of this dissertation was the corresponding author for the article. This publication was a result of research in a research project where all authors participated in. The value clover framework and installed base information sources resulted from a workshop participated by all authors. Following the workshop, the writing of the article was started with all authors participating, but later continued by a smaller team lead by the author of this dissertation. This team included authors 1-4. Data collection was conducted by authors 2 and 8. All authors participated in the literature review, and all gave comments during the writing of the paper.

Publication II: Importance of maintenance data quality in extended warranty simulation

The author of this dissertation was the corresponding author for the article. The problem setting and research design were originally conducted by the fourth author. The simulation model was created by the third author who also collected the data needed for simulation. The user interface was created by the second author. Literature review and writing of the article were conducted by the first and second author. The primary author described the current data collection practices within the case company on the basis of discussions with the case company representatives. The content and structure of the paper was discussed and implemented by the first, second and fourth author.

Publication III: Factors Influencing the Quality of Manually Acquired Asset Data

The author of this dissertation was the corresponding author for the article. The problem setting and research design were conducted collaboratively by the authors and other research project participants. The author of this dissertation

conducted all interviews with another researcher and she also analyzed the interview data. Both authors were present in all but one contextual inquiry, the last one being conducted by the second author alone. Literature review and the development of the framework were done by the authors collaboratively. Both authors discussed the content and framework of the article with the other members of the research project.

Publication IV: Analysis of Manual Data Collection in Maintenance Context

The author of this dissertation was the primary author of this article. The problem setting and research design were conducted collaboratively with other researchers participating in the research project. The primary author carried out the data collection with other researchers in the project. The primary author performed the analysis of the study. The authors participated in joint discussions of the content, model, and structure of the publication.

Publication V: Introducing User Experience in Manual Data Collection: The Effect of Social Influence, Usefulness and Managerial Support

The author of this dissertation was the primary author of this article. The problem setting and research design were conducted collaboratively with other researchers participating in the research project. The primary author carried out the data collection and analysis of the study with another researcher in the project. The authors participated in joint discussions of the content, model, and structure of the publication.

1. Introduction

Maintenance technicians report data of the maintenance tasks they complete. This includes reporting hours spent and spare parts used, among other details of the task. This is typically done in a computerized maintenance management system (CMMS). These systems are complex enterprise systems that require certain skills from their user, transferring maintenance work more towards knowledge work. In such settings, the technicians' experience of their interaction with the CMMS, i.e., their user experience (UX) becomes important. If the tools require too much manual input of information, the usability of the systems can be a challenge (Antonovsky, 2016; Tretten & Karim, 2014). If a new tool is not performing as expected it can cause resistance (Molina et al., 2013; Riege, 2005). Furthermore, the access points for the tool can be located far from where the actual work takes place and this can further complicate the use of those tools (Betz, 2010).

Previous research has studied manual data collection from the viewpoint of managerial pressure and technological input control (Molina et al., 2013). Following studies by Tretten and Karim (2014) and Antonovsky et al. (2016) extend the view of technological input control to usability issues in CMMS. More recently, Haegemans et al. (2019) proposed that making the information systems easier to use could improve the attitudes of data collectors towards data collection. In this study, we extend the previous research that has identified baseline usability challenges by studying CMMS use as a holistic UX as suggested by Oja and Galliers (2011). UX includes the instrumental aspects of interaction, such as usability, but it also covers the experiential elements of interaction that are 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 & Tractinsky, 2006).

1.1 Background

Contemporary industrial service provision typically requires data of the equipment being serviced. Industry 4.0, Industrial Internet, Internet of Things and other current views of industrial activity rely on intelligent devices equipped with sensors. There can be huge amounts of this kind of data available for analyses. Internet of Things and smart products enable timely and remote repairs, reduce field-service dispatching costs, improve inventory control of spare parts,

and reduce breakdowns through early warnings (Porter & Heppelmann, 2014). However, there remains data that is difficult and expensive, if not impossible to acquire automatically. Manually collected data is required to supplement the vast amounts of automatically produced data in service provision and data-centric decision making (Madhikermi et al., 2016). Examples of such data are operational and cost related data from service operations, such as hours spent on maintenance tasks and spare parts used (Unsworth et al., 2011) or the reasons for an equipment not running (waiting for service, waiting for spare parts, or redundancy; Publication II). The quality of this manually collected data has been the concern of several previous studies (e.g., Betz, 2010; Lehtonen et al., 2012; Unsworth et al., 2011).

The starting point for this research was a research project that attempted to create a simulation model to be used for extended warranty pricing (Publication II). It was soon discovered that there were severe challenges with the quality of the data that should have been used for the simulations. This was especially apparent in the manually collected data. Extended warranties can cover all corrective and preventive maintenance costs, as well as a promise of a certain level of availability or performance for an annual flat fee (Bouguerra & Nidhal, 2012). Naturally, the pricing of such contracts creates a risk for the service provider if they do not have accurate data about the costs of maintaining similar equipment. This cost data is typically collected manually. It includes the duration of maintenance, spare parts used, reasons for downtime, etc.

Installed base information includes both manually and automatically collected data (Publication I). Installed base information consists of item, location, and event information about the installed base (Ala-Risku, 2009), as well as condition information (Seilonen et al., 2011) and information about the usage, environment and the product's role in customer's processes (Publication I). For example, the item information can include product type and individual product structure, location information can include access information, contacts, and specific location within a customer site, in addition to address, event information describes service actions, among others, condition information may include notes about spare parts needing to be replaced in the near future, and environment information can describe the dust and heat in a specific site while product's role in customer's process tells about the importance of keeping the piece of equipment running. Installed base information can originate from three sources: the manufacturer of the equipment, the customer and the service provider (Publication I).

Installed base information is needed for providing maintenance services. Forecasts of spare part demand and return can be made timelier and more accurate using installed base information (Dekker et al., 2013). Using machine location data to derive transportation costs, travel times and demand forecasts has been reported to result in cost savings of 1 – 58 % (Jalil et al., 2011). Data quality issues can diminish these advantages. While the quality of data is important

both for manually and automatically collected data, the process of data collection is different. Therefore, the actions to improve data quality also differ to such a large extent that it is not meaningful to address them both in one study. As a consequence, this study concentrates on the manually collected data, acknowledging that sensor data quality is equally important.

The focus in this study is on manually collected maintenance data. It is here defined as data produced by operation and maintenance personnel (technicians, planners, managers) about maintenance activities and the equipment maintained. Thus, it is a subset of installed base information described above, including item, event and condition information. Typically, these data are collected during maintenance activities and reported after maintenance in a work report. In the cases studied, this was called “back reporting” or “closing work orders”.

1.2 Goal of the study

The goal of this study is to describe, analyze and model the manual data collection performed by maintenance technicians in industrial maintenance. This is achieved by identifying the factors that affect manual data collection. More specifically, this study examines the effect on manual data collection that UX has resulting from managerial support, usefulness and social influence. This research aims at understanding manual data collection as an integral part of maintenance work. This understanding can help in improving data collection processes for better data quality.

1.3 Research questions

The main RQ of this dissertation is:

What factors influence manual data collection and the quality of collected data?

This question is broken down to three sub questions as follows:

RQ 1: Users and tasks: How is maintenance data collected and by whom?

RQ 2: What challenges are there with the quality of manually collected maintenance data?

RQ 3: How do contextual UX factors relate to the quality of manually collected data?

These questions are highly connected to real industrial activities and the questions originate from real industrial challenges. Therefore, the research questions are answered by studying real life practices in multiple industrial cases. This limits the scope of the study and the generalizability of the results, but it gives us a rich view of state-of-the-art in the industry.

In this study, the elements of installed base information value are defined [Publication I]. These elements are the quality, scope, management and utilization

of the information. This is followed by an example of the importance of manually collected data [Publication II]. The example is of using maintenance data in the simulation of extended warranties. In order to discover the contextual UX factors related to the quality of manually collected data, a broad set of factors that affect the manual gathering of maintenance data in general is identified [Publication III]. The factors are categorized in technological, organizational and people factors and an analysis of how these factors differ between sites that differ in the quality of their manually collected data is presented [Publication IV]. Finally, we create a survey to analyze the contextual UX factors of social influence, managerial support and usefulness factors in more detail [Publication V]. Each publication's contribution to the research questions is presented in Table 1.

Table 1. Publications' contribution to research questions

	I	II	III	IV	V
RQ 1	X	X	X	X	
RQ 2	X	X			
RQ 3			X	X	X

1.4 Scope

This study examines manual data collection in an industrial maintenance context. Thus, the use of IT (information technology) is mandatory for data collectors, and it is a part of their work. The focus of this thesis is on the data collector as a user of the IT system. As manual data collection is typically conducted with a CMMS (Labib, 2004; Tretten & Karim, 2014), the adoption of these systems is a relevant question. The Technology Adoption Model (TAM; Davis, 1989) and several following theories that have modified or built on this model, most notably the Unified Theory of Acceptance and Use of IT (UTAUT; Venkatesh et al., 2003) have been used in analyzing IT adoption and the factors affecting it. TAM predicts behavioral intention to use and actual use of systems from perceived usefulness and ease of use of the systems (Davis, 1989). IT adoption literature has made a distinction between voluntary and mandatory use of systems (e.g., Ojiako et al., 2012) and the adoption and use of enterprise information systems, such as enterprise resource planning (ERP) has been studied (e.g., Cheng, 2018). The results of these studies are relevant for CMMS as it is a complex enterprise information system whose use is mandatory for the maintenance technicians. In the manual data collection context, however, adoption and use alone are not the decisive measures of success. In addition, the quality of inputted data determines the possibilities for its use. For example, we have observed that the quality of manually collected data in these systems may be insufficient for purposes such as simulation (Publication II). This changes the question of whether or not the system is adopted and continued to use to a question of *how* the system is used. Therefore, this study focuses on the quality of data inputted in the

systems and the performance of manual data collection. We look at the use of these systems from the user's (i.e., data collector's) point of view: the user experience and how it affects the motivation to collect high quality data.

The case companies of this study were in various phases with their CMMS. Some companies were in the process of updating their systems and either already using mobile tools or considering their use. Therefore, the switch from desktop systems to mobile tools was of special interest to some of the case companies and it was included in our questionnaires and interviews. However, the motivation for using mobile tools is not addressed in this thesis. It will provide interesting material for future research.

1.5 Research approach and process

The research approach of this dissertation aims at characterizing manual data collection empirically. The starting point for this research was an industrial need for better quality in manually collected data (Publications I-II). A literature review revealed a gap (Publications I-II and chapter 2) in current literature regarding this challenge, as the state-of-the-art remains at usability level. Current approach to human computer interaction also considers experiential aspects of interaction, but these UX aspects have not been considered in the manual data collection context. This justified further research on the subject. This study follows a case study approach (Yin, 2009), supplementing qualitative methods with a quantitative study.

An explorative approach is taken in studying maintenance work and the contextual factors affecting manual data collection. First, the factors affecting manual data collection are identified (Publication III). To address the significance of these factors, they are operationalized in the maintenance context (Publication IV). Case studies of sites that produce good-quality data and sites that face more challenges are analyzed and compared with these constructs (Publication IV). Drawing on previous studies, the constructs social influence, managerial support, and usefulness are conceptualized in the context of manual data collection. The constructs are used in a conceptual model for understanding their effects on manual data collection performance, which is then quantitatively validated (Publication V). Finally, the results of the study are disseminated both in scientific as well as industrial forums.

The research framework of this study is depicted in Figure 1. It is an adaptation of the Hevner et al. (2004) IS research framework that combines behavioral-science and design-science paradigms. In this study, the full design science cycle is not conducted. However, the overall research framework describes this study well. Similar to Hevner et al. (2004), the problem space is defined by the environment: the research is rooted in industrial practice, starting with an industrially relevant research question that is then studied scientifically. The industrial environment includes the people

(maintenance technicians, managers, etc.), organizations (industrial maintenance service providers) and the technology (CMMS). Basing research on business needs assures the relevance of research (Hevner et al., 2004). The scientific background comes from several disciplines: Human-Computer Interaction (HCI) and UX, Information Systems (IS), Engineering Asset Management and Operations & Maintenance. These foundations and the methodologies used provide the applicable knowledge for the study. The results contribute both back to these scientific disciplines, as well as to industrial practice. While this study does not include designing and evaluating system or process artifacts to solve the problems discovered, the developed conceptual and theoretical artifacts can be used as input for such purposes.

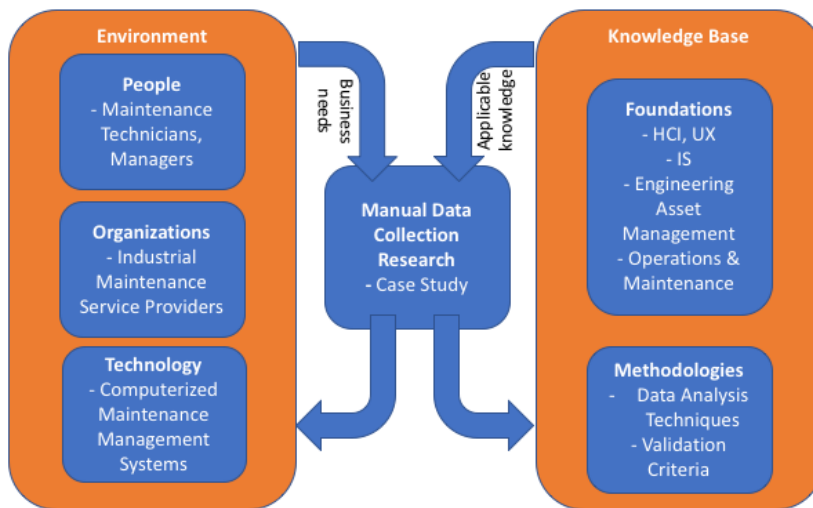


Figure 1. Research framework of this thesis based on the IS research framework by Hevner et al. (2004)

1.6 Contribution

This thesis delivers both scientific and practical contributions. The analysis of maintenance technician work in socio-technical settings reveals technological, organizational and people factors that affect manual data collection.

This work extends previous research of CMMS use by Tretten & Karim (2014) and Antonovsky et al. (2016) that introduce and address the importance of usability in the context of CMMS and manual data collection. In order to proceed from these studies, this study adds quantitative measures of CMMS usability to current state of the art and also looks beyond usability towards the facets of UX. In addition to the pragmatic aspects of UX, i.e., usability and utility, also con-

textual aspects of social influence both from managers and colleagues is analyzed. This extends the work of Molina et al. (2013) on managerial pressure and introduces the social norm of IT adoption literature to manual data collection.

The practical contributions of this study are in the development of CMMS and the practices of manual data collection beyond the instrumental, the direct operational outcomes and benefits. Describing the quality issues in manually collected data helps managers to identify similar issues in their own organizations. Including UX point of view in CMMS by linking its use to meaningful goals can add emotion and affect in the use of these enterprise systems. Examples of the meanings and importance technicians assign to data collection are given by Unsworth et al. (2011) in their study of goal hierarchies: if technicians feel that collecting data is only weakly related to shutdown preparations or other important goals it is unlikely that they would collect high-quality data. Furthermore, the user-centric approach offers maintenance operations a novel approach to building motivation into the design of data collection processes and tools.

2. Conceptual and theoretical background

2.1 Socio-technical context of maintenance data collection

The socio-technical context at a work place includes the social system – structure and people – as well as the technical system – technology and tasks – that all interact with each other (Bostrom and Heinen, 1977). Effective systems design should incorporate the socio-technical aspects: technical, organizational, economic, and social (Mumford, 2000). This also applies in the design of the manual data collection system: the CMMS and the practices in using it.

In this study, the socio-technical context is maintenance. Maintenance refers to all technical, administrative and managerial actions during the life cycle of an item to keep it in a state in which it can perform the required function, including observation of the item state and active maintenance actions (SS-EN 13306, 2017). eMaintenance techniques add sensors, signal analysis, and the use of Internet to provide data that can support diagnosis and prognosis (Jantunen et al., 2010). The aim is to move from reactive to predictive maintenance (Jonsson et al., 2010). Smart Maintenance combines data-driven decision making, internal and external integration, and human capital resource (Bokrantz et al., 2020). Relevant data do not always exist or are difficult to access and this may lead to the underutilization of certain maintenance measures, while some other measures are overemphasized despite their lack of relevance due to readily and routinely available information (Simões et al., 2016).

This thesis focuses on maintenance work and the requirements set by the recent eMaintenance and Smart Maintenance approaches. This focus on human activities extends the traditional technical approach to maintenance. With Industry 4.0, factory work has been forecasted to change into production strategy creation, supervising self-organizing production processes, and creative problem solving (Gorecky et al. 2014). This transition is supported by digitally facilitated knowledge processes that can empower production workers by leveraging their knowledge processes, decision-making skills and social interaction practices

(Hannola et al., 2018). Maintenance work is similar to production work in that it has traditionally been “blue-collar work”. However, the shift towards knowledge work has been happening for decades as a quote from Roth et al. (1994, p. 31) demonstrates: “Workers are expected to possess skills for data gathering, problem solving, experimentation, and information technology use.” The use of complex enterprise systems, such as CMMS, as a part of maintenance tasks is one example of this shift towards more knowledge intensive work. This shift results in increased requirements for new capabilities from maintenance technicians and their supervisors.

We have identified four groups of possible data collectors: own staff, customers, equipment users and other parties (Rämänen et al., 2013). Own staff is the typical choice in an industrial context, but the other groups can also provide valuable information; customers have valuable information of the use context of the equipment: the process where it’s used, use environment, etc.; equipment users can give reasons for downtime and report anything out of the ordinary in equipment functioning; and, finally, other parties can include, for example, authorities auditing the equipment (Rämänen et al., 2013). In this thesis, however, the focus is on the most typical case: own staff as data collectors.

2.2 Data quality

Strong et al. (1997, p. 104) define high-quality data as “data that is fit for use by data consumers”. The quality of manually collected data can be assessed on several dimensions. Data quality dimensions, such as accuracy, accessibility, relevance, completeness and timeliness, depend on the task the data is used for and their relative importance may change as work requirements change (Strong et al., 1997). In maintenance data context, Aljumaili et al. (2018) used a set of 12 attributes (Completeness, Metadata constraints, Accuracy, Source reputation, Relevancy, Amount of data, Usability, Conciseness, Availability, Navigation, Security, Up to date) whereas Madhikermi et al. (2016) identified the three most important attributes: believability, completeness and timeliness. The latter set is also used in this thesis. Here, data consumers are the maintenance managers and planners who use the data collected by maintenance technicians.

Data quality is a function of its use, and data quality improvement efforts should include improving the linkage among the various uses of data (Orr 1998). Data should not be collected for some yet unknown future use, because if the data is not used then it will most likely not be updated and over time the quality of collected data will decline (Orr 1998). For service provision and use in data-centric decision making, manually collected maintenance data should be provided in a timely manner (timeliness), with enough detail (completeness) and in line with other data sources (believability) (Madhikermi et al. 2016). Poor data quality may result in lowered customer satisfaction, increased costs, and lowered employee job satisfaction (Redman, 1998).

Previous literature has identified quality issues with manually collected data (e.g., Aljumaili et al., 2012; Betz, 2010; Lehtonen et al., 2012; Unsworth et al., 2011). Lehtonen et al. (2012) studied the service network of a capital goods manufacturer and found that almost 40 % of failed service visits were caused by missing information. Betz (2010) examined several hundred maintenance cases and discovered that more than 80% of performed repair activities were reported as “maintained and repaired”. Aljumaili et al. (2012) studied maintenance data quality in eight large companies and found data quality issues of duplicate data, questionable reliability, differences in the level of detail between data collectors, data loss or corruption because of manual transfer between systems, material costs not followed on equipment level and inaccurate data of work time execution and work order status.

Typical causes for data quality issues include a customer changing the location of the equipment without notice, missing information about the use environment, and third-party maintenance provider not sharing updated equipment information with the manufacturer (Dekker et al., 2013). Further examples of data quality problems include using wrong codes because of misinterpreting the guidelines, using wrong codes because of typos, missing information, inconsistency and questionable information (Sandtorv et al., 1996). Lack of instructions results in different ways to collect data and makes data inconsistent (Aljumaili et al. 2012). Wrong data, data that is out-of-date, validity with respect to related data, violation of standards or rules, and duplicate records have also been reported as data quality problems (Lin et al., 2007).

2.3 TOP factors

Lin et al. (2007) propose a research framework for asset data quality in engineering organizations. Their framework describes how data quality is influenced by technology, organization and people (Lin et al., 2007). A similar categorization has been used by Yusof et al. (2008) in their HOT-fit framework for the evaluation of health information systems that looks at human, organizational and technology issues. Yusof et al. (2008) construct the HOT-fit framework building on the IS Success Model (DeLone and McLean, 1992) and the IT-Organization fit model (MIT90s; Scott Morton, 1991). The focus of this thesis is on the data acquisition phase. Previous research has identified several factors that affect manual data collection. In this section, these factors are categorized into technical, organizational and people (TOP) factors and presented in more detail.

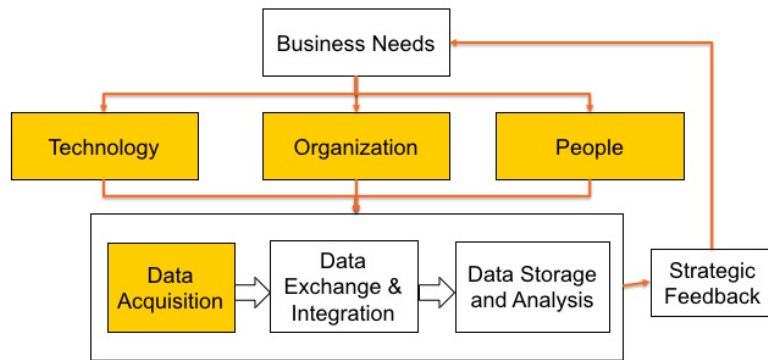


Figure 2. Figure 1 Asset Data Quality in Engineering Organizations (adapted from Lin et al., 2007)

2.3.1 Technological factors

Lazar et al. (2006) report frustrating experiences with computers at the workplace wasting over 40 % of users' time on the computer. Usability is defined as the effectiveness, efficiency, and satisfaction of achieving a specific goal in a specific context by specific users (ISO 9241-210, 2019), i.e., not wasting time on the computer. The usability of CMMS has been studied by Tretten and Karim (2014) who discovered several usability issues with these systems, for example, the system can require too much manual input of information. This challenge was also noticed by Antonovsky et al. (2016). Furthermore, if access points are located far from where the actual work takes place, it makes system use more complicated (Aljumaili et al., 2012; Betz, 2010). Usability and user experience are discussed in more detail in section UX in industrial context. The effectiveness of the CMMS can be compromised when used over a poor or non-existent Internet connection, a situation still typical in some developing countries (Assoumou et al. 2019). Molina et al. (2013) studied technological input control and how it affects the motivation of data collectors and their performance. Described as interaction between a data collector and CMMS, Molina et al. (2013) were also in the direction of usability and user experience. However, they used only one item, "The PDA ensures that I collect accurate data", to measure technological input control by personal digital assistants (PDA) and, therefore, their study had a rather limited view of interaction and the technological factors.

2.3.2 Organizational factors

Successful implementation of data collection tools requires organizational readiness (Lin *et al.*, 2007). Managers' role in assuring data quality is very important (e.g., Lin *et al.*, 2006, Tayi & Ballou 1998, Tee *et al.*, 2007). This becomes apparent if management structures do not promote the accuracy, completeness, and timeliness of data collection and specify appropriate data quality levels for manually collected data (e.g., Lin *et al.*, 2006, Tayi and Ballou 1998). Managers are also responsible for evaluating whether the value of collected data is worth the effort and cost of data collection (Kumar *et al.* 2013).

Molina *et al.* (2013) studied the effect of managerial pressure on manual data collection and discovered that managerial pressure is effective in improving manual data collection performance for those data collectors who are only extrinsically motivated, whereas for intrinsically motivated data collectors the effect is the opposite. This view of managerial role as pressure that creates fear of punitive actions is rather limited, though. Murphy (2009) sees the managerial role in manual data collection as a supportive one. A manager can even take a coaching role (Ellinger *et al.*, 2003). This supportive point of view is also adopted in this study. Furthermore, Murphy (2009) notes that attitudes towards data collection can be influenced through goal statements that specify appropriate data quality levels.

Training is important when introducing a new tool for data collection as the benefits of data collection are not immediately visible (Kortelainen *et al.*, 2003). Training can also affect trust: data collection should not feel like a control function. Fearing that collected data could be used against the data collectors would make them reluctant to collect data (Unsworth *et al.* 2011, Riege 2005).

2.3.3 People factors

The use of complex IT systems, such as CMMS, requires certain capabilities from the users. People have varying skills and abilities with regard to such system use, and these differences can be significant even within a site, let alone when the users are located in different countries and have different backgrounds and education. The education level and experience of data collectors can become barriers to knowledge sharing (Riege, 2005). Furthermore, the differences in experience as well as individual differences of maintenance technicians result in different aptitudes for technology (Woods *et al.*, 2019). User competence refers to the ability to apply technology in a specific job task (Marcolin, 2000), in this case, to use the CMMS for data collection. The use of any computerized equipment is a significant determinant of competence (Tomlinson, 2002). It can be difficult to find people with adequate competences for data collection (Sandtorv *et al.*, 1996). Sometimes poor IT competence of technicians results in having supervisors fill in data to the CMMS even if they did not participate in the actual maintenance task (Aljumaili *et al.*, 2012). Furthermore, not

feeling competent in data collection can make technicians reluctant to participate in data collection (Unsworth et al., 2011). System implementation also requires enough skilled people to train others in using the new system (Lin et al., 2007).

In addition to user competence, the users need verbal and language skills to formulate the information in a clear form when inputting it in the system. Poor written communication skills can be a barrier in knowledge sharing (Riege, 2005). Multinational organizations typically use English as the company language and employees are required to input information in English no matter what their native language might be. This can be a challenge in IT adoption (Vat-
anasakdakul et al., 2004).

Lack of direct benefits from data collection is one of the reasons behind poor maintenance documentation (Betz, 2010). Collaborative systems can fail because some people are required to do additional work, but they do not see a direct benefit from what they do as the people using the data are at other levels of the organization (Grudin, 1988). Demonstrating the benefits of data collection could improve the quality of collected data, but the benefits of data collection are not visible before there is enough data in the database to demonstrate the benefits (Kortelainen et al., 2003). Furthermore, motivation for data collection can be low if it is not considered as part of the job (Unsworth et al., 2011). Motivation is supported by the attitudes and control of the individual data collector and norms of the group (Murphy, 2009). Data quality awareness (Unsworth et al., 2011) and strategic understanding (Lin et al., 2007) are also important.

These people factors are similar to the mechanisms of meaningful work presented by Rosso et al. (2010): authenticity, self-efficacy, self-esteem, purpose, belongingness, transcendence, and cultural and interpersonal sense-making.

2.4 UX in industrial context

User experience (UX) is a recent approach in HCI research. In this approach, HCI is seen as experiences, not simply as completing tasks. UX is defined as “user’s perceptions and responses that result from the use and/or anticipated use of a system, product or service” (ISO 9241-210 2019, p.4). Whereas usability covers the instrumental aspects of interaction, i.e., the ability to carry out a task successfully, UX also includes the experiential elements, the user’s entire interaction with the system, and the thoughts and feelings resulting from the interaction (Tullis and Albert, 2013). Thus, usability is a contributing factor of UX. Measuring UX is sometimes seen as a synonym for measuring usability (e.g., Sauro and Lewis, 2012), but it can also include measures of emotions, using eye-tracking of heart-rate monitoring techniques, for example (Tullis and Albert, 2013). Hassenzahl and Tractinsky (2006, p. 95) state that UX is “A consequence of a user’s internal state (predispositions, expectations, needs, motivation, mood, etc.) the characteristics of the designed system (e.g. complexity, purpose, usability, functionality, etc.) and the context (or the environment) within which the interaction occurs (e.g. organisational/social setting, meaningfulness of the activity, voluntariness of use, etc.)”. It is the most widely accepted UX definition (Aranburu et al. 2018). Furthermore, UX is context-dependent, dynamic, and subjective (Law et al. 2009).

Usability covers the task completion related issues in UX. Nielsen (1993) defines usefulness as the combination of utility and usability, where utility describes whether the needed features are provided and usability includes learnability, efficiency, memorability, errors (both low error rate and easy recovery from errors), and satisfaction. ISO 9241-210 standard defines usability as the “extent to which a system, product or service can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use.” (ISO 9241-210 2019, p. 3). Thus, ISO standard includes effectiveness in the definition of usability. In this thesis, however, utility is defined as a separate concept from usability: it includes more than the effectiveness in achieving a specified goal of manual data collection. We see the utility as benefiting from the inputted data in data collector’s own work.

In a work context, UX is connected to development of practices, enjoyment and flow in work, motivation, and professional identity (Savioja et al. 2014). Kaasinen et al. (2015, p. 976) define UX at work as: “The way a person feels about using a product, service, or system in a work context, and how this shapes the image of oneself as a professional”. Wurhofer et al. (2015) identified factors that were relevant for operator’s experience in a semiconductor factory. One of these factors was the cognitive effort required to interact with a system when completing a task. In addition to this perceived workload, Wurhofer et al. (2015) list stress caused by the interaction, feeling of control, perceived ease-of-use, perceived usefulness, performance expectancy, satisfaction, perceived safety of interacting with the system, trust in the system behaving as intended, and positive and negative emotions and feelings. Whereas Palviainen and Väänänen-

Vainio-Mattila (2009) see a contradiction in user's needs of development and self-fulfillment and the safety of systems, Savioja et al. (2014) argue that a UX that compromises safety at work could hardly have a positive effect on users' needs of development and self-fulfillment.

UX in industrial contexts has been studied from the viewpoint of defining UX goals (Kaasinen et al. 2015) and as a differentiating factor in value-based selling in the metals and engineering industry (Väätäjä et al. 2014). Woods et al. (2019) propose the introduction of adaptive user interfaces for maintenance procedures to overcome the personal and environmental differences of CMMS users and use environments. Roto et al. (2016) studied UX in 7 companies of heavy industry, and conclude that in a business-to-business (B2B) setting, also customer experience has to be accounted for in touchpoints such as marketing and sales. In a B2B context, the customer who makes the buying decision is typically not the user of a product or service and, therefore, the value of UX for the customer comes through the perceived impacts of experiences for the users (Väätäjä et al. 2014).

Oja and Galliers (2011) recommend studying enterprise systems from a UX point of view. UX has been studied in industrial settings in a semiconductor factory (Wurhofer et al. 2015) and in a nuclear power plant (Savioja et al. 2014). These studies did not examine a specific enterprise system, but took a wider view of work experience (Wurhofer et al. 2015) and the design of control room solutions (Savioja et al. 2014). Aranburu et al. (2018) have created a framework for analyzing UX of human-machine interaction in industrial workplaces. Their study focuses on machine-tool companies and the digital user interfaces of these tools. However, experimental evaluation of the framework is still lacking.

UX of enterprise systems has been studied in the adoption phase (Hwang 2014). However, Karapanos et al. (2009) have described the temporal aspects of UX from initial orientation to incorporation to identification. Lu and Roto (2015) have investigated how to define meaningful experience goals for work tool design, combining the mechanics of meaningful work and the positive design framework. Their work introduces experiential aspects to work tool design.

Wurhofer et al. (2015) identified influences on UX and categorized these as individual (from the user, such as motivation, attitude, pre-experience, well-being, reflexivity, flexibility, and routines), system (appearance, visibility of information, autonomy, adaptivity, flexibility, consistency, persuasiveness, reliability, complexity, intuitiveness, efficiency, and effectiveness), and context (physical: noise, light, temperature, clothing, contamination, action space, and social: interpersonal reliability, equal treatment, appreciation, and hierarchy). This categorization follows Hassenzahl and Tractinsky's (2006) definition of UX. Aranburu et al. (2018) have a similar categorization in their evaluation framework that looks at the context of an industrial workplace, employee's characteristics, needs and previous experiences, as well as the functionality and usability

of the system. However, Aranburu et al. (2018) evaluate both pragmatic and hedonic qualities in the interaction between the user and the system, arising from system aesthetics, information architecture and usability.

2.4.1 UX of CMMS

Large enterprise systems, such as CMMS, have users on several levels of the organization: operators, maintenance personnel, maintenance planners, maintenance managers, accountants, and senior management (Labib 2004). One challenge with such collaborative systems is that the people who input data into the systems are not the same people who benefit in their work from using the data in the system (Grudin 1988). Lack of direct benefits from providing good quality maintenance data has been reported as one of the reasons behind poor maintenance documentation (Betz 2010).

CMMS usage has been studied by Tretten and Karim (2014) who identified several usability issues. These issues include too much manual input of information, CMMS being too complex, and limited access to necessary documentation (Tretten & Karim 2014). Aljumaili et al. (2012) found a similar usability issue of difficulties to find relevant information in the CMMS. User interface (UI) design becomes especially important when the CMMS is used with a mobile device (Emmanouilidis et al., 2009). Usability covers the productivity related issues, such as effectiveness and efficiency (ISO 9241-210 2019). However, motivation for manual data collection could be influenced more with the experiential aspects of interaction. There is a gap in literature on the use of CMMS as previous literature has covered the usability of these systems, but not looked at the UX. Looking at CMMS use that is a mandatory part of maintenance work, the emphasis of studying the UX in this research is on the social context, motivation, utility and usability of the system. In other words, the technology factors, organizational factors and people factors.

Wurhofer et al. (2015) identified feelings and emotions that are relevant to UX in a factory, both negative (fear, anger, and frustration; mostly linked to production tasks) and positive (joy, fun, and pride; mostly linked to administrative tasks). Over 40 % of user's time on the computer at the workplace has been reported to be wasted because of frustrating experiences (Lazar et al. 2006). Unnecessary information in the UI can give the user a feeling of losing control (Wurhofer et al. 2015).

2.4.2 UX context: Social influence

Social influence refers to the context of using the system: the colleagues and managers at workplace. Several IT adoption models, such as UTAUT (Venkatesh et al., 2003), include social influence, i.e., the degree to which a person perceives that important others expect him or her to use the system. The social influence model of IT adoption by Vannoy and Palvia (2010) model social computing aspects as augmenters of usefulness and ease of use and as antecedents

to social influence. Managerial influence to manual data collection has been studied by Molina et al. (2013), and my study extends that previous research with social influence from colleagues. This approach is similar to that of Brown et al. (2010) who categorized social influence in peer influence and superior influence when studying IT adoption and Eckhardt et al. (2009) who compared the social influence of colleagues and superiors in technology adoption.

Collecting high-quality data is related to knowing why the data is needed and what it will be used for (Lee and Strong 2003). Furthermore, it is necessary to know why the data is important (Haegemans et al. 2017). To study social influence, this study also measures the importance of knowing who is going to use the data.

2.4.3 Pragmatic aspects of UX: Usefulness

The focus of this study is on the incorporation phase of UX, which involves forming of functional dependency through usability and usefulness (Karapanos et al. 2009). Roto and Rautava (2008) list usability and utility as the pragmatic aspects of UX.

Wurhofer et al. (2015) define perceived usefulness as the utility of interacting with the system, which means, in a factory context, that the system improves the user's effectiveness and efficiency. These are usability factors (ISO 9241-210 2019). Nielsen (1993) has presented usefulness as a combination of usability and utility of the system. In this study, usefulness is defined similarly, including the usability of the system and its utility to the user. Utility here refers to the benefits of using the system, i.e. benefits of collected data to the data collector. One reason for poor maintenance documentation is lack of direct benefits from providing good-quality data (Betz, 2010). This is a typical challenge of large, collaborative systems: data collectors who must put in effort to collect the data are not the same people who use the data and benefit from data input (Grudin, 1988). In case of CMMS, it is used on various levels of organizations by operators, maintenance personnel, maintenance planners, maintenance managers, accountants and senior management (Labib, 2004).

2.5 Synthesis and hypotheses

The socio-technical context of manual data collection needs to be analysed from the perspectives of technological, organizational and people factors. The UX of data collection tools includes the user's internal state, the characteristics of the system, as well as the organizational and social setting of the data collection. Previous research has demonstrated the importance of managerial support and the usability of CMMS on manual data collection. This study extends these studies by examining the effect of social influence and usefulness of the CMMS. So-

cial influence from colleagues is tested separately from that of managers, combining both perceived expectations of colleagues and knowing who will use the data and for what purpose. This forms the first hypothesis of the study:

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

As managerial support has been shown to be of importance, it is also included in this study. Managerial support is seen as a special case of social influence. The second hypothesis is about the supportive role of managers:

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

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 combined into a research model showing the relations between the constructs in Figure 2.

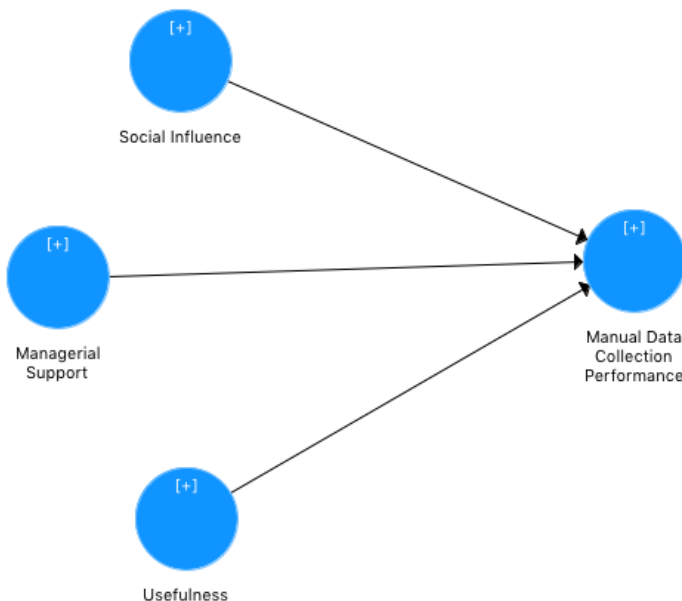


Figure 3. The research model and hypothesized relations between constructs (Publication V)

3. Methods and data

Multiple case study was chosen as the research approach for this dissertation. Case studies provide an opportunity for an in-depth and detailed examination of the subject (Yin, 2009). Similar approach has been used by several authors studying manual data collection in maintenance context (e.g., Tretten & Karim, 2014; Sandtorv et al. 1996). This research advances from initial, explorative and descriptive case studies aiming to understand the context [I-III] to very specific studies investigating defined factors in detail [IV, V]. An iterative approach was used in data collection, coding and analysis, as recommended by Eisenhardt (1989). Some case companies participated in several research projects during the course of this work and this allowed for a very iterative approach over the years.

Single case studies provide an opportunity for more in-depth observation. In this study, however, multiple case studies have been used. This way exploratory case studies (Publications I and II) could be followed by a pattern-matching approach and comparisons between polar opposites (Eisenhardt 1989, Publication IV). While Eisenhardt (1989) does not give an ideal number of cases, she does suggest that 4-10 cases typically work well.

3.1 Interviews

Semi-structured interviews were conducted in all cases (see Appendix 1 for interview themes and questions). Our interview questions covered a wide array of topics ranging from maintenance data collection and use to CMMS use, managerial practices, etc. The questions asked at each interview depended on the role of the person interviewed, and the semi-structured format allowed us to continue discussion in new direction when interesting observations were made during the interview.

We started with each company by having multiple background discussions with our contact persons, who were responsible for the development of maintenance systems and operations. The first persons to be interviewed were decided on in these meetings, and further interviews were planned in the first interviews. For example, the maintenance development manager would recommend interviewing maintenance managers who would then recommend maintenance technicians for interviews. For each case, we interviewed people in development roles

at company headquarters, maintenance managers at the sites, and maintenance technicians. Furthermore, people in relevant positions were identified and interviewed in each case. These roles included plant managers, maintenance planners, and IT personnel. We continued with the interviews until no new information about manual data collection or related themes arose, i.e., until data saturation was reached (Saunders et al. 2018).

3.2 Contextual inquiry

Participatory methods, such as contextual inquiry (as described in, e.g., Beyer and Holzblatt, 1998) involving real users and real industrial environments were used in the investigation of user experience. Contextual inquiries have also been used by Palviainen and Väänänen-Vainio-Mattila (2009) in their study of UX in machinery automation. In a contextual inquiry, the researcher observes the user performing normal activities and discusses those activities with the user. In this study, the researchers observed the maintenance technicians opening work orders, conducting maintenance, and closing work orders and reporting about the maintenance in the CMMS. In addition, some other reporting tasks with the CMMS were observed.

Observations in the contextual inquiries followed a guideline listing focus areas (see Appendix 3). Notes and photographs were taken during the contextual inquiry, and a diary describing the environment, task, and interaction with the CMMS was written afterwards.

3.3 Quantitative survey

In Case X, we followed the initial interviews and contextual inquiries with a quantitative survey to confirm the findings from previous cases. The hypotheses for the survey were formed after a literature review and experiences from previous cases. The hypotheses were presented at the end of section 2.2 UX in industrial context. They were tested with a survey of CMMS users in Case X. Link to the online survey was sent to all 245 technicians working in the company and 81 responses were received. The 33% response rate is comparable with similar surveys, such as the one by Molina et al. (2013) with a 20% response rate. For the survey, an initial pool of 17 items was formed on the basis of previous research. This literature review established content validity for the survey (Straub et al., 2004). The items represent the 3 factors to be tested: social influence, managerial support and usefulness, in addition to the dependent variable (Manual data collection performance). All items were measured on a five-point Likert scale. Composite reliability (CR) was used to test for internal consistency of the factors and average variance extracted (AVE) for convergent validity (Hair et al. 2011). See Appendix 2 for the survey items and section 4.1 for CR and AVE values.

3.4 Cases

The first case studies were explorative in nature, and the main goal for them was to understand the context of manual data collection: maintenance technician work and the use of CMMS and other data collection tools. The following case studies were comparative in nature. Representative case sites were chosen from sites that produce good-quality data and from sites that are facing more challenges with their data collection. The cases were compared and the factors on which they differed were identified. The final case study included a survey for quantitatively measuring the effect of three factors: managerial support, usefulness and social influence. These constructs were based on the previous case studies.

The cases illustrate the various features of industrial maintenance services. The first case included maintenance of products manufactured by the case company as well as competitors' products. In some cases, the maintenance technicians travel to customer sites for servicing the equipment, in others both the equipment and the technicians are permanently located on site, and in others equipment is sent to the workshop where technicians service the equipment and return it to use. The operating mode varied from maintenance invoiced separately for each task to maintenance contracts with some preventive maintenance included to operations and maintenance service contracts that include all preventive and corrective maintenance with plans of even offering the equipment as a service, similar to the Rolls-Royce Power-by-the-Hour concept that provides a complete engine and accessory replacement service on a fixed-cost-per-flying-hour basis (Rolls-Royce 2012).

The CMMS used in the case companies were widely used enterprise software offered by an external vendor. All companies had different systems, but with similar functionality. At the time of research, Company F was in the middle of moving from a dedicated PDA system to an Android application for manual data collection. Similarly, Company X was planning to introduce a mobile tool for data collection, to be used with their CMMS. Company IC had recently introduced a new CMMS. The company had previously used a different CMMS that was used by a maintenance manager who e-mailed work orders to sites and closed work orders in the CMMS with data received by e-mail. The new system involved site personnel using the CMMS directly on a desktop PC.

In Company IC, we wanted to compare sites that were performing well after the introduction of the new CMMS with sites that were facing challenges with the introduction and the quality of data in the system. To do this, we analyzed the data quality in the CMMS and ranked the sites by the quality of the data they produce in terms of believability, completeness and timeliness (Madhikermi et al., 2016). The dimensions of data quality were chosen together with company representatives. Examples of the criteria include length of work description (believability), asset location being reported (completeness) and the average delay

of reporting (timeliness). Following this analysis, case sites were chosen from India (I1, I2) and from the Caribbean region (C1, C2, C3).

Table 2 presents the main characteristics of each case company and the research methods used.

Table 2. Case companies

	Company F	Company IC	Company X
Case	Case F	Cases I1, I2, C1, C2, C3	Case X
Equipment manufacturer	Company F and others	Company IC	Others
Equipment owner	Customer	Customer	Leased to Company X
Equipment location	Customer site	Customer site	Company X/mobile
Maintenance technician location	Mobile	Customer site	Company X
Research methods	Interview, contextual inquiry	Interview, contextual inquiry, survey	Interview, contextual inquiry, survey
RQs	RQ1, RQ2, RQ3	RQ1, RQ2, RQ3	RQ1, RQ3
Publication(s)	I, III, IV	II, IV	V

3.5 Data

Collected data consisted of interview transcripts and diaries of contextual inquiries (Beyer and Holtzblatt, 1998). We also collected data from maintenance systems in the form of work orders. The work orders were from real maintenance cases, meaning that the data was not created for the case study. Work orders were used to identify the information that was manually collected. Furthermore, we analyzed operational documentation, such as process and role descriptions and organizational structures around maintenance and operations. These operational documentations provided a picture of how the data collection process was intended to work. We identified roles to interview from the process descriptions. The interviews then gave us a view of how the process actually works, and it became clear that the documentation alone would have given an insufficient picture of how the data collection actually happens. The operational documentation used as research data is summarized in Table 3.

Table 3. Research data: operational documentation

Operational documentation	Finland Case F	India Cases I1, I2	Caribbean Cases C1, C2, C3	Finland HQ Cases I1, I2, C1, C2, C3	Finland Case X
Internal presentations		1		1	2
Role descriptions	2				1
Process descriptions	4			1	1
CMMS/ERP instructions	1				2
Maintenance manuals	1				2
Work order examples	6		2		5
Total	14	1	2	2	13

All case studies included interviews of the maintenance personnel on several organizational hierarchy levels from the shop floor to management and even director level in some cases. All except one of the interviews were conducted by two researchers, one asking questions and the other one taking notes. The interviews were recorded and transcribed by an external service provider and the author of the dissertation checked all transcriptions. The author of the dissertation was present in all interviews. She checked the transcriptions and corrected any mistakes with the help of the interview notes. Interviews by roles and cases are listed in Table 4.

Table 4. Conducted interviews and contextual inquiries

Role of the person interviewed	Finland Case F	India Cases I1, I2	Caribbean Cases C1, C2, C3	Finland HQ Cases I1, I2, C1, C2, C3	Finland Case X
Maintenance development manager	3			1	2
Area HQ director	2	1 (AHQI)			
Area key user		1 (AHQI)	1 (AHQC)		
Maintenance planner		1 (AHQI)	2 (AHQC, C1)		1
Contract manager			1 (C1)		
(Operations & Maintenance manager)	4	2 (I1, I2)	1 (C1)	1	3
Plant manager		2 (I1, I2)	3 (C1, C2, C3)		
Workshop manager			1 (C1)		
Safety manager			1 (C1)		
Shift/team leader (CMMS user)		4 (3 I1, 1 I2)	6 (2 C1, 1 C2, 3 C3)		1
Technician	4		6 (3 C1, 1 C2, 2 C3)		6
Inventory			3 (1 C1, 2 C3)		
Maintenance system manager				1	
IT consultant			1 (C1)		
Total	13	10	26	3	13

In addition to the interviews, contextual inquiries of maintenance and the use of CMMS were conducted. They are listed in Table 5. Diaries were written of each case visit, and the contextual inquiries and observations were described in the diaries. Furthermore, photos were taken when permitted and some photos were added in the diaries to create a rich description of maintenance work.

Table 5. Observations by case

Observation	Finland Case F	India Cases I1, I2	Caribbean Cases C1, C2, C3	Finland Case X
Maintenance	3	1	3	2
Use of CMMS	1	1	1	
Maintenance/op- erations manage- ment				1
Customer service work order han- dling				1
Total	4	2	4	4

The last case, Case X, included a survey that was conducted online. An invitation to fill in the survey was sent to all 245 technicians working in Company X at the time of research. We received 81 responses (33% response rate). The respondents had been working on average 20 years in the case company, of which 14 years in their current position of a technician (N=60) or team leader (N=21).

3.6 Data analysis

Data analysis started by the researchers familiarizing themselves with the transcripts. The transcripts were then provisionally coded (Saldana, 2009) using Atlas.ti software and the TOP factors as predefined codes. This was done in an iterative manner, refining the TOP factors after each company project.

Pattern matching technique (Yin, 2009) was used to compare each case with the predicted pattern of the TOP factors and their effect on manual data collection. This was followed by cross-case analysis for the Indian and Caribbean cases. These cases were combined by country and then the Indian and Caribbean sites were compared on all TOP subfactors.

The results were compared with existing literature to discover similarities and conflicting findings, thus improving the credibility and generalizability of the study (Eisenhardt, 1989).

Partial Least Squares (PLS) was chosen as the method to analyse the survey data. PLS is being used more frequently by IS researchers as it allows researchers to examine a set of research questions in a single analysis (Gerow et al. 2010). PLS is also the recommended approach for exploratory research and

small sample sizes (Hair et al., 2011). While our sample size (N=81) is, indeed, rather small, it is well above the recommendation given by Hair et al. (2011) of using a sample ten times the largest number of formative indicators used to measure one construct. The survey data were analyzed using SmartPLS software¹ for a path analysis of the proposed model. PLS does not assess overall model fit, thus the explained variance (R²) of the dependent variables was examined.

3.7 Validation

The results were validated with case company representatives. The results were presented to them in written reports or slide sets followed by meetings where the results were discussed. Some modifications were made after these discussions, but, overall, the company representatives agreed with the structure of the findings. The modifications concerned issues such as number of technicians employed at the time of research. Discussions were mainly focused on our company-specific recommendations that are not included in the thesis.

The sample size heuristic proposed by Hair et al. (2011) has received criticism from Kock and Hadaya (2018), among others. They propose two alternative methods for minimum sample size estimation: the inverse square root method and the gamma-exponential method (Kock & Hadaya, 2018). As these methods are applied after the PLS analysis, using path strengths in the equation, we will use the inverse square root method to validate the results.

3.8 Research ethics

Any study on human subjects requires ethical consideration. Aalto University Research Ethics Committee follows the guidelines for ethical principles of research in the humanities and social and behavioral sciences given by the Finnish Advisory Board on Research Integrity (TENK, 2018). According to this guideline, participation in research should be voluntary and based on informed consent. Furthermore, the guideline implies that assenting to a request for an interview indicates that the subject has consented to be studied. The guideline also states that ensuring the genuineness of consent is particularly important when research intervenes in personal integrity. In this case, the research is about work practices of the research subjects and does not intervene with the subjects' personal integrity. In our research, based on voluntary participation, interview participation is an implicit consent to research. However, we have additionally asked for explicit consent to the recording of the interview.

Following the above guideline, we have given each research subject information about the study at the beginning of data collection sessions. As required by the

¹ <https://www.smartpls.com>

guidelines for ethical principles of research by TENK, this has included information about researcher's contact information, the research topic, the method of collecting data and the estimated time required, the purpose for which data is collected and how it will be analyzed and archived, the voluntary nature of participation, and the publication of results.

The guideline further states that if a study deviates from the principle of informed consent, an ethical review from the research ethics committee is required. In this case, the principle of informed consent was followed. The guideline gives examples of deviating from the principle of informed consent, and observation of work processes with permission from management is one such example. In our case, observations were conducted following the interviews and the subjects were asked for permission to observe them in their work. Therefore, in our case, explicit prior ethics review by the ethics committee was not necessary.

4. Results

4.1 Service technician work

The first research question of this thesis, *RQ1: Users and tasks: How is maintenance data collected and by whom?* was answered for the studied cases in interviews and observations of maintenance technician work. This work is conducted in socio-technical settings. The first case studies were explorative in nature, and the main goal for them was to understand the context of manual data collection: maintenance technician work and the use of CMMS and other data collection tools.

Using previous literature and Case F, criteria for successful manual data collection was created. These criteria follow the TOP factors presented in section 2.1.2. Each TOP factor is broken down to subfactors and each subfactor is analyzed in the CMMS context. These criteria applied to the CMMS context is presented in Table 6. For example, Technology factors include the effectiveness of the CMMS system, which means that data collectors feel that they are able to successfully perform and complete data collection tasks with the CMMS. Table 6 also gives references to where the factor comes from. These criteria were used as a tool for analyzing the following cases.

Table 6. TOP factor criteria in CMMS context (Publication IV)

Factor	Criteria applied to CMMS context	Reference
Technology		
Effectiveness	Data collectors feel that they are able to successfully perform and complete data collection tasks with the CMMS.	ISO 9241-11 (1998)
Efficiency	Data collectors feel that they can perform data collection tasks with using the CMMS in a reasonable amount of time and physical and cognitive effort.	ISO 9241-11 (1998)
Learnability and memorability	Data collectors can learn to use the CMMS in a reasonable amount of time and remember how to use it.	Nielsen (1993)
Satisfaction	Data collectors experience that the CMMS supports them in reaching their goals for manual data collection.	ISO 9241-11 (1998), Publication III
Organization		
Management support	Supervisors give feedback on data collection and require good quality data.	Molina <i>et al.</i> (2013), Lin <i>et al.</i> (2006), Publication III
Trust	Data collectors feel that the data they collect is used for developing the process, not for sanctioning.	Riege (2005), Unsworth <i>et al.</i> (2011)
Time pressure	Data collectors have enough time for data collection tasks.	Murphy (2009)
Competence development	Data collectors are given training for using the CMMS.	Riege (2005), Publication III
Work descriptions	Instructions for using the CMMS as part of the maintenance and repair tasks are available.	Publication III
Goal statements	Appropriate data quality level is specified.	Tayi & Ballou (1998)
People		
Competences	Data collectors feel competent what comes to data collection and using the CMMS.	Unsworth <i>et al.</i> (2011)
Work identity	Data collectors consider data collection as being part of their job.	Unsworth <i>et al.</i> (2011)
Own benefit	Data collectors benefit in their own work from the use of CMMS and the data that they collect.	Grudin (1988), Publication III
Data quality awareness	Data collectors understand the importance of good quality data.	Lin <i>et al.</i> (2007)
Language skills	Data collectors have adequate skills in the reporting language (usually English).	Riege (2005), Vatanasakdakul <i>et al.</i> (2004)
Verbal skills	Data collectors have adequate skills for verbal/written communication using the CMMS.	Riege (2005), Publication III
Use of computerized equipment	Data collectors use computerized equipment in their daily work.	Tomlinson (2002)

Typically, manual data collection happens during and after operation, maintenance and repair in the form of closing work orders with details of spare parts used and hours spent on the task. Technicians open work orders in a CMMS, conduct the tasks in the work order, and close the work order in the CMMS and report relevant details of the task. The cases introduce the complexities and challenges of CMMS usage in service technician work.

We observed several technology issues in the case companies, ranging from network connection preventing the use of the CMMS to technicians not being able to close a work order due to the complexity of the UI. Technicians and engineers did not complain about time pressure in manual data collection, although sometimes emergency repairs resulted in postponing the reporting of regular maintenance tasks. All interviewees felt that closing work orders and reporting task details is a part of the maintenance task. Goal statements regarding data quality were not present in any of the cases. However, managers and supervisors told us that they give feedback of data quality if needed, that is, the level of data quality is below acceptable level. All data collectors used computerized equipment in their daily work, although there were differences in the amount of time spent in front of a computer.

Data collectors should trust that data is not collected to control or evaluate their work. Our results showed that this kind of trust is not always present. Furthermore, situation awareness for maintenance managers would improve if the location of maintenance technicians was tracked. In case F this is a reality: it is a safety feature in the handheld CMMS for technicians who travel to maintenance sites alone. If the tool is not used for a certain time period, it will ask if everything is ok. Not answering the question in a predefined time period will cause an alarm. The technicians felt that if an accident were to happen, it would be too late to send help at that point and they felt annoyed by the requests to confirm that everything is ok. Nevertheless, having their location tracked was not mentioned to bother them. In case X, however, managers were afraid that plans to track maintenance technicians' location to improve situation awareness would be met with labor union resistance.

There were differences in competence development and work descriptions. While some cases organized training for all CMMS users, some cases only trained key personnel and some cases left it to the users to learn to use the system on their own. Competences of data collectors also varied between sites from university educated engineers to technicians with only vocational education. Language skills ranged from native English speakers to having received higher education in English to working in a foreign language. Doing the reporting in a foreign language can make the descriptions shorter. However, some managers mentioned that it's better to let the technicians do the reporting in their native language and then use Google translate than not to have reporting at all. Language issue was not seen as a major challenge.

4.2 Use of manually collected data

To answer *RQ2: What challenges are there with the quality of manually collected maintenance data?*, the case companies were asked how they are currently using manually collected maintenance data and what kinds of challenges they are facing with the data.

In case F, maintenance data is a key source for making preventive maintenance plans. The data is also used by sales personnel when targeting modernization package or new, substitute equipment sales. Challenges with data quality included missing data and questionable reliability.

In the Caribbean and Indian cases, data is used for making preventive maintenance plans. The company was also planning to use the data in extended warranty sales (Publication II). However, several challenges were discovered during this project. The main challenges with data quality were

- Missing data: from some sites altogether, from some sites for certain time periods or for small repairs; partly filled maintenance reports
- Inconsistencies and questionable reliability: for example, monthly values do not add up to cumulative values
- Ambiguity in the meaning of data: an outage could include waiting for spare parts or even redundancy
- Quality variation across sites, no standard data format for all sites
- No single source of data: data is scattered in various databases
- Data censoring on a monthly level: no details of single incidents

In Case X, manually collected data was used to prove that all required maintenance tasks had been conducted. This is required both by the owners of the leased equipment as well as by the governing authorities. For this case, the biggest challenges had to do with the timeliness of reporting. It was sometimes difficult for shift supervisors to keep up to date of maintenance progress in an environment where maintenance time is limited and keeping the equipment in use is a top priority.

The biggest challenge was when data was missing from the CMMS totally. Having work orders closed and reported on paper and not transferred to the CMMS meant that the data was not usable by maintenance planners or managers outside the site, and even within the site it was difficult to find information that is only on paper.

Madhikermi et al. (2016) defined the three most important attributes for the Caribbean and Indian cases: believability, completeness and timeliness. Table lists the observed challenges from all cases categorized under these attributes.

Table 7. Categorization of challenges by data quality attributes

Believability	Completeness	Timeliness
Inconsistencies, questionable reliability (Cases F, C&I)	Missing data (completely, partly, for certain time periods) (Case C&I)	Delays in reporting (Case F, C&I, X)
Ambiguity in the meaning of data (Case C&I)	Data censoring on a monthly level (Case C&I)	
Variations across sites (Case C&I)		
No single source of data, some data only on paper (Case C&I, X)		

4.3 Manual data collection context

The third research question of the thesis has to do with the socio-technical context of manual data collection: *RQ 3: How do contextual user experience factors relate to the quality of manually collected data?* This analysis started by comparing sites that produce good quality data with sites that have more challenges in the quality of manually collected data. For this purpose, we compared sites I1 and I2 with sites C1, C2, and C3 by the TOP factors identified in Publication IV. The factors include both specific usability factors as well as contextual UX factors. UX factors are studied in more detail in section 4.4.

The results are summarized in Table 7. They show that technological factors were a problem in both geographical areas. However, whereas they even prevented the use of the CMMS in some Caribbean cases, Indian sites were still able to use the CMMS. Differences were found in the way managers dealt with problems: while Indian managers supported the engineers by training, instructions and communication about the issues with the headquarters, in the Caribbean region managers felt that more push was needed to make the technicians use the system. While the Caribbean technicians had the advantage of using their native language in reporting, the better education of the Indian engineers overweighed this advantage. The engineers also understood the importance of manually collected data in their daily operations, whereas the Caribbean technicians had only vague ideas of what the data was collected for.

Table 8. Cross-country comparison (Publication IV)

Factor	India	Caribbean
Technology		
Effectiveness	Despite connectivity and usability issues, team leaders were able to complete data collection tasks.	Technicians often fail at closing work orders and cryptic error messages do not help them.
Efficiency	Poor internet connectivity at remote sites.	Cryptic error messages need to be solved by planner.
Learnability and memorability	In team leaders' opinion, the system is not user friendly.	It was difficult for the technicians to remember how to close work orders.
Satisfaction	Frustration with issues that have been reported to headquarters, but haven't been fixed.	Frustration with frequent errors and inability to do required tasks with the system.
Organization		
Management support	Managers made sure that engineers had training and instructions.	Managers felt that more "push" was needed.
Competence development	Hands-on training for everyone using the system.	Training for some people who are expected to help others. Training 4 months prior to system access.
Work descriptions	Instructions for using the software on shared laptop.	No instructions.
People		
Competences	University education of system users.	Vocational education of system users; some technicians not comfortable sitting in front of a computer.
Own benefit	Team leaders said that they are doing the reporting for themselves.	Shift leaders did not see how they would personally benefit from reported data and they only had a vague idea of who would need the data and for what purpose.
Language skills	English is not users' native language.	English is users' native language.

4.4 Partial Least Squares modelling

In order to take a closer look at the differentiating factors in the Indian and Caribbean cases, a survey was used in case X to study in more detail the factors social influence, managerial support, and usefulness. The third research question of this study is RQ 3: How do contextual user experience factors relate to the quality of manually collected data? This question was detailed as “What is the effect of social influence, managerial support, and usefulness on manual data collection performance?” in publication V. To analyse the survey data and thus to test the hypotheses, PLS analysis was conducted. The result of this analysis is shown in Figure 4.

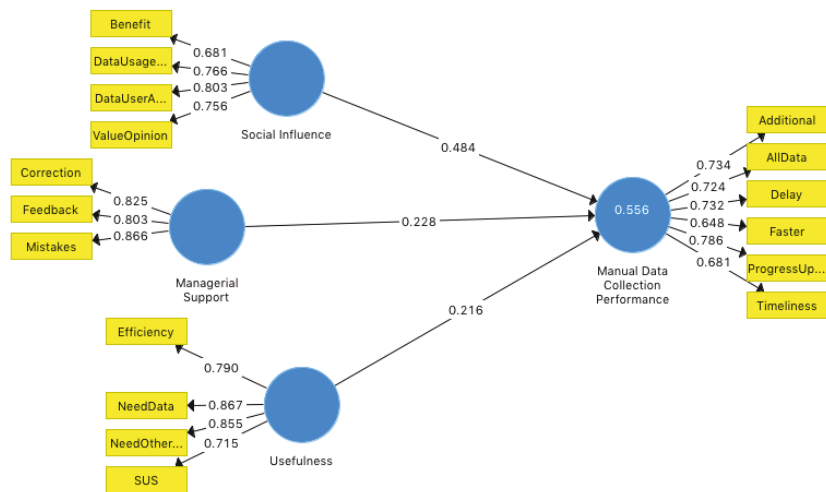


Figure 4. Path model (Publication V)

The first hypothesis “*Social influence will be positively related to the collection of high-quality data.*” was supported as a statistically significant ($p < 0.01$) positive effect was found of social influence on the performance in manual data collection ($\beta = 0.484$, $t = 5.53$). The path coefficient 0.484 was the strongest of the three paths.

The second hypothesis “*Managerial support will be positively related to the collection of high-quality data.*” was also supported with a positive effect of managerial support on good performance in manual data collection ($\beta = 0.228$, $t = 2.55$, $p < 0.05$).

Finally, the third hypothesis “*Usefulness will be positively related to the collection of high-quality data.*” was also supported with a positive effect on manual data collection performance ($\beta = 0.216$, $t = 2.2$, $p < 0.05$).

Together, social influence, managerial support, and usefulness explained 55% of the total variance. This can be described as moderate (Hair et al., 2011). Although all hypotheses were supported, social influence was the strongest predictor of manual data collection performance when compared to managerial support and usefulness.

4.5 Summary

The main RQ of this dissertation was:

What factors influence manual data collection and the quality of collected data?

This question was broken down to three sub questions as follows:

RQ 1: Users and tasks: How is maintenance data collected and by whom?

RQ 2: What challenges *are there with the quality of manually collected maintenance data?*

RQ 3: How do contextual user experience factors relate to the quality of manually collected data?

The results of this study have provided answers to these questions. First, a description of manual data collection in the maintenance context was provided. Furthermore, criteria for successful manual data collection was given from the viewpoints of technology, organization and people. Section 4.2 gave examples of the main challenges the case companies are facing in the use of manually collected maintenance data. Finally, sections 4.3 and 4.4 provided a view to the contextual UX factors affecting manual data collection.

5. Discussion

The starting point for this research was a notion of inadequate data quality in manually collected data. The managers of the company in question made guesses of what possible reasons there could be behind this phenomenon. My approach was to try to understand the data collectors' point of view: their work and how data collection is related with their other work tasks, and how they feel about data collection and the tools used for it. The publications of this dissertation present the various phases of constructing this understanding. My claim is that managers and designers benefit from this understanding when they design the processes and tools for maintenance data collection.

The socio-technical perspective to system design requires attention to the interaction between the technical, economic, organizational and social factors when systems are used (Mumford, 2000). The socio-technical context of manual data collection includes the CMMS, the economic perspective of industrial maintenance, the organizational practices and structures, and the social connections at the workplace of the maintenance technicians. All these different aspects need attention when designing the CMMS and its use in industrial maintenance.

5.1 Scientific contribution

The research process of this study provides an example of how industrially relevant research questions can be identified and characterized in order to systematically and reliably study them. Furthermore, this study shows how initial, explorative, qualitative case studies are used to refine the following case studies in more detail, and, finally, to use gathered knowledge to create a scale for measuring the impact of what appear to be the most relevant factors.

Previous studies of manual data collection have addressed the effect of social influence either from technology adoption point of view (e.g., Brown et al. 2010; Eckhardt et al. 2009) or as social pressure (Haegemans et al. 2018, Murphy 2009). In the context of this study, however, the issue is not whether or not technicians adopt a CMMS, it is the extent of adoption. It is mandatory for the technicians to close work orders in the CMMS, and the technicians also find that closing the work order and reporting task details is an essential part of the maintenance task. However, there are differences in the quality of the reported data. We observed challenges with the timeliness, accuracy and completeness of

the manually collected data. Therefore, in this context, the question is not about adopting technology, it is about the performance of using it.

Murphy (2009) studied social pressure in the form of subjective norm in theory of planned behavior. While Haegemans et al (2018) did not find support for social pressure having an effect on data collectors' intention to enter data correctly, this study found a relation of social influence to manual data collection performance. This study included the knowledge of who needs the data and what the data is used for as factors of social influence. However, in Haegemans et al (2018) study, social pressure was measured with only two items, both dealing with the relationship to the head office ("The head office expects that I enter the appreciation completely correctly." and "In general, I comply with the instructions of the head office."). Therefore, their study is more about managerial pressure than about social influence from colleagues as in this study.

Managerial influence to manual data collection has been confirmed by several earlier studies (e.g., Lin et al. 2006; Murphy 2009; Tayi and Ballou 1998). In this study, the effect of intrinsic or extrinsic motivation combined with managerial influence as studied by Molina et al. (2013) could not be repeated. We attempted to use the General Causality Orientations Scale by Deci and Ryan (1985) to understand more about the motivation of the technicians. This survey was added to the end of our own survey and the respondents were asked to continue by filling in this other survey. Unfortunately, we only received 33 responses for this part of the survey and due to the very low response rate (13%) were not able to use the data. We received comments that this other survey did not feel like it was related to technicians' work and they felt uncomfortable answering the questions. Exploring the motivational orientations and their relation to manual data collection performance would thus require a different approach in the study. This could, however, provide an interesting avenue for future research.

Another difference of this study compared to that of Molina et al. (2013) was the view on managerial influence. Whereas Molina et al. (2013) see managerial role as pressure and fear of disciplinary actions, we followed Murphy (2009) on seeing the managerial role as a supportive one. This was also in line with the first discussions in one of the case companies where the maintenance manager stated "If things would get fixed by shouting we would have already solved the problem" (Publication III, p. 6).

Murphy (2009) proposes that operators may view data collection as a superficial element of their job role that does not reflect on their maintenance and repair capabilities and this could affect their willingness to collect good quality data. The interviews conducted in this study did not give support for this line of thought. All interviewed technicians felt that closing work orders and reporting task details is an essential part of a maintenance task. Furthermore, Murphy (2009) lists time pressure as one influential factor in manual data collection.

While this sounds reasonable, the current study could not confirm this. The technicians who were interviewed all stated having enough time to do the data collection.

The findings of data quality issues are similar to what has been observed in previous literature: missing data, questionable information, wrong data, out of date and validity issues (Sandtorv et al. 1996, Lin et al. 2007). Information sharing issues with third party providers were present in Case F, similar to the observations of Dekker et al. (2013). As similar results are found decade after decade it seems that this challenge is too difficult to overcome. However, it could be that the requirements for data quality also increase by time as more advanced data processing requires better quality data.

Palviainen and Väänänen-Vainio-Mattila (2009) add the need of being socially connected to others as a possible threat to safety, but the results of this study show that social support can actually improve performance, and thus, improving UX with social connectivity would be advisable.

While this study concentrated on the pragmatic aspects of UX, one could argue that in a work context the hedonic, enjoyment and self-development aspects manifest in being considered an expert in one's work, as well as from a flow experience at work. In this respect, the social aspects of data collection can also affect the hedonic aspects of UX as they can make the expertise of the data collector visible to others. The UIs of data collection systems should also make it possible for data users to acknowledge the expertise and effort made by the data collectors to reward them in this aspect.

5.2 Managerial contribution

Previous research has proposed ways to overcome the data quality issues in maintenance data. Hodkiewicz and Ho (2016) describe how historical work order data can be cleansed for reliability analysis and Lukens et al. (2019) summarize research on using natural language processing and machine learning can be to extract information from unstructured free text fields in maintenance data. However, Lukens et al. (2019) also note that there is another avenue in dealing with data that requires improvement: improving work processes. The results of this thesis contribute to this latter approach by pointing out the opportunities that managers have in improving the data collection procedures and motivating the data collectors to collect good quality data.

The level of detail required in data processing sets requirements for data collection processes. While the interviewed managers had understood the importance of motivating technicians, the results of this study can provide guidelines of how to motivate them. Knowing why the data is collected – who uses it and for what – can increase motivation to collect data in a timely manner with sufficient qual-

ity. This can be achieved either through training where data collectors are educated about data usage, or by making it visible in the CMMS or a special data collection UI. A prototype of such a UI was created by Jussi Rämänen during our research on the basis of creative workshops with the author of this thesis (Mahlamäki et al. 2016). The UI gives data collectors access to the collected data, thus allowing them to benefit from the equipment history their data is describing. The UI also shows the names of data collectors and allows data users to comment on collected data. Screenshots of the UI are shown in Figure 5.

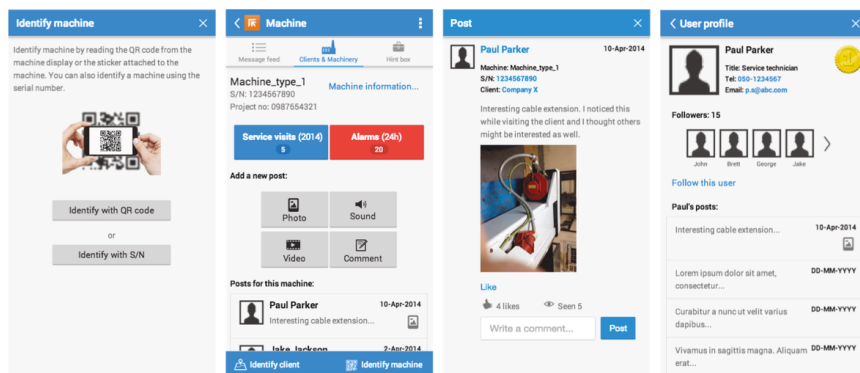


Figure 5. UI prototype for a mobile data collection tool (Mahlamäki et al. 2016)

Making the use of collected data visible to the data collector shows the significance of their work and gives it meaning. As the results of this study have shown the importance of social influence, it is something that should be considered in the design of data collection tools. We have seen that usability issues can be overcome if there is motivation to produce good quality data: when data collectors need the data in their own work they are willing to spend extra time in inputting the data to the CMMS.

Another advantage in making data usage visible is that it also shows what data is not needed. Collecting and storing data “just in case” is time-consuming and expensive. Requiring each justification for all collected data can reveal data that is not necessary to collect. This will ease the burden on data collectors. Furthermore, this can help in deciding whether the data is worth the expenses of its collection (Kumar et al. 2013). Data collectors also expect their tools to help them in their work and not make them input information that could be collected otherwise:

It should function like a thought, it must be like, you just wave something, or a simple UI and a fast tool. [...] It must be something already proven, working, fast system, easy to use. Those work order numbers must be there in the tool already. (Technician, Case X)

The survey that was developed in this study can also be used by managers who want to better understand the data collectors in their organization. The survey can be conducted to create a baseline before any improvement actions are taken.

After new procedures or tools are introduced, the survey can be repeated to see if the changes have caused positive effects.

5.3 Limitations

Case studies have provided a detailed understanding of maintenance data collection in the case organizations. Multiple sources of evidence, including interviews, observation, documentation, and a survey, have been used to increase construct validity (Yin 2009). While the results of case studies cannot be generalized directly to other contexts (Yin 2009), a sense of generality can be found in terms of implications to theory (Ketokivi & Choi, 2014) as presented above. However, generalizing the results to other contexts can only happen with future research. Haegemans et al. (2018) studied manual data collection in a financial institution, and it would be interesting to see manual data collection studies in other sectors, such as health care.

Collaborating with companies can introduce a certain level of unpredictability in research. Running the daily business is, usually, a priority for the people in operations. Participating in studies, such as this one, can be an important development project, but if a piece of equipment breaks down the priority is in fixing it and not in participating in an interview. For this reason, the timespan of the case studies has been rather long. We were able to find case companies of varied industrial fields and we had considerable freedom in planning the interviews. However, there were also cultural differences in how freely we were able to conduct the interviews. In India, we did not have time to conduct personal interviews with all engineers, instead we had a group interview session. Furthermore, the plant manager and maintenance manager were present in the interview, making it more formal than the individual interviews in other cases. With a limited time granted at customer premises, we had to settle for these interviews. Luckily, observing maintenance and conducting a contextual inquiry of the use of their CMMS allowed us to ask further questions in more relaxed environment.

Another limitation due to the context comes from evaluating the quality of collected data. While it would have been beneficial to be able to compare the quality of collected data with the attitudes of the data collector, getting an objective measure of each person's data collection performance was not possible. We considered asking a supervisor for to assess the data collection performance of each data collector, and, also, measuring data quality from the collected data for each data collector (similarly to what was done for different sites that were compared in India and the Caribbean). However, evaluating employee performance is a very delicate issue, and doing that even for research purposes would have caused negative feelings and possible conflicts. Therefore, we settled for each data collector's personal evaluation of their data collection performance, despite possible common method variance.

The limitations of the survey are related with the sample size. The sample size can be evaluated using the inverse square root method proposed by Kock and Hadaya (2018). This method looks at the path coefficients in the PLS model, in this case $\beta=0.484$ for social influence, $\beta=0.228$ for managerial support, and $\beta=0.216$ for usefulness. Using significance level of 0.05 and statistical power of 0.8, which are normally chosen in the IS field (Kock & Hadaya, 2018), we can estimate the minimum sample size for β_{\min} . In this case, β_{\min} is 0.216 and the minimum sample size is estimated as 133. Removing usefulness from the analysis would change path coefficients to $\beta=0.566$ for social influence and $\beta=0.232$ for managerial support. Now, β_{\min} is 0.232 and the minimum sample size is estimated as 115. Finally, if we only look at social influence, the path coefficient becomes $\beta=0.691$ and the minimum sample size estimate 13. Although the inverse square root method leads to slight overestimation of the sample size (Kock & Hadaya, 2018), the estimated sample sizes for managerial support and usefulness are well above our sample size of 81. As collecting more data is not an option, we have to conclude that while the path coefficients of managerial support and usefulness were found significant ($P < 0.05$), the analysis has failed to support the hypotheses 2 and 3. The effect of managerial support and usefulness are not strong enough to show with the small sample of this study, and measuring their effect would require a larger sample.

5.4 Future work

The interviews included sections on attitudes to mobile tools. The reason for this was that some of the companies were considering or had already shifted to using mobile tools for maintenance data collection. This theme was out of the scope of this thesis, but it would provide interesting directions for future research. One interesting theme would be to compare the attitudes toward mobile tools to data collection performance after the introduction of mobile tools. Also, it would be interesting to see if there is a change in the attitudes towards mobile tools after using them for a while. In any case, the results of this study should be applicable to the interaction design of mobile tools as well. For example, knowing who is using the data and for what purpose should be a motivating factor regardless of the tool used for data collection.

Culture as a possible influencer of manual data collection was noted in Publication III, referring both to organizational culture and national culture. Going deeper in this direction would be enough for another dissertation, but worth investigating. This would be especially beneficial for multinational companies, such as several of the case companies in this study.

Blockchain technology can be used to enforce quality in IoT collected data (Tian 2016), and it could also be applied in the manual data collection context. Of course, all ways of restricting data input also endanger the quality of data inputted as people are very clever in finding ways to avoid attempts to force them to collect accurate data and any workarounds can be more dangerous than not

inputting the data in the first place. However, for critical contexts, such as aircraft or nuclear power plant maintenance, such strict approaches could be worthwhile. This would build trust in the maintenance process for all parties – equipment owner, maintenance and operation organization, regulator and the general public.

6. Conclusions

This study has brought attention to the issue of quality problems in manually collected data. The main contribution of the thesis is a comprehensive and multifaceted view of manual data collection in industrial maintenance. Similar data quality challenges were observed in three case companies. The challenges are related with the timeliness, accuracy and completeness of the data. The results of this study reveal factors affecting the performance in manual data collection. The factors have been categorized in technological, organizational and people factors. A comparison of sites that produce good quality data and sites that have more challenges with data quality found that while both sites using the same CMMS were struggling with its usability, the better performing data collectors were aware of the reasons for collecting the data and used the data in their own work. CMMS are complex enterprise systems whose use is mandatory for their users. However, for some users the system was too difficult to use, and they were struggling with it. Some users were performing better despite the usability issues with the system. Social influence was found to have a positive effect on manual data collection performance. This included knowing who needs the collected data and what they use it for.

This study has supplemented qualitative research with a quantitative survey. The explorative part of the study introduced us to the challenges in manual data collection and taught us what the working environment is like. It would have been difficult, if not impossible, to ask the right questions in the survey, had we not spent time with the maintenance technicians in their workplaces. Comparing sites was possible after an analysis of data quality in different sites. However, without the quantitative study it would have been very difficult to say what is the most important factor affecting manual data collection performance. At the same time, the limitations of working with real industrial organizations also introduced the challenges of getting a sample size large enough for statistical evaluation when there is only a limited number of maintenance technicians in the whole population. Combining the qualitative and quantitative results have led to recommendations of how to improve data collection processes and tools.

Differences in data collectors' competences are partly given, such as education and language skills. Many factors can be affected by management, though. Managers can make data users and usage and their requirements for data quality visible to data collectors by organizing training and by giving detailed instructions for data collection. Furthermore, it is important to take the data collectors' point of view and to note local conditions when selecting or designing data collection tools. Improvements in usability can replace the need for training and instructions if using the system is made self-explanatory and all data that is already known is filled in the work orders to minimize the amount of data that needs to be collected manually.

When data collectors are motivated to collect data, they can overcome the challenges brought by usability issues of the data collection system. While improving the usability is important in removing the struggles with the CMMS, it is more important for managers and interaction designers to make a connection from data users to data collectors. When data collectors know who needs the data and what they are going to use it for, they are more likely to put effort into data collection. This would also make data collection tasks more meaningful, thus improving the meaningfulness of work.

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Appendix 1: Interview questions/themes

Background

- Work history, education?

How does maintenance reporting work in practice?

- What **roles** are involved in reporting? Who does what? Who is responsible?
- What **systems** are used in each phase? Pen and paper?
 - Does the tool force you to report compulsory items?
- **When** is the reporting done? (Before/during/after the maintenance)
Where is it done?
- When are the **work order statuses** changed?
- What level of **detail** and how much **time** is used for reporting?
- Does someone **authorize** the data entry? Can anyone enter data or only specialized people?
- What **processes** are followed at the workshop/on site?
 - Have the work processes been discussed or informed, if then what way?
- What else is reported, e.g. **for the customer**? How?
- **For whom** do you do the reporting? (system, manager or customer???)
- What kinds of **instructions** and training are given for reporting?
- How could the reporting process/tools/tasks/responsibilities be **improved**?
- What kinds of **challenges** are there with the current process/tools etc.?
- Are there any kinds of **bonus/compensation/rewards** for good reporting?
- How long have you been **using the CMMS**? How often do you use it?
- What kind of **experiences** do you have with the CMMS? How is it compared with the old tools? How could it be improved?

Maintenance manager/planner/supervisor

- Does the supervisor **give feedback** of reporting and data quality?
- Where do you order **spares** from?
 - Do you use a generic equipment ID or the ID of the piece of equipment that needs it?
- What info do **managers need** about the equipment's operation/maintenance history?

- What kinds of reporting **instructions** are given to the persons reporting the work?
- **How is maintenance data used in analysis and decision making?**
 - What kinds of analyses are made – **how detailed** information is needed?
 - How well does current data support decision making? Where are the biggest **challenges**?
 - What information is **most valuable**? What makes the information valuable? Timing/correctness/trustworthiness/frequency/relevance/comprehensibility/accessibility?

Decision makers

How does maintenance reporting vary across sites?

- What differences are there in the **quality** of maintenance reporting from different sites?
- What differences are there in maintenance reporting **practices** in different sites?
- What could be the **reasons** causing the differences?

Technician

- Does the supervisor give **feedback** of reporting and data quality?
- What kind of feedback would be needed/nice? Do you know who uses the reported data and what it is used for?
- Who **benefits** out of reported data?
- Do the current **tools** support high quality data collection?
- How do you evaluate **your performance** in reporting?
- How would you describe your **relationship** with your supervisors/managers?
- What useful information to **support your work** would you like to have that is currently missing?
- What happens if you **don't** report?
- What kinds of **challenges** are faced by the maintenance technicians?
 - Machine breakdown
 - Management not accessible
- Where can you get **help** if you can't fix the drive? How: phone, e-mail, in person?
- Why is official reporting process (sometimes?) **bypassed**?
- **Typical faults** requiring fixing the equipment?

Maintenance data analysis with field technician

- What is a **typical data** entry?
- What was done at the site/workshop and what was reported?
- If there happened the case that work was not done according to rules/process, what would be your interpretation/explanation to that?
- Why is the time spent/spares used/when finalized not always reported?

- Do you report spares for the exact piece of equipment or just any equipment?
- When you take a spare from your local storage do you change the equipment ID for that spare to correspond with the exact piece of equipment you are working with?
- How do you report **emergency** repair work?

Mobile reporting

- Do you have a company mobile phone/a personal mobile phone/a tablet?
 - How much do you use the above-mentioned devices and for what purposes? Do you play mobile games?
- Would you be interested in using mobile phone or tablet for maintenance reporting purposes? For what tasks could it be useful and for what tasks not so much?
- Do you use social networking services (e.g. Facebook or Twitter)? Do you use them with your mobile devices?
- Do you think that certain social networking service elements would be useful in your work? What elements would be most useful?
 - These elements could include e.g. making work-related posts, commenting & liking your colleagues' posts, and following some of your colleagues who post useful information
- What is your opinion of using photos/audio/video in maintenance reporting?

Appendix 2: Manual Data Collection Performance Survey

Data collection performance

1. "I close work orders with accurate and correct information." (ACCURATE)
2. "I close work orders with useful additional information." (ADDITIONAL)
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)

Managerial support

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

1. "I need the information that I fill in in the CMMS in my work." (NEED-DATA)
2. "With the CMMS I can get things done faster." (EFFICIENCY)
3. "I use the information others have filled in in the CMMS in my work." (NEEDOTHERSDATA)
4. SUS Usability (mean of the SUS items) (SUS)

Social influence

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." (DATAUSER-AWARE)
4. "I know what the information from closed work orders is used for." (DATAUSAGE-AWARE)

Appendix 3: Manual data collection observation guideline

Communication

- How do people communicate with their colleagues?
 - Official/Unofficial
- Coffee rooms
- Are people meeting and chatting?
 - Who?
 - Where do people interact?
- What languages are used?
 - What is official language?
 - Spoken/Written
 - Instructions & manuals
 - Dialects? Minorities? Subcultures?
- Do the technicians use any kind of reference material or instructions?
What?
- Message boards/walls
 - Instructions
 - Worker of the month etc.
- How much information exchange with colleagues and what is discussed?
- Who communicates with who?

Organizing

- What does the manager do on site? Typical day
- Where is the site manager's office?
- Where do the technicians sit? Do they have a place to "sit"?
- Are managers in any level involved in the actual reporting and data collection tasks?
 - Asking or ordering?
 - Fixing, rewriting, translating
- Dynamics between subordinates and supervisors
 - Teamwork or hierarchy? What are the symptoms/show cases of "teamwork" or "hierarchy"?
 - Work orders given or negotiated?
- Age structure
- Breaks, coffees, lunch hours; official & unofficial

Tools

- Mobile phone usage
 - Own and/or company phone
 - Take pictures?
 - What applications are used?
- Computer access
- Data entry - context of the study
- Any noticeable social and cultural factors affecting the manual data entry?

Work process

- How does the technician start the day?
- Walls
 - Process description
 - Information
- A typical day of a maintenance technician
- How hectic is the work environment?
 - Are people busy or just hanging around?
- How big part of working hours is spent waiting?
 - What kind of "waiting"?
- Work load/pressure?
 - Average work day
- Division of maintenance/reporting/observation/breaks
 - What is the role and experience of reporting work? Of the totality of time at work

Environment

- Waste management
- Safety
 - safety matters considered, accidents
 - safety instructions available
- Air conditioning, lights
- Floors, corridors
- Cleanliness
 - Are there cleaners?
 - Instructions for cleaning
 - Sand, dirt visible?
 - Cleaning up after maintenance by technician or someone else?
- Spare part storage
 - Organized?
 - Large/small?
 - Location
- Security
 - How easy is it to get to the [equipment to be maintained]?
 - Doors, access control
 - 24/7 monitoring?

Appendix 3: Manual data collection observation guideline

- Lunch and coffee breaks
- How many days a week working?
- What are the working hours?

Brand

- Are [company] logos visible?
- Customer people or subcontractors?
- [Company] materials



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