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Effect of mobile technology on information quality in human-mediated information collection

MSc program in Information and Service Management

Master's thesis

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Abstract of master's thesis

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Abstract

Acknowledging the paramount importance of information quality in the modern data-driven society and the prevalence of mobile devices, this thesis assesses the effect the use of mobile devices in human-mediated information collection has on information quality. More specifically, the thesis delves into a specific use of mobile devices as information collection devices in environments of high mobility, which do not permit use of less compact and accessory dependent computer technology.

The implications of mobile device use in information collection are two-fold; on one hand the devices' radical mobility could enable supported information collection directly at the source, potentially improving information quality, but on the other hand the small screen with cumbersome text input via on-screen keyboard could entail a number of unintended errors as well as narrower range of recorded information.

The thesis assesses two sets of patient notes from a Finnish residential elderly care facility, one produced solely with desktop computers and the other with desktop computers and mobile devices in parallel. On the intrinsic information quality dimensions of accuracy, completeness, timeliness, and consistency, the complementary use of mobile device results in enhanced information quality; particularly the completeness and timeliness of information show significant improvement. Additionally, anticipated difficulties in data input with mobile devices do not seem to have any remarkable effects on the produced information.

Keywords information quality, data quality, mobile technology, residential care

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1. Introduction

Already decades ago the importance of information quality and the reliance on information was recognised (e.g. Fisher & Kingma 2001, Miller 1996, Marsh 2004), and in the current information-driven society the quality of the information is paramount; it is evident that decisions can only be as good as the information they are based on (Redman 1998).

In the current fourth wave of computer technology, touch-screen mobile devices such as smartphones and tablets have emerged and conquered the globe, with almost 8 billion devices currently (Cisco Visual Networking Index 2016, Kavanagh 2015, Struminskaya et al. 2015). Some revolutionary features of these mobile devices, such as their compact computing power, ubiquitous opportunities for sensor use, and constant connectivity, have been widely discussed in academia, but their features such as lightness, compactness, and radical lack of accessories compared to other computers also provide an opportunity to utilise them in high mobility human-mediated data collection (Adiguzel 2008, Chan-Olmstedt & Shay 2014, Händel et al. 2014, iPass 2014, Sessions & Havens 2012, Wetzlinger et al. 2014, Yurish & Canete 2013). Before computer devices with this degree of mobility, these high mobility environments such as healthcare, population surveying, and construction have had to rely on delayed data input, either producing intermediate paper-based notes or memorising the data until a computer is available (Byass et al. 2008, Houston 2010, Mickan et al. 2013, Ozok et al. 2008, Sessions & Havens 2012, Struminskaya et al. 2015).

While businesses have detected the opportunity provided by mobile devices in high mobility data collection and seized it, the information quality research has yet to evaluate how the use of mobile devices at information capture affects information quality. The point of entry is a critical point in producing high quality information, changes to which could have substantial effects on the quality of information (Bai et al. 2004, Chen et al. 2010, Eckerson 2002, Haan et al. 2004, Marsh 2004, Olson 2003, and Sessions & Havens 2012, Stephens et al. 2010). The first question is about whether the mobile data collection yields the anticipated benefits by enabling supported input directly at the source. Secondly, the features enabling the radical mobility, particularly the small screen size and the lack of accessories, entail differences into the way the data is entered. The resulting text entry via on-screen keyboards has in some circumstances been observed to cause longer times for task completion, less accurate input, and less content produced altogether than on a traditional personal computer (PC), suggesting possible negative effects on information quality (Lugtig & Toepoel 2015, Mavletova 2013, Odell 2015, Struminskaya et al. 2015). This thesis focuses on this gap in research by assessing the effects of mobile technology utilisation on intrinsic information quality in human-mediated information collection.

1.1. Research question

Enhancing data collection with truly mobile technology is an opportunity grasped by organisations in increasing numbers (e.g. Byass et al. 2008, Houston 2010, Ozok et al. 2008, Sessions & Havens 2012). While the mobile technologies indeed have appeal in their non-restricted circumstances and environments of use, the features such as the lack of external accessories and smaller screens enabling the degree of mobility may have degrading influence on the produced information. In information collection the quality of the information is obviously of utmost importance, and this thesis seeks to shed light on the effects the new medium of data collection has on the resulting information. The research question is as follows:

> **How does utilising mobile technology in human-mediated information capture affect the quality of collected information?**

The research question is built around the question of the effect of mobile technology on information quality. Additionally, there are two other key components that define the scope. First, the thesis focuses on information collection, which means that it assesses the inherent, objective qualities of information and does not discuss the contextual, subjective factors present when the information is finally utilised in decision making. Secondly, it discusses human-mediated information collection, leaving automated information collection such as sensor-mediated or online information collection outside the scope.

1.2. Research objectives

The emergence of modern mobile devices is a quite recent phenomenon (Kavanagh 2016, Zimmerman 2015), and no literature combining a comprehensive set of information quality dimensions to mobile-produced human-mediated data was found. First of all, this thesis aims to raise awareness of the possible information quality implications of mobile technology in information collection. Even without strict requirement of assessing information multidimensionally, the academic research assessing any quality aspect is sparse. Secondly, the thesis aims to identify the characteristics of mobile devices which could affect the information and then assess mechanisms through which the possible impact takes place. The need for such precise understanding of the mechanisms of value creation by mobile devices is called for by Mickan (2013) and Prgomet et al. (2009), who regarding mobile devices in healthcare detect a great deal of enthusiasm without deep understanding of the actual value, effects, and the necessary pre-conditions. Due to relatively sparse prior research in the field of mobile devices and information quality, these possible effect relations will be synthesised from a range of mobile device related literature. Finally, the thesis will develop a set of intrinsic information quality measures and hypotheses on how mobile device use in information collection could affect the collected data, and then empirically tests these hypotheses on live field data. This approach of testing the hypothesis is particularly ambitious since obtaining suitable data is a complex process, and information quality research often uses a survey approach (Arazy & Kopak 2010, Lee et al. 2002, Wang & Strong 1996).

From a practical point of view, the thesis aims to produce a recommendation for mobile device use in human-mediated information collection and provide a basis for more informed information collection medium decisions. With regard to information quality, do the properties of the device warrant use for information collection in the first place, and if so, what kind of purposes are mobile devices best suited for? Consequently, it gives an evaluation of the usefulness of mobile devices in human-mediated information collection for organisations from information quality perspective, commenting on the trending use of mobile devices and basing its assessment on solid quantitative evidence.

1.3. Structure of the thesis

The thesis begins by synthesising an understanding of information quality from the vast base of information quality literature, defining the concept, discussing the components it consists of, briefly outlining the issue of optimal level of quality, assessing information quality within the information production process, and finally examining typical information quality issues and implications of information quality to businesses. This section provides the context within which the study is conducted, highlights the importance of high quality information from a business perspective, and sets the stage for the rest of the thesis.

In the third section, more detailed account on the information quality dimensions present at the data input stage is presented, outlining the relevant dimensions when discussing intrinsic information quality at the input stage and assessing how the literature describes these dimensions. The fourth section introduces the other major stream of literature the thesis builds on; the mobile device literature. The section begins by explaining what the study considers a mobile device, and then lists the most distinct features of mobile devices in relation to PCs, the computing technology primarily used for human-mediated input. Moreover, the prevalence of mobile devices as well as the drivers of the adoption are considered in the fourth section. The fifth section fuses the information quality literature with the mobile device literature, finding mechanisms of how the characteristics of mobile devices might affect the information quality at the collection phase.

The sixth section begins the empirical part. The quantitative approach and the methodology used are presented and their merits explained in the first sub-section, and the dataset from a Finnish residential elderly care organisation enabling the comparative study is introduced in the second sub-section. In the third sub-section, a set of eleven hypotheses and corresponding measures on how the information quality dimensions of accuracy, completeness, timeliness, and consistency might be affected by the new data collection technology are developed based on information quality and mobile device literature and then tested for differences utilising t-tests. The results are presented in the seventh section, and their implications for theory and practice are further discussed in the eighth section. Moreover, the eighth section lists the limitations of the study and suggests avenues for future study. The ninth section presents a summary of the key findings and the concluding remarks.

2. Information quality

The evident importance of information in the information age inspires a number of pompous expressions like Eckerson (2002) paralleling data for companies to oxygen for humans. The already flattened expression "data is the new oil" is better replaced by Carl Malamud's statement "information is a form of infrastructure; no less important to our modern life than our roads, electrical grid or water systems" (The Economist 2010, p. 1). While the information quality research began by justifying its importance, currently there is no question of its fundamental necessity; the information quality conferences and workshops as well as the number of information quality researchers are proliferating, software vendors are integrating data quality technologies in their products and services, and companies are appointing data specialists to senior executive positions like Chief Data Executive/Officer and Information Strategist (Madnick et al. 2009, Soni et al. 2012, Xu et al. 2014).

In the purest sense of the term, information typically signifies meaningful and processed data while data refers to raw facts (e.g. Kokemüller 2011, Wang 1998). However, when discussing data quality and information quality these definitions bear little significance and the terms are used interchangeably, perhaps due to the difficulty of distinguishing between the two (Kokemüller 2011, Madnick et al. 2009, Stvilia 2007). Madnick et al. (2009) recount also tendency to use the term data quality when referring to technical issues and information quality when referring to non-technical issues. Unsurprisingly, the topic of information quality does not have a strictly regulated structure (Weiskopf & Weng 2013, Nelson et al. 2014) but the terms used are vague and overlap, and Weiskopf & Weng (2013) found inconsistencies in terminology even within articles. Due to the fuzzy boundaries and mixed use of the terms information quality and data quality, this thesis also considers these terms synonymous and interchangeable.

The section begins by giving a definition of information quality, after which it briefly presents components of information quality in the form of categories and dimensions. After this, sub-section 2.3 will briefly visit the topic of the necessary level of information, and 2.4 explains information quality from the perspective of information production process. Then, the typical issues found in literature are described and the significance of information quality for businesses is outlined.

2.1. Definition

As widely studied as the topic of information quality is, no universal agreement on the definition has been reached. Perhaps the most widely accepted definition for quality of information is captured in 'fitness for use'; is the information suitable to fulfil its purpose, meeting the needs of the user, and expressed in a way the user understands (e.g. Fisher & Kingma 2011, Strong et al. 1997, Wang & Strong 1996, Weiskopf & Weng 2013). Precisely, Wang & Strong (1996) define quality information as data that is fit for consumption. This usability and usefulness centered view (Strong et al. 1997) borrows from the quality theory of quality research grand old man Juran (1992), who defines quality through fitness for use. Another definition with similar perspective is the goal-oriented view, where the focus shifts from the user to use; information quality is "the potential of a data set to achieve a specific goal by using a given empirical method" (Dalla Valle & Kenett 2015, p. 1284), or information quality is appropriate when it serves the need of the information user in pursuit of their goals (Weiskopf & Weng 2013).

As Kokemüller (2011) points out, while the fitness for use definition captures the essence of information quality, it is rather unhelpful in practical assessment. On a similar note, Strong et al. (1997) write that providing information consumers high quality information is in practice an ever-moving target due to the multitude of parties using the same information, each having their own requirements, and the information consumers' needs evolving together with the world and the tasks.

Mai (2013) observes that in addition to this perspective where information quality is a subjective mental construct of the user, a perspective understanding information quality as an inherent property of the information seems to be embraced by those who do not define it through users. For instance Orr (1998 p. 67) defines information quality through this perspective as "the measure of agreement between data views presented by an information systems (sic) and that same data in the real world", emphasising the role of information as an enabler of reasonable decisions. This absolute view of information quality seems to have been popular in the early information quality thinking, where intrinsic measures, especially accuracy, were the focus of research (Ballou & Pazer 1985, Strong et al. 1997, Wang & Strong 1996). In the modern literature a similar definition, correspondence of system and actual values, is often used for accuracy and is only one of the quality components (e.g. Falge et al. 2011).

The evolution of information quality research seems to be closely tied to that of computer technology (Batini et al. 2009). The information quality literature started truly emerging in the nineties (Cai & Zhu 2015, Lee et al. 2002) as Figure 1 depicts. This is when PCs had become a more common resource in business and personal life, instead of precious resources owned by only large institutions (Davis 1977, Kavanagh 2016), and the enterprise data warehouses were growing and direct managerial and information user access to data was becoming more popular (Lee et al. 2002).

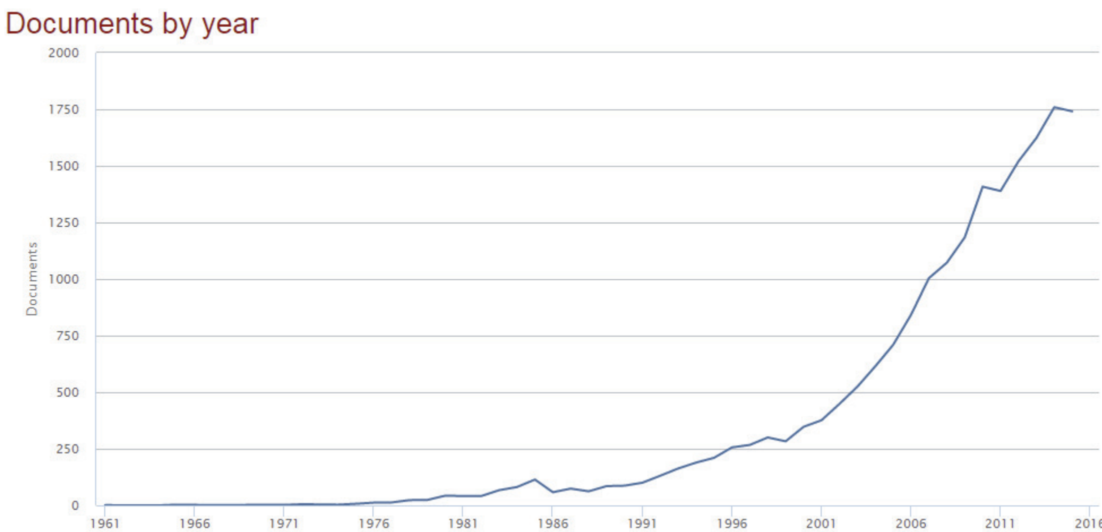

Figure 1 Number of data quality related documents over time in reference database Scopus[1]

With the digitisation, the information became editable, transferable, copiable, shareable, and searchable, and it could be indexed and hyperlinked (Mosleh 2013), enabling more sophisticated utilisation of information. In the nineties, a radical development in information use and accessibility was also the widespread use of Internet (Orr 1998). Currently the fourth

[1] The graph for search term 'information quality' is very similarly shaped, but yields only some 4 700 results in comparison to over 19 000 results for 'data quality'. Consequently the graph for search term 'data quality' is used.

generation of computers have emerged in the form of smaller laptops and an arrangement of handheld devices (Kavanagh 2016), a new era of mobile computing beginning with the introduction of iPhones and iPads (Zimmerman 2015). The increasing volume, variety, and velocity driven by data generating systems such as sensors and social media and the ubiquitous presence of digital assets present information quality research with new challenges in the form of changing business environments, regulatory demands, and forms of information storage, manipulation, and consumption (Lukyanenko 2016, Madnick et al. 2009). To successfully navigate these challenges and opportunities and capture the new dimensions such as the human experience in digital form (Lukyanenko 2016), more cross-disciplinary efforts will be required in the currently Management Information Systems and Computer Science dominated field (Madnick et al. 2009, Sadiq et al. 2011).

2.2. Components

Information quality literature agrees that information quality consists of multiple dimensions (e.g. Batini et al. 2009, Lee & Haider 2013) and is contextual (Mai 2013). However, no collective agreement of what these dimensions are or the implications of the contextual nature of information quality dimensions has been reached. Typically the components of information quality are viewed in three tiers; information quality attributes, information quality dimensions, and categories of dimensions (Figure 2). This structure, while often not explicitly stated, seems to prevail in the literature.

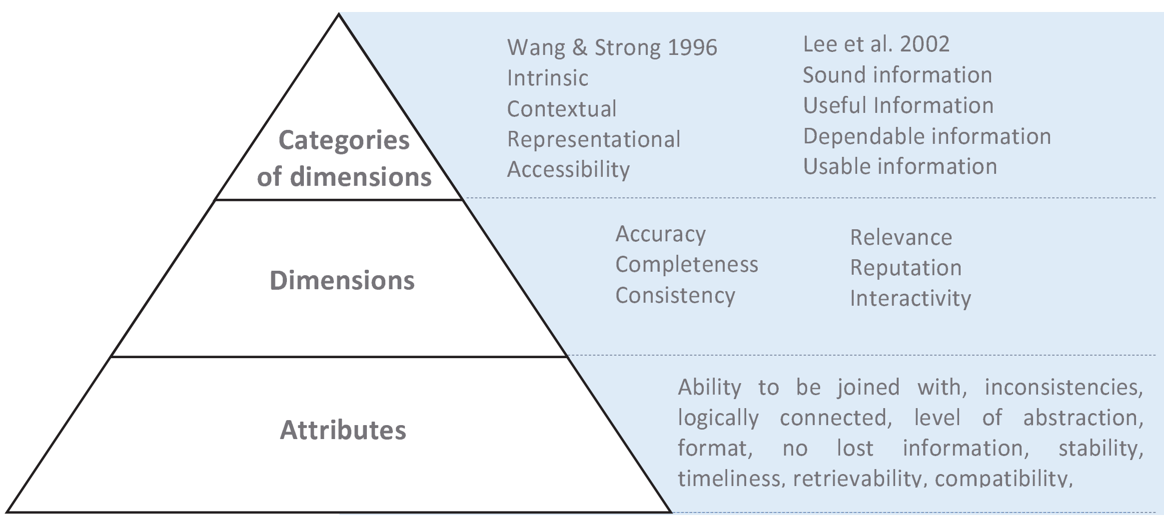

Figure 2 The concept of information quality

On the lowest level, there are the information quality attributes, which are the fundamental characteristics with which information quality can be described. For instance Wang & Strong (1996) surveyed information consumers on the attributes they associate with information quality and came up with 118 attributes like ability to be joined with, inconsistencies, logically connected, and format. These most granular components of information quality can be grouped to form information quality dimensions. According to Wang & Strong (1996, p. 6), an information quality dimension is “a set of data quality attributes that represent a single aspect or construct of data quality”. Stvilia et al. (2007) define information quality dimension as any component of information quality. Dimensions seem to be the meaningful level of analysis utilised in the majority of literature, providing sufficient granularity while not delving into too much detail. While there is a consensus that information quality is built of multiple dimensions, what these dimensions are is still under debate and varying views have been presented. From the popular information quality assessment methods, Batini et al. (2009) derived altogether 28 different dimensions, some of which were also overlapping. In academic literature, the dimensions have been derived from theory (e.g. Wand & Wang 1996) and empirical research (e.g. Wang & Strong 1996) and deduced from a priori judgements (e.g. Redman 1996).

Despite of the number of proposed dimensions, there are certain dimensions that seem to be somewhat prevalent in the literature. Accuracy, completeness, timeliness, consistency, and relevance are according to Falge et al. (2011), Fisher & Kingma (2011), and Watts et al. (2009) a widely accepted set of major information quality dimensions that enjoy a standard-like position. Moreover, these dimensions are quite consistently cited in the most prominent literature in the field (Table 1).

The choice of dimensions as well as the definitions for a particular study are affected by a number of factors. The most evident is the fitness for use versus inherent quality perspective and the consequent presence or absence of information consumer perspective (Lee et al. 2002). Observing information quality from the consumer perspective leads to inclusion of subjective dimensions such as accessibility and relevance, whereas perspective of objective information qualities limits the study to dimensions like accuracy.

Table 1 Information quality dimensions in literature

	# of citations	*Accuracy*	*Completeness*	*Consistency*	*Timeliness*	*Relevance*	*Others if any*
Ballou & Pazer 1985	224	x	x	x	x		No
Batini et al. 2009	241	x	x	x	x		No
Fisher & Kingma 2011	124	x	x	x	x	x	No
Orr 1998	186	x		x	x		No
Redman 1996	284	x	x		x	x	Yes*
Strong et al. 1997	523	x	x	x	x	x	Yes**
Wang & Strong 1996	523	x	x	x	x	x	Yes**

* Granularity, level of detail, format, ease of interpretation, privacy, security, ownership

** Believability, Objectivity, Reputation, Valued-Added, Appropriate amount, Interpretability, Ease of understanding Representational consistency and conciseness, Accessibility

Moreover, the information user centric view of defining information quality leads to varying importances and varying emphases on the information quality dimensions within companies as well as across companies and industries (Sadiq et al. et al. 2011), which shows as favouring particular dimensions important in that area. For instance Weiskopf & Weng (2013) determine completeness, correctness, concordance, plausibility, and currency as the most important dimensions in electronic health records (EHR), and Le Dû & de Corbière (2011) identify accuracy, completeness, and representational consistency as the most crucial information quality dimensions for ordering process, and relevancy, interpretability, and accessibility for information synchronisation between different parties in the supply chain. As opposed to the academic literature, Lee et al. (2002) note that the practitioner information quality dimensions tend to strongly relate to their context – e.g. information quality in input to database and information quality in environments with multiple incompatible databases. Additionally, the information quality dimensions are not independent but affect each other (Panahy et al. 2014), and consequently the emphases arising from the context of use affect the set of dimensions in a dynamic way. For instance completeness and consistency seem to be negatively correlated, and accuracy and timeliness positively correlated (Panahy et al. 2014).

In order to assess information quality, the dimensions need to be measured. Information quality measures are symbols or numbers that characterise a dimension in an objective manner (Stvilia et al. 2007). Measuring information quality in a cost-effective and accurate manner is a somewhat complex endeavour due to the complexity of information systems and the information production process (Madnick et al. 2009). In practice, the measuring activities can be conducted either periodically or continuously (Madnick et al. 2009); Eckerson (2002) noted that in organisational context the information quality measurement is often executed ad hoc prior to a project, or continuously by counting the number of user complaints. Some dimensions like accuracy and completeness can be measured with objective measurements, also called data tags, data quality information, and data quality metadata (Watts et al. 2009). Other dimensions such as relevance and believability do not lend themselves to objective measurements (Watts et al. 2009), and empirical studies often capture these dimensions by surveying information consumers (Arazy & Kopak 2010).

Some researchers like Arazy & Kopak (2010) and Fidler & Lavbic (2015) question the measurability of information in the first place since quality measures seem elusive. Arazy & Kopak (2010) studied reviews of the information in Wikipedia articles, and observed that the raters did not agree on the quality of the articles. The dimensions accuracy, completeness, objectivity, and representation were considered. Fidler & Laybic (2015) continue on this idea, studying whether better explanation of the context would yield more unison information quality assessments. They incorporate factors such as rating inputs and mechanics, the rater's characteristics, and situation of rating in their study. The results have yet to be published.

Finally, the highest level of information quality hierarchy (Figure 2) are the categories, which further group the dimensions into categories reflecting common traits. While there are a number of classifications, the pioneering categorisation from Wang & Strong from 1996 (Figure 3) enjoys wide acceptance and is predominant (Michnik & Lo 2009). In their groundwork laying study, Wang & Strong collected 118 data quality attributes through surveying process and with factor analysis reduced them to 20 data quality dimensions of greatest importance to data consumers. These 20 dimensions they then further classified into four categories, intrinsic data quality, contextual data quality, representational data quality, and accessibility data quality, creating a hierarchical data quality framework to aid information quality measurement, analysis, and improvement capabilities.

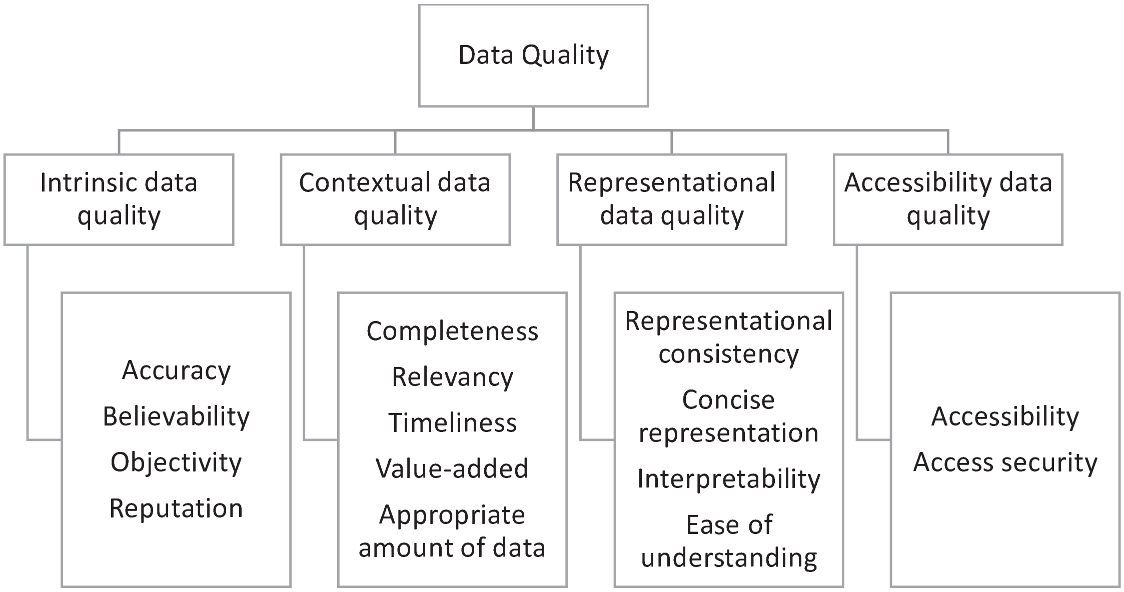

Figure 3 Data quality categories and dimensions (Wang & Strong 1996, p. 20)

The intrinsic category is about the inherent quality of information and its correspondence to actual values, and it comprises of dimensions accuracy, believability, objectivity, and reputation. Contextual dimensions completeness, relevancy, timeliness, value-added, and appropriate amount of data are closely linked to the fitness for use and refer to the applicability of the information to the task at hand. Representational dimensions have to do with the communication of the information; whether the information is communicated in a compact and consistent form. Representational consistency, concise representation, interpretability, and ease of understanding belong to this category. The final category is accessibility, which refers to whether the user can access the information and whether the access is secure.

Other categorisations vary for instance on the continuum theoretical-practical and with regard to the topic the categorisation is developed for. For instance Lee et al. (2002) propose categories of sound, useful, dependable, and usable information for a practical information quality assessment methodology. The group of researchers contains Wang and Strong from Wang & Strong (1996), and the dimensions rearranged into these categories are very similar to those in Wang & Strong (1996); this exemplifies how the intended use of categorisation shapes the categories, even if the core dimensions remain the same. In information quality assessment methodologies, categorisations of for instance inherent and pragmatic (Total Information Quality Management) and schema, information, presentation, and information policy (Cost-effect of Low Data Quality/Loshin methodology) have been used (Batini et al. 2009). Also the original categories of Wang & Strong have been combined to better reflect other researchers' understanding of information quality; e.g. Stvilia et al. (2007) utilise the categories but combine contextual and representational categories into one category, 'Relational or contextual information quality'.

In vast majority of the categorisation it is stated that information has at least intrinsic qualities, i.e. qualities that express whether the information is in conformance with the actual values, and contextual qualities, i.e. qualities that express whether the information is suitable to the user's task at hand. However, there is no agreement to which category certain dimensions like completeness and timeliness should be classified (Lee et al. 2002), again depending on the perspective of information quality as an inherent quality or as an information consumer defined quality. These differences caused by the contextuality provoke a great deal of discrepancies in the definitions (Batini et al. 2009). For instance completeness is perceived quite differently depending on which category it is placed in. From an intrinsic point of view, completeness measures whether there are any missing values like nulls or empty values (Lee et al. 2002, Stvilia et al. 2007, Todoran et al. 2015). On the other hand, as a contextual dimension completeness measures whether all the data the user needs is present (Lee et al. 2002, Stvilia et al. 2007, Todoran et al. 2015). This could have two kinds of implications; first, not all missing values in the system are necessarily needed by the information consumer and thus not included in this definition of completeness, and secondly, there might be information needed by the information consumer that is not included in the system in the first place and even if all the intended values were in the system the information would not be complete according to this definition.

This difference is underlined by Todoran et al. (2015), dividing information quality into data quality (intrinsic) and information quality (contextual), and Stvilia et al. (2007), dividing information quality into intrinsic quality and relational quality. In this paper, the dimension completeness is considered to belong in the intrinsic category. This is primarily because completeness can be objectively measured (Watts et al. 2009), for instance by calculating the missing instances in the information. This view supposes that the information collected by the system is the necessary information, and the necessary information is defined in the context of information use while mapping system requirements.

However, all the categories and their dimensions are to a certain extent affected by contextual factors, even the intrinsic dimensions. Considering for instance the most clearly intrinsic quality accuracy, the required level of correctness is defined by the task at hand. For instance a company sending a marketing email to its emailing list will not suffer significantly if some of the addresses are faulty and some recipients do not receive the marketing material; however if those email addresses are used to send invoices to the customers, the required accuracy level is entirely different. Surely also in the first situation perfectly accurate information is preferable, but given the realities of resource constraints of enforcing perfectly accurate information does not make sense.

2.3. Sufficient quality of information

A central topic in defining information quality is the outlining what constitutes high quality or low quality information. The aim of information quality assessment and improvement is, after all, not to chase perfect quality but to find and reach the point at which information is of sufficient quality (Eckerson 2002, Haug et al. 2011, Olson 2003, Orr 1998).

Perfect quality information is even theoretically a vague concept with the varying definitions, and in practice Orr (1998) fittingly calls it a utopia. He underlines the mismatch between the constantly changing real world and the static database data, which without constant feedback and updating will inevitably become outdated. Wang et al. (1995) discuss zero-defect data, which rules out some of the most obscure dimensions like completeness and relevancy and focuses on accuracy and consistency. While they denote that zero-defect data would be optimal, they acknowledge its economical infeasibility and occasional unnecessity. Olson (2003) estimates that for most users, a database with 5 percent inaccurate elements is very troublesome to use, whereas 0.5 percent inaccurate element rate would mostly be considered very useful and of high quality. This estimation seems to lean on Olson's personal experience and expertise, and is not supported by any studies.

The optimal level of information quality can be defined via two points of view; by matching the level of quality with the user needs or by optimising the total cost of poor quality information. The first view is embraced for example by Eckerson (2002), who states that the goal of information is to meet the end user needs, which not only defines the relevant dimensions but also the degree of quality needed on those dimensions. Turning the statement around, Strong et al. (1997, p. 104) define information quality problem as a difficulty in any of information quality dimension that leads to information being "completely or largely unfit for use". Wang et al. (1995) use sending a letter as an example where an element of information can be wrong or missing and cause no issues; the postal system will be able to deliver it with just the zip code even if the city name is incorrect or missing. Orr (1998) takes an even more practical approach and writes that the quality of the information is sufficient when the organisation is able to make reasonable decisions based on it and survive. While this emphasises the use – making reasonable decisions – and provides a practical perspective, it is not clear what a reasonable decision is and whether companies should accept reasonable decisions and not optimal decisions as the goal.

The cost optimisation view is used by Haug et al. (2011), who argue that information quality should only be improved until the point of minimal costs is achieved. This optimal level of information quality is found by assessing the two categories of information quality costs, the cost of cleaning and ensuring high information quality and the cost of poor decisions made on poor information, and finding the minimum for the combined total costs (Figure 4). Wang et al. (1995) also acknowledge this cost-quality trade-off and the consequent economical infeasibility of absolutely pure information.

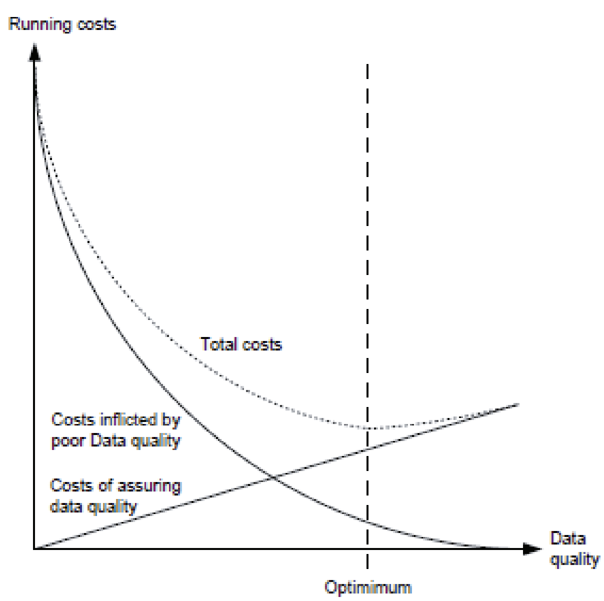

Figure 4 Total costs incurred by data quality on the company Haug et al. (2011, p. 179)

Nevertheless, this optimisation only gives a theoretical means of defining the optimal level, and in practice estimating the costs incurred from poor information quality are difficult to estimate due to the intangible and indirect nature of some of these costs (Haug et al. 2011). It is furthermore debatable whether the cost of information assurance is linear or whether it is an exponential curve. Haug et al. (2011) also point out that the differences in the industries, for instance the cost of information maintenance and the cost of poor information quality, shift the optimal point; for instance, in airplane manufacturing the costs of poor information quality are very high, and thus more information maintenance yields an optimal solution.

2.4. Information quality as a process

The discussion of dimensions can perhaps be better understood by inspecting it through the process of information production. A trichotomy of roles in information manufacturing is widely used in information quality literature (e.g. Kokemüller 2011, Madnick et al. 2009, Strong et al. 1997). The first role is that of information producer, who, like the name of the role suggests, generates and provides information. Then there are the information custodians, who are the IT cavalry providing and managing resources for data storage, processing, and maintenance as well as security. Finally, there are the information consumers who use the information facilitated by the first two roles for decision making processes. Strong et al. (1997) present the information consumer as the ultimate test for the information, whose use of the information defines its value and quality.

The roles of information producer, information custodian and information consumers are tightly intertwined with the information manufacturing process, where three stages can be identified as Figure 5 illustrates (e.g. EY 2014, Wang 1998). The first is the input stage, where raw data is entered into the system. In the second stage, the information is processed in the information system, and in the third stage the output, information products, are delivered to the information consumers. Some information manufacturing processes choose to for instance distinguish between data collection and data input (Ballou & Pazer 1985) or between data pre-processing and data processing (Todoran et al. 2015). While this continuum of processes carries similarities to the manufacturing process of physical products, the two differ in several aspects; for instance, the physical raw material can only be used for a fixed number of products, whereas data, information raw material, can be utilised by numerous consumers for decisions without it depleting (Wang 1998).

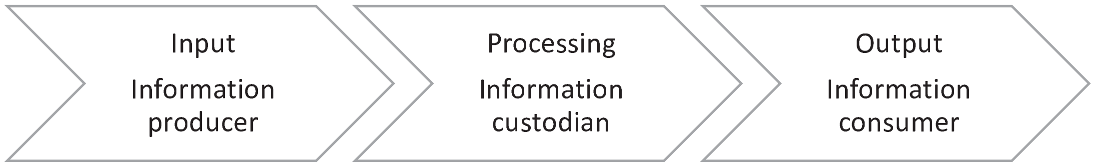

Figure 5 The information production process and roles

In some studies, data quality is understood as the quality of data in the database (Strong et al. 1997) – either the data is correct or it is incorrect in the database. For instance Ballou & Pazer (1985) employ this view. This stricter definition enables more straightforward analysis of the data with objective, clearly defined measures as there are very few subjective factors present. Figure 6 depicts the information quality dimension categories with relation to information production process; the studies focusing on inherent information quality only focus on the far left of the continuum (line A), omitting contextual, representational and accessibility dimensions.

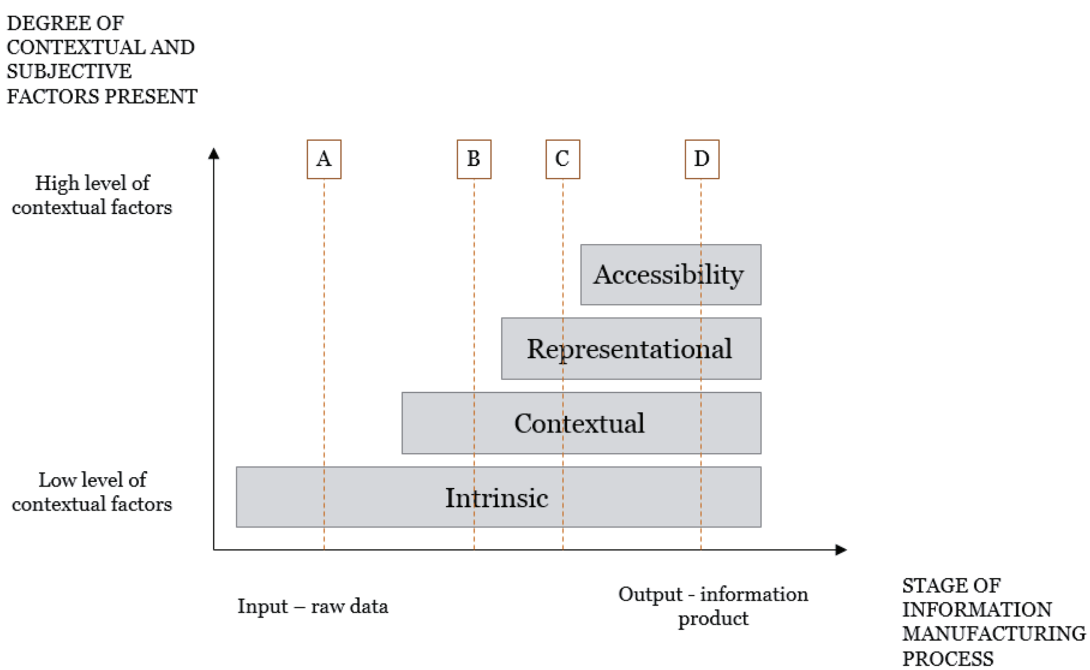

Figure 6 Information quality categories within the information production process

The contextual view, viewing information quality from the end-user point of view as the quality of the information product, involves a number of additional variables beyond the inherent information quality; the correctness of the automated or human-generated reports, the understandability or relevancy of those reports, the accessibility, the security of transferring information etc. The latter stages like line D in Figure 6 are subject to a number of subjective human variables, which increase the complexity of the quality analysis significantly. For instance Fisher & Kingma (2001) view information quality from the decision making point of view, and list factors such as information overload and time constraints that affect the transformation of information into decision.

The categories are incremental; the quality of the end product as perceived by the information consumer builds on the previous categories. Thus for the information to be perceived of good quality, the antecedent categories need to be of high quality; akin to the manufacturing of physical products, the raw material quality does not ensure the quality of the final product, but adequate raw material quality is a pre-requisite for adequate quality end product. Similarly clearly, concisely, and understandably presented information is worthless if the data is inaccurate, incomplete, or outdated. Strong et al. (1997) emphasise the importance of this broader understanding of information quality, where data quality is understood beyond mere intrinsic view.

In order to assess the quality of the information and understand the point of distortion, it might make sense to evaluate information quality along the information production process. Even if the final information product utilised by the information consumer is not timely, it does not directly mean that the data in the database is not timely; the data might be entered in its due course, but the consumer might not be able to access the data in a timely manner. This could be due to a reporting system that separates the consumer from the information, or the information consumer might have issues with the system use, taking so long to extract the data and analyse it that it is no longer timely (Strong et al. 1997). Thus the issue is primarily with the data analyst team, or the information consumer, not with the information itself. Paralleling with the physical products, the product can be of excellent quality even if it is not where the consumer is, but in that case the product cannot fulfil its purpose and create value. The information product view is closer to the information system quality, which incorporates all the aspects of successful information system (Nelson et al. 2005).

In order to clarify the discussion about information quality, it would be beneficial to distinguish where on this continuum the researchers operate. Perhaps the intrinsic qualities could be called data quality and the overarching quality should be called information quality, using the original definitions of the words data and information. Or perhaps, to make the separation more distinctive, the original categories proposed by Wang & Strong (1996) could also be employed.

2.5. Typical issues

The inadequacy of information quality in companies seems to be a widespread issue (Haug et al. 2011); Strong et al. (1997) give an example of 50-80% of the records in the criminal record database in the USA being flawed with regard to accuracy, completeness or unambiguity. Redman (1998) gives a more modest estimation of typically 1-5% of data fields being erroneous. Given the very nature of information, this is not surprising. The information production and manufacturing is a complex process, and the dynamic nature of information itself adds to the complexity of obtaining usable information; the intrinsic quality may be affected during the collection, update, maintenance, or deleting of data, or if these actions are not carried out and the data decays (Kokemüller 2011).

A term often used in relation to information quality is ‘dirty data’. Kim et al. (2003) and Marsh (2004) define the term as inaccurate, incomplete, and inconsistent data. This notion seems to refer to the inherent quality of the data and not concern e.g. the dimensions of accessibility or timeliness. Nevertheless, Strong et al. (1997) claim that information quality should not be limited to only errors in database, but a broader scope has to be assumed to address other significant information quality problems. This sub-section gives an overview of some typical information quality issues businesses might experience.

2.5.1. Error taxonomies

There are many ways to categorise the information quality shortcomings. First is the source of the issues; the issues in quality may stem from either the users or the system. Deming (1986), a major influencer within the discipline of quality research, states that majority of quality problems are problems in the systems, not problems stemming from the workers. Orr (1998), however, acknowledges that in addition to these systems problems, also individual errors contribute to the information quality issues.

Redman (1996) introduces a taxonomy of information quality issues into four categories, mirroring the information quality framework of Wang & Strong (1996). First, there are the issues associated with data views, i.e. how the real world is modelled in the data. These include data quality issues with relevancy, granularity, and level of detail. Second, there are issues related to data values, including information quality issues with accuracy, consistency, currency, and completeness. The third category are the issues associated with the data presentation such as format appropriateness and ease of interpretation. Finally, the fourth category is about issues associated with privacy, security and ownership.

The errors can also be viewed within the data production process, which provides a basis for practical approaches. For example Kokemüller (2011), Fisher & Kingma (2001), and Olson (2003) present this view to information quality issues. Fisher & Kingma (2001) list the opportunities for flaws to incur in data in the following processes; available information, i.e. what has been put into the system, integration of the information, and communication of information. Olson (2003, pp. 44-64) goes into more detail to describe the sources of erroneous data, but lists the areas as initial data entry, data decay, moving and restructuring, and using (Figure 7).

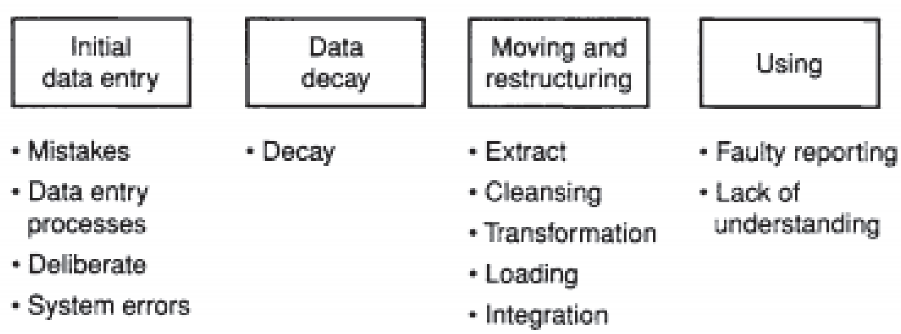

Figure 7 Sources of reduced information quality (Olson 2003 p. 43)

Stvilia et al. (2007) identify four major sources of information quality variance related to the lifespan of the information; mapping, which refers to incomplete, ambiguous, inaccurate, inconsistent, or redundant mapping between a state, event or entity and information entity; changes to the information entity; changes to the underlying entity or condition; and context changes, which refer to temporal or spatial changes in the context of culture or sociotechnical structures. The most detailed taxonomy is presented by Kim et al. (2003), who aim to produce an exhaustive list of data defects, focusing on the intrinsic qualities. They start out by dividing the data into missing data, not missing but wrong data, and not missing and not wrong but unusable data, and then derive further categories all the way to very granular and specific issues visible in the data.

2.5.2. Data entry

Olson (2003) states that the most common source of inaccuracies in data is the human mistake at input, supported by Sessions & Havens (2012, p. 3); "The point of entry is the most important time for gathering high quality data". Additionally Eckerson (2002) finds that data entry by employees is seen as the most prevalent source of information quality problems, with 76 percent of respondents viewing it as a cause for information quality problems. Marsh (2004) and Bai et al. (2004) agree that the human entry is a major source of multiple types of data errors, and Haan et al. (2004) conclude that data entry at the point of care is a key component in achieving better information quality with regard to completeness and accuracy. In addition to plain mistakes, confusion about the data to be entered can cause incorrect values to be entered, as well as users entering wrong values deliberately (Olson 2003). Moreover, some entry issues have to do with the organisational factors; employees feeling like their job is "not to fill out forms" could lead to incomplete data (Strong et al. 1997, p. 108), or a person with no proper understanding of the information might have to fill in the data (Mendes & Rodrigues 2011).

Correcting data can be more costly than getting the data right in the first place, and erroneous data residing in the systems unnoticed, distorting decisions, can be most costly of all (EY 2014). Bai et al. (2013) also point out that the consequences of these errors are also significant as they replicate in the data processing and affect a multitude of outputs, and thus controls are most effective upstream. They also notice that the studied organisation had detected this and allocated most error control resources to this task. Chen et al. (2010) agree that point of entry is one of the best opportunities to improve information quality, and point out that this is especially true for low resource organisations that cannot afford information quality enhancement measures like double entry for validation or post hoc data cleaning. The entry can be supported with a number of semantic and syntactic rules as well as detailed instructions for the person filling in the data (Olson 2003).

2.5.3. Fragmented information

The local management of data, e.g. according to department and geographical location, produces information silos which create an issue of redundant data as well as issues of accessibility and consistency (Haug et al. 2011, Soni et al. 2012). The siloed systems lead to manual updates, which are subject to miscommunications and human errors, and might lead to for instance unnecessary resource reservations and inconsistent data (Soni et al. 2012). Additionally, the inconsistencies and inaccuracies in data cause believability and reputation problems and eventually reduced use of such data (Strong et al. 1997). Redman (1998) and Strong et al. (1997) agree that inconsistencies across databases are a common issue.

A major issue with fragmented information is the semantic issue; there is no shared meaning or understanding of the information. Semantic confusion may also occur within a system or within a department. Madnick & Zhu (2006) and Madnick et al. (2009) observe that a number of issues perceived as information quality issues are in fact issues of information misinterpretation. The concepts might be incompatible, which means the element with same name does not mean the same thing in different contexts or alternatively the same element has multiple names due to which they are not recognised to mean the same thing (Mendes & Rodrigues 2011, Madnick & Zhu 2006). An example of the first, which Madnick & Zhu (2006) refer to as ontological heterogeneity, are hospital registration timestamps, which were observed to have six different meanings from the moment of walking in to a midnight at previous day to estimation of leaving within the hospital organisation (Laine et al. 2015). Tierney (2001) adds that having large amounts of poorly organised information can be just as harmful as having too little information, and unclear information can just add to the burden of uncertainty.

Madnick & Zhu (2006) also recognise representational heterogeneity. It refers to the same concept having multiple representations; for instance, the company’s revenue could be presented in euros in one system and in yen in another or one system might use imperial units and another metric units. They further point out that the representation units or meanings could change within the system over time, for instance when a country changes currency, and that aggregate measures such as amount of revenue or amount of debt may differ due to different interpretations of the terms revenue and debt, for instance when deciding whether to calculate the subsidiaries’ sales into a company’s revenue.

The semantic issues have a variety of consequences. They cause misreporting and misclassification as the items in the data are understood differently by users, and in addition to misreading the existing data, new data is entered incorrectly or differently (Eckerson 2002, Fisher & Kingma 2001, Strong et al. 1997). Moreover, the differing definitions and understandings of data lead to non-comparability of the data like utilisation measures (Strong et al. 1997, Laine et al. 2015), which hinders for instance efficiency and target achievement assessments and spreading best practices.

Providing a data dictionary with one definition for each data element and the relationships for all related data elements is a means to preventing the miscoding in the database (Fisher & Kingma 2001, Strong et al. 1997). Madnick et al. (2009) suggest this issue could be alleviated by contextualising the data source and data consumer needs, so that the consumer receives interpretable data in their preferred form. Batini et al. (2009) recommend integrity constraints, which ensure that certain rules are followed in the data so that the data values make sense with regard to each other. For instance in Europe, if the data shows that the person's information shows ownership of a driver's license, the integrity rule states that the age of the person has to be greater than or equal to 18. Borek et al. (2011) suggest column analysis and semantic profiling as a solution. In practice, Strong et al. (1997) observed manual adjusting of data, development of a single data production point aided with entry support, and re-evaluation of the system to correct a systemic issue. Another solution to promote understanding of what the data actually represents is metadata (Laine et al. 2015, Wang et al. 1995). The metadata could be used to tell the origins of the data including its characteristics, circumstances in which it was created, and the consequent processing (Laine et al. 2015, Wang et al. 1995).

Also syntactic issues, i.e. the issues in the way of writing the data, the data format, and the code structures (Eckerson 2002), are a common information quality problem stemming from various sources and systems as well as other factors (Borek et al. 2011, Eckerson 2002, Strong et al. 1997). For instance, syntactic issues concern the use of decimal point; are decimals included in the values and are they marked with a comma or a full stop. Borek et al. (2011) propose column analysis as a software solution to this issue, and Eckerson (2002) proposes data validation routines. Last but not least, the gathering of data from the disparate sources might degrade the quality of data as the data conversion or integration can cause defects (Eckerson 2002, Olson 2003).

2.5.4. Unintended uses

Data is often used for purposes other than those it was created for, which Olson (2003) names as "the single biggest problem with databases" (p. 27). Similar to fragmented information, unintended uses also have to do with syntactic and semantic factors; new uses of information might not take into account all the details of the information origins and processing, thus distorting the understanding of information. Also the quality of the information and the needed quality of information for the task need to match for successful use of information, and the level of e.g. information accuracy might vary substantially between tasks (Olson 2003, pp. 24-25).

On the syntactic sides, business expansions to new areas might impose new requirements for the data fields and their format (Eckerson 2002, Olson 2003, pp. 28), and changes in the source systems might cause quality issues through changing system architecture (Eckerson 2002). The preventive measures are similar to semantic and syntactic matters, and additionally Olson (2003) highlights the importance of flexibility and anticipation of future needs when building a database.

2.5.5. Information expiration and redundant information

Orr (1998 p. 68) identifies the change of the real world as a critical issue for information quality; if the values in the system are not constantly updated and receive feedback from the real world, their quality will deteriorate over time as per the law of atrophy – "use it or lose it". This lack of feedback is the ultimate information quality issue according to Orr (1998, p. 68); "While these other errors can create data quality problems, those created by lack of consistent user feedback dwarf all the other kinds of errors". Eckerson (2002) and Marsh (2004) support this statement by reporting 2 percent monthly and 25 percent annual decay in consumer information.

The lack of feedback and deteriorating data quality in the system is, according to Orr (1998), result of storing unnecessary data that is not needed by users, justified by the expectation that someone might need the data at some point. When the data is not used and of no particular importance to anyone, the users will suffer from lack of motivation to enter correct data or to use the data to its alleged purpose, thus distorting also the metadata. Vice versa, often used elements will be frequently updated and reflect the actual values well. Obtaining the feedback for even non-redundant data is difficult, partly due to technical stakeholders feeling that the feedback is the responsibility of the business users, and the business users feeling that they do not understand the systems and data well enough to make the changes. Also organisational factors such as perceiving documentation as an additional burden contribute towards insufficient feedback (Strong et al. 1997). While Orr (1998) views any infrequently used information as redundant, redundancy might also refer to duplicate values (Falge et al. 2011). Redman (1998) emphasises the prevalence of redundancy in corporate databases, and Eckerson (2002) estimates duplication rates of 5 to 20% in customer files.

To address this issue, Orr (1998) presents a user-centered systems design, where the design starts at the uses and from there traces back to database and to inputs. He further points out that the popular solution of increasing internal controls is not a sustainable solution to produce optimal information quality results. Moreover, Orr (1998) proposes that the entities with the best understanding of the information should be incentivised to maintain the data. As an example he uses the frequent flyer system, where the passengers have interest to make sure that all their flight are recorded to the one account so that they get the best rewards.

2.5.6. Quality assurance

After a couple decades of active information quality research, there are a number of methodologies, both academic and practitioner, to facilitate systematic and holistic assessment and improvement of the quality of information (e.g. Lee et al. 2002). Moreover, Eckerson (2002) and Olson (2003, p. 256) recommend dedicated quality assurance function for all companies to ensure adequate level of information quality.

An information quality methodology is “a set of guidelines and techniques that, starting form input information describing given application context, defines a rational process to assess and improve the quality of data” (Batini et al. 2009, p. 16:2). Typically the information quality assessment methodologies consist of three steps; first state reconstruction, which aims to collect contextual information from the organisational processes and services; second assessment/measurement phase, where the information quality dimensions are measured and then these measured are assessed against reference values, for instance industry benchmarks or target values; and third improvement, where steps, strategies and techniques for quality improvement are presented. The methodologies take a number of perspectives to the assessment and improvement; they might concern the steps and phases of the methodology or the strategies and techniques, or they could focus on the information quality costs, or types of data or information systems, or view the information quality from the point of view of organisations involved, processes or services. (Batini et al. 2009)

The enhancement methodologies employ either data-driven or process-driven strategies (Batini et al. 2009). Data-driven strategies aim to improve the data by direct modification, for instance by replacing outdated values with values from a more current database, standardisation of values, or by unifying schemas. Process-driven strategies then modify the processes of data creation or modification through either process control by inserting checks or controls along the information production process or process redesign by modifying the production process to remove the causes of poor quality data.

Total Data Quality Management methodology is a widely used set of principles, guidelines, and techniques to ensure and improve data quality, similar to physical product oriented Total Quality Management TQM (Wang 1998). The methodology examines information products form the perspectives of information product characteristics, information product quality and information manufacturing system, and provides means for defining, measuring, analysing, and improving. These are illustrated in summary in Figure 8.

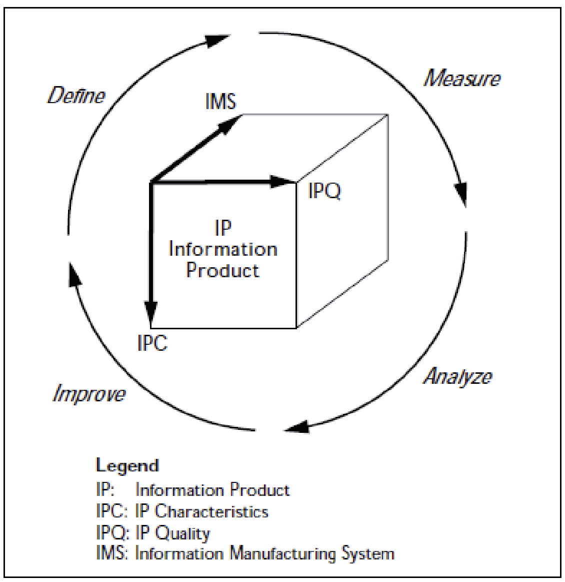

Figure 8 A schematic of the TDQM methodology (Wang 1998, p. 60)

Kokemüller (2011) proposes a model called IQUATE for information quality analysis which breaks down the information product quality issue to causes and impacts, providing detailed components for the analysis of each. AIMQ is a widely cited information quality assessment methodology by Lee et al. (2002), where information quality is evaluated by surveying the company and then performing a gap analysis. The survey is built on a quadrant with information quality as a product and information quality as a service on one axis and conformance to specifications and exceeding consumer expectations on the other. Validated with academics as well as organisations, Lee et al. (2002) view the methodology a strong basis for information quality assessment.

Stvilia et al. (2007) propose a framework with sources of information quality variance, the affected activities, and a defined set of the information quality dimensions and related metrics to be assessed. Baskarada & Koronios (2014) identify a set of 11 critical information quality success factors including information security management, storage management, requirements management, training management governance, risk management, information product lifecycle management, information architecture management, assessment/monitoring, continuous improvement, and continuous management improvement. They further identify dependencies between these success factors and thus preferred sequence of implementation. Todoran et al. (2015) propose an evaluation method that starts with the local, elementary module data quality, then evaluates the quality of the transfer and finally evaluates the quality of the information system as a whole based on the first two steps.

Marsh (2004) translates the ’define, measure, analysis, improve’ cycle to a more catchy, hands-on methodology to improve information quality. The first stage is ‘Audit: the data health check’, which systematically assesses the shortcomings of the data – missing data, incorrect values, duplicate records, inconsistencies, and any type of inaccuracy. The second step is ‘Clean: the data detox’, which aims to remove errors, inconsistencies, and problems. Third, in ‘Error prevention: keep it clean’ systems such as data quality software will be implemented to maintain the data quality. Finally, ‘Compliance: fit for future’ refers to the establishment of compliance criteria to monitor, measure, and manage data quality.

In addition to the full methodologies, there are a number of stand-alone operations and techniques used as part of the methodologies or as one-off data improvement methods; for instance Strong et al. (1997) mention edit checks, database integrity constraints, and program control of database updates as traditional techniques to control data quality issues, and Olson (2003, p. 119) mentions data profiling, data cleansing, metadata repositories, data filtering and data monitoring technologies. Moreover, in Table 2 a list of most typical techniques of assessing the quality of data presented by Borek et al. (2011) are introduced. A number of these and other specific solutions for problems were mentioned together with the typical issues earlier in this section.

Table 2 Data quality assessment techniques (collected from Borek et al. 2011)

Type of data quality assessment	Description
Column analysis	Set of key values; the number of unique values, frequency of values of instances, minimum and maximum values, total and standard deviation, mean, median
Cross-domain analysis	Identification of redundant data across tables from different sources (also from same sources in some cases)
Data validation	Verification of values from a reference dataset
Domain analysis	Ensuring that the values are within certain domain of values
Lexical analysis	Mapping of unstructured content to a structured set of attributes utilising rule-based or supervised-model algorithms
Matching algorithms	Identification of duplicates utilising e.g. Sorted Neighbourhood Method
Primary key and foreign key analysis	Identification of unnoticed primary key-foreign key candidates in the data models
Schema matching	Identification of semantically equivalent attributes
Semantic profiling	Assessment of the semantic consistency through specified rules (e.g. IF AGE < 18, THEN PROFESSION = 'CHILD')

2.6. Impact on businesses

In a world where the vast majority of decisions is based on information, information is undoubtedly of utmost importance; as the famous expression states, “garbage in, garbage out”. The reliance on information has been heavy already before the turn of the century (e.g. Fisher & Kingma 2001), and the sprawling digitalisation is only extending the influence of information quality. The importance of information quality has been recognised e.g. in the areas of Enterprise Resource Planning, Business Intelligence, Supply Chain Management, Data Warehousing, advanced datamining and analytics, health information systems, product data management as well as in decision making in general (Baskarada & Koronios 2014). In practice, poor data quality manifests itself on throughout the organisation, threatening the effectiveness of the companies’ strategies and tactics (Haug et al. 2011, Redman 1998).

It is evident that decisions based on flawed information are likely not optimal decisions. As Redman (1998, p. 81) states, “decisions are no better than the data on which they are based”; thus poor quality information can only be expected to yield poor quality decisions. The non-optimal decisions can be rather innocent, like sending a consumer the wrong sized t-shirt, or they can be on the catastrophic end of the continuum, like when information quality problems lead to explosion of a NASA space shuttle and a US missile cruiser shooting down a civilian airbus resulting in 290 civilian casualties (Fisher & Kingma 2001, Redman 1998). The decisions and actions based on the information are reflected in the performance of the company (Kokemüller 2011), and Batini et al. (2009, p 16:2) crystallise information quality as “a relevant performance issue of operating processes, of decision making activities, and of inter-organisational cooperation requirements”.

The necessity of information quality is often viewed through the costs it inflicts. This might have to do with the early view of IT as a cost center as opposed to a strategic function, or it might be an attempt to build a business case for highlighting the importance of information quality initiatives; if the concrete costs could be developed for the issue and the unquantified quantified, it would be easier to argue for the necessity and benefit of the case (Eppler & Helfert 2004, Marsh 2004).

There are multiple estimates of the cost of poor quality information, but the total cost is elusive; while some costs can be estimated in a somewhat reliable manner, the hidden costs are quite difficult to capture (Haug et al. 2011). Davenport (1997) concluded that “no one can deny that decisions made based on useless information have cost companies billions of dollars" (p. 221), and the increasing reliance of information is only likely to have increased the stakes. Equally as vaguely, Strong et al. (1997, p. 103) state that "the social and economic impact of poor-quality data costs billions of dollars". Redman (1998) offers an estimation of the poor quality costs being some 8-12% of revenue, or in a service organisation poor data quality accumulating 40-60% of the costs. The imprecision of these estimates is acknowledged, in addition to which they are from the previous millennium, but they do underline the significant repercussions of operating on poor quality information. Nevertheless, whatever the exact costs, it is clear that there are multiple mechanisms how poor quality information negatively affects both the top and bottom line.

The provided cost estimate figures can also be interpreted as an estimation of the magnitude of the benefit which lies in producing and maintaining good quality data. Additionally, the exploding amounts of information combined with the new processing capabilities provide companies unprecedented opportunities to realise their aim to make "better, smarter, real-time, fact-based decisions" (EY 2014, p. 1). For instance, high quality data is a necessity in order to benefit from big data in the form of understanding customer needs, improving service quality, and predicting and preventing risks (Cai & Zhu 2015).

Eppler & Helfert (2004) reviewed information quality cost literature and developed the following taxonomy to aid the cost-benefit analysis needed to define optimal information quality level (Table 3). The key idea is that the information quality costs can be grouped to two categories, one of which is the costs inflicted by the level of information quality, including direct costs of managing business with poor quality information and indirect costs such as costs of the resulting poor decisions, and the other being costs caused by assuring and improving information quality, i.e. costs of prevention, detection, and repair.

Table 3 A data quality cost taxonomy (Eppler & Helfert 2004, p. 316)

Costs caused by low data quality	Direct costs	Verification Costs
		Re-entry costs
		Compensation costs
	Indirect costs	Costs based on lower reputation
		Costs based on wrong decisions or actions
		Sunk investment costs
Costs of improving or assuring data quality	Prevention costs	Training costs
		Monitoring costs
		Standard development and deployment costs (systems and process setup costs)
	Detection costs	Analysis costs
		Reporting costs
	Repair costs	Repair planning costs
		Repair implementation costs

Building on the idea of Eppler & Helfert, Haug et al. (2011) also divide the costs of information quality to these two categories and propose a perspective of viewing the costs inflicted by poor information quality through two dimensions, the visibility of costs and the level of decisions affected (Table 4). They note that the direct costs are more often considered, but the hidden costs can have serious consequences on both operational and strategic level. Especially the hidden costs poor information quality inflicts in strategic decision making could have enormous impact on the profit potential of the company, when the information might lead to targeting wrong markets and suboptimal pricing policies (Haug et al. 2011, Marsh 2004). Olson (2003) concludes that companies are not well aware of the costs of bad information quality, and tend to underestimate the costs.

Table 4 Four types of costs incurred by poor quality data (Haug et al. 2011, p. 181)

Hidden costs	E.g. long lead times, data being registered multiple times, employee dissatisfaction, etc.	E.g. focus on wrong customer segments, poor overall production planning, poor price policies, etc.
Direct costs	E.g. manufacturing errors, wrong deliveries, payment errors, etc.	E.g. few sales, low efficiency, problems in keeping delivery times, etc.
	Effects of poor quality data on operational tasks	Effects of poor quality data on strategic decisions

The thesis utilises the costs categories of Haug et al. (2011) to structure the costs discussed in the literature. The division into these categories is not, however, strict since the categories are tightly interconnected and affect one another.

2.6.1. Direct operational costs

Batini et al. (2009) recognise information quality as a relevant issue for operating processes., and Marsh (2004) reports startling numbers regarding the extent of costs from ‘dirty data’ from industry reports by Gartner, PwC, and The Data Warehousing institute; for instance, 611 billion dollars is lost in the US due to only poorly targeted mailings and staff overheads and poor data is the leading cause of CRM system failure. Olson (2003) gives an estimate of daily operational costs of poor information quality going as high as 20% of operating profit, but does not specify whether this entails direct or indirect costs, and whether also strategic effects are accounted for. Gattiker & Goodhue (2005) also observed information quality to explain significantly the overall benefits experienced from an ERP, high information quality resulting in both improved task efficiency and coordination. Information quality issues in the master data, the core data defining the basic characteristics of business entities like customers and products, are especially perilous since they mirrored in the derived transactional data downstream and may wreak havoc in the daily operations (Haug et al. 2011).

Marsh (2004) further points out there are costs due to data reconciliation and the resulting downtime, which trickle down to other categories. For instance downtime could have further hidden costs such as longer lead times due to reduced production and frustrated employees, or direct costs in the strategic area where there could be issues with delivery times or brand reputation and consequently sales.

On operational level, the direct effects of poor data quality include increased costs and reduced employee satisfaction through e.g. incorrect order information, the entailing order problems, and the resources needed to correct the issues and the frustration arising from correcting these issues (Haug et al. 2011, Marsh 2004, Redman 1998). Bad information quality might furthermore degrade organisational trust and intra-organisational credibility (Marsh 2004, Sadiq et al. 2011) and lead to demoralised teams through unproductive, frustrating work environment (Marsh 2004). Marsh (2004) takes the scenario as far as flashing the possibility of the company leaking the best talent to competition. Moreover, automation is a great opportunity for companies to reduce required human capital and improve the efficiency and quality of their production. Automated processes, however, mean that there is no “human sanity check” involved, and the automated operations may perform sub-optimally as coding all possible data defects is not practical nor feasible.

2.6.2. Hidden operational costs

A number of non-direct operational issues are related to customers. First of all, the difficulty of operations and the mistakes and their reconciliation might reduce customer satisfaction (Marsh 2004, Redman 1996, Sadiq et al. 2011). Redman (1996) also points out that what he calls re-engineering, i.e. utilising the data better in serving the customer, is more difficult since the data is not useful in serving the customers and since the poor information quality makes implementation and shared systems of data warehousing and shared systems more difficult. Additionally, the poor information quality affects also operational processes and may prolong e.g. lead times (Haug et al. 2011). Marsh (2004) further remarks the opportunity costs on operational level; putting out the fires caused by poor data requires extensive amounts of time and money, which could have been used to serve other objectives.

On tactical level, Redman (1996) explains the poor decisions managers are likely to make on bad data, but also points out that suspicions about unreliable data lead to delayed or cancelled decision making and excessive time used on debating different versions of the truth from different datasets. Of course, this applies to both operational and strategic decision making, but is perhaps more remarkable on operational level since there the decisions might be exposed to more time pressure.

2.6.3. Direct strategic costs

While the effect of poor data with regard to decision making is well known, full understanding of its implications on strategic decision making is only emerging (Batini et al. 2009, Sadiq et al. 2011). First of all, the operational level issues may escalate to strategic level. The customer dissatisfaction from operational level might also reflect negatively on the brand, the sales might not reach their full potential, and promised delivery times might suffer (Haug et al. 2011, Marsh 2004). Marsh (2004) further points out that the poor quality information decisions might also be used for formulating policies within the organisation, which might have long-reaching effects. In addition, the growing regulation and industry and quality standards pose requirements for the data, and insufficient quality of data may disable the company's ability to comply with the requirements (Marsh 2004).

Information sharing is seen a crucial aspect of tightening supply chains (Batini et al. 2009, Le Dû & de Corbière 2011), and one precondition for successful supply chain integration and supply chain wide collaboration is that the data it is built on is correct and consistent. Considering trends like Industry 4.0, the next wave of industrial revolution relying on data exchange, the central role the quality of information plays is clear. Integrating data from multiple systems seems to be a considerable challenge intra-organisationally, not to mention inter-organisationally. Additionally, with inter-organisational information the information users grow less familiar with the data, unable to detect if there are obvious errors in the data. In addition to the economic benefits of supply chain integration, Le Dû & de Corbière (2011) highlight the environmental benefits such as reduced carbon footprint. On a similar note, Falge et al. (2011) examine the relationship of business networks, including a desired many-to-many relationship between a number of suppliers and customers, and information quality, and deem information quality as a critical component in achieving collaborative business processes. The increased collaboration in networks requires the companies to produce high quality data as well as trust the data from other companies. According to Marsh (2004), less than 50 percent of companies are very confident in the quality of their own data, and 15 percent are confident in the quality of external data supplied to them.

One indicator of the strategic importance of information quality is from Korean financial markets, where Xiang et al. (2013) found significant connection between the quality of data and firm performance. In the study, the quality of data consisted of effectiveness (including accuracy and consistency) and usability (including usefulness, accessibility, timeliness, and security) assessed by the Korea Database Agency data quality maturity model on a scale from 0 to 5. Regressing data quality on total sales, operating profit, and value added (total sales – cost + selling and administrative expenses) showed that improving the data quality metric by one unit on the scale yields increase of 34 percent in sales, 64 percent in operating profit, and 26 percent in value added. It is, however, not investigated whether the changes stem from operational or strategic factors, but it can be agreed on that changes of this magnitude are strategic. Additionally, Slone (2006) developed a method to systematically measure the relationship and firm performance, and the results obtained also found evidence that quality could be used to predict organisational outcomes.

2.6.4. Hidden strategic costs

On strategic level the decision making processes are founded on the same unreliable data, and due to the scale of strategic decisions the consequences are likely to have great impacts (Redman 1998). Moreover, Redman explains that an important factor in the development and implementation of strategy is the feedback loop, which allows the executives to assess the impacts of their decisions and adjust them for improved results, and that poor quality information prevents a functioning feedback loop.

In hidden strategic costs, there are similar costs as observed in other cost categories. In addition to the issues with regard to customer deliverables, like challenges with longer lead times or missed delivery times, on strategic level the poor quality data might lead to failed and prolonged projects within the organisation (Haug et al. 2011, Olson 2003). Also on strategic level battling with data issues and responsibilities can drain a company's resources, leading to opportunity costs and internal disorganisation (Redman 1996).

One remarkable opportunity cost is the crafting and implementation of new business models, which poor information quality could hamper (Haug et al. 2011, Marsh 2004, Olson 2003). For instance successfully pricing services with a subscription model instead of directly billing the customer for each service use requires good understanding of the cost structure and customer behaviour. More currently companies like Uber and Airbnb, providing a platform connecting shareholder groups such as sellers, buyers, and advertisers, have been wildly successful, and a significant component of these business models is the data. Frequent difficulties stemming from poor information quality would destroy the trust and user base the companies enjoy. Additionally, the hype around sophisticated analytics and big data technologies has been relentlessly growing over the past years, but poor data quality could prevent companies from using these applications and gaining the associated competitive advantage; if the very foundation of the decision making and applications is wrong, the system is rendered useless. Lack of useful analysis could also mean lack of understanding of consumers, which could entail that the company is in fact serving wrong markets (Haug et al. 2011, Marsh 2004).

3. Quality dimensions in information collection

This thesis focuses on the collection of information. As Bai et al. (2004), Chen et al. (2010), Eckerson (2002), Haan et al. (2004), Marsh (2004), Olson (2003), and Sessions & Havens (2012) argue, the point of entry is a critical stage in producing high quality information and succinct opportunity to improve the quality of information (see 2.5.2 for more details). Moreover, the information entered into the system provides the foundation on which the usefulness of the information builds.

The restriction of scope to information collection means that only non-subjective qualities can be considered. In the framework of Wang & Strong (1998) this means focusing on intrinsic dimensions and finding the dimensions from other categories that can be interpreted in a non-subjective manner. From the intrinsic dimensions, the thesis will consider accuracy and completeness since they are included in the set of widely considered core dimensions (Falge et al. 2011, Fisher & Kingma 2001, Watts et al. 2009) and readily observable in a context-independent manner (Batini et al. 2009, Stvilia et al. 2007, Watts et al. 2009). Moreover, Haan et al. (2004) write that accuracy and completeness in particular can be improved at the point of entry. From contextual dimensions the thesis borrows timeliness, since an absolute time of input can be observed independent of context (Batini et al. 2009). From representational dimensions the thesis will consider the inherent qualities of consistency; the form of input and redundancy. Formulating an approach for intrinsic information quality in electronic health records, Amjad et al. (2014) also find the same set of dimensions relevant.

This section will examine the literature on these dimensions in more detail, providing definitions, perspectives, and some measures for each dimension.

3.1. Accuracy

Accuracy has to do with the correctness of the information. Wang & Strong (1996, p. 31) define it as "the extent to which data are correct, reliable and certified free of error" and Ballou & Pazer (1985), Miller (1996) and Falge et al. (2011) as the extent to which information correctly represents the real value. Accuracy can also be understood as the absence of error (Fisher & Kingma 2001).

Accuracy can be further broken down into syntactic accuracy (correct form) and semantic accuracy (meaning) (Batini et al. 2009). Hogan & Wagner (1997) expand accuracy to mean both correctness and completeness, the core elements of intrinsic quality in this thesis, in order to receive a full picture of the accuracy in a system. This seems to be common in healthcare information system literature as Weiskopf & Weng (2013) also notice. Another categorisation is made by Todoran et al. (2015) who use the term 'accuracy' for quality of data and 'correctness' for quality of information.

Accuracy is nominated the most important characteristic of information quality in many research papers, e.g. Fisher & Kingma (2001), and in the early information quality research and discussion it had a very dominant position in defining information quality (Wang & Strong 1996). This could be due to the obvious nature of accuracy as an information quality attribute – in essence it seems to define whether the information is right or wrong. Still, accuracy has a very strong importance on the perceived quality of information; for instance in the work of Michnik & Lo (2009) accuracy received the highest importance in the surveys in Taiwanese semiconductor business and to this day it has been main topic in practitioner books, book chapters, and scientific articles (Laine & Lee 2015).

Ballou & Pazer (1985) claim that accuracy is the easiest dimension to evaluate since it merely requires comparing the value in the system to the value in the real world. In the modern context this observation seems slightly naïve when the data residing in the systems is more complex than straightforward numbers, and the actual real value might not even be known; if the system measures the public sentiment on social media, no absolute truth exists. Moreover, Arazy & Kopak (2010) observe low levels of agreement with regard to accuracy among different evaluators assessing Wikipedia articles, hypothesising that the lack of evident heuristics in the articles they studied as well as domain expertise required to judge accuracy resulted in mixed accuracy reviews. While these findings are significant, the approach is quite different from comparing the system value to a known real value, and should be clearly separated from intrinsic accuracy.

The following measurements have been proposed to measure accuracy:

- The ratio of the system value and the real value (Amjad et al. 2014)
- The proportion of recorded observations in the system that are correct (Hogan & Wagner 1997)
- The distance between the value stored in the database and the correct one (syntactic accuracy, Batini et al. 2009)
- Number of correct values per number of total values (syntactic accuracy, Batini et al. 2009)
- Standard deviation (measure of data quality), degree of validity (measure of information quality) (Todoran et al. 2015)
- The extent to which information is legitimate or valid according to some stable reference source such as a dictionary or set of domain constraints and norms (soundness) (Stvilia et al. 2007)
- Count of spelling errors (Borek et al. 2011, Eppler & Helfert 2004, Stvilia et al. 2007)
- Survey questions to measure accuracy in Lee et al. (2002)
  - This information is correct
  - This information is incorrect
  - This information is accurate
  - This information is reliable.

3.2. Completeness

Completeness is not an easily defined characteristic of information quality. Fisher & Kingma (2001, p. 110) briefly describe completeness as recording and retaining “all values of all variables”, and Ballou & Pazer (1985, p. 153) similarly define completeness as “all values for a certain variable are recorded”. While these definitions convey the idea of comprehensiveness of the information, they are slightly imprecise taking into account the inherent unattainability of capturing all the values.

As discussed in 2.2, the definitions depend on whether they view completeness as intrinsic or contextual property, or if the definition takes into account both views. For instance

Falge et al. (2011, p. 4317) view completeness as an intrinsic quality and define it as "the extent to which values are present in a data collection". From their information consumer perspective, Strong & Wang (1996, p. 32) and Wand & Wang (1996 p. 92) define completeness as "extent to which data are sufficient in breadth, depth, and scope for the task at hand". Also Miller (1996) has similar definition where the user and their needs define the level of completeness needed. In addition to entirely different information needs, the information consumers might also need different degrees of completeness like levels of granularity and detail for the same information (Miller 1996, Stvilia et al. 2007). Miller (1996) points out that the information could also be too complete; there could be too much information to find the relevant information. Obviously information overload is possible and the early works of Wang & Strong (1996) list appropriate amount of information as one dimension, but it is questionable whether too complete means the same as excessive amount.

A third option, defining completeness both as an intrinsic and contextual quality, is adopted by Stvilia et al. (2007), who define intrinsic completeness as granularity or precision of the model or the content values of an information object as defined by an ontology. Contextual completeness, on the other hand, is defined as the degree to which the information fulfils the user's needs for it with regard to precision and completeness. For the purpose of this study, analysing the data produced, intrinsic perspective will be considered.

Completeness, according to Ballou & Pazer (1985), is easy to measure if the extent of completeness has already been defined. In that context, the measurement is simply the percentage of filled values versus expected filled values. This kind of thinking seems to be typical in the early information quality literature (e.g. Ballou & Pazer 1985, Fisher & Kingma 2001), but a broader understanding of completeness does not automatically assume the values decided to be collected in the system form a complete set of data but questions what data needs to be recorded for each use case. From contextual point of view, completeness is a dimension about which different information consumers agree on the most (Arazy & Kopak 2010).

The following measurements have been proposed to measure completeness:

- Actual number of produced values versus expected number of produced values (Amjad et al. 2014)
- Number of data items delivered per expected number (Batini et al. 2009)
- Filled values versus expected filled values (Ballou & Pazer 1985)

- Number of elements present from the set of required elements (relational completeness, Stvilia et al. 2007)
- The proportion of observations that are actually recorded in the system (Hogan & Wagner 1997)
- Count of empty or incomplete values, count of distinct elements (intrinsic completeness, Stvilia et al. 2007)
- Proportion of missing values, population completeness (for data quality), degree to which all the basic information is present (for information quality) (Todoran et al. 2015)
- Number of not null values per total number of values (Batini et al. 2009)
- Survey questions to measure accuracy in Lee et al. (2002)
    - This information includes all the necessary values.
    - This information is incomplete.
    - This information is complete.
    - This information is sufficiently complete for our needs.
    - This information covers the need of our tasks.
    - This information has sufficient breadth and depth for our task.

3.3. Timeliness

The dimension of timeliness signifies whether the value is up-to-date or out-of-date (e.g. Ballou & Pazer 1985, Fisher & Kingma 2001), whether the age of the information is appropriate for the task (Wand & Wang 1996, Wang & Strong 1996), and whether the information represents the real world at a given point in time (Falge et al. 2011).

When viewed as a contextual dimension, timeliness is closely tied to the user and use purpose (Fisher & Kingma 2001). In addition to the context of use defining the degree of timeliness needed, the context of the information also affects the rate of decay in the information. Eckerson (2002) and Marsh (2004) estimate the decay in consumer-related data to be 2 percent per month or 25 percent annually, where as some data such as the names of the countries in the world might not experience any changes within a year. Timeliness becomes an especially critical factor when remarkable amounts of short lifespan data are involved; the analysis needs to be conducted swiftly in order to produce actionable insights before the data expires (Cai & Zhu 2015). For the intrinsic purposes of the study, the intrinsic definitions mentioned by Batini et al. (2009) will be considered; timeliness is the age of the information and describes when it was entered into the system.

Timeliness and currency are very close concepts; for instance Miller (1996) defined timely information as “still current”, Stvilia et al. (2007) and Watts et al. (2009) use the term currency in place of timeliness, and Batini et al. (2009) find the definitions of time-related dimensions of currency, volatility, and timeliness to bear great resemblance. Timeliness in also tightly intertwined with the quality aspects measured by other dimensions. Orr (1998) claims that the lack of feedback and updating, which are closely tied to the dimension of timeliness, are the most significant source of poor quality information. Similarly Ballou & Pazer (1985) and Miller (1996) connect timeliness with accuracy, since outdated information is not accurate and does not, like Falge et al. (2011) define information, effectively conform with the real values.

Ballou & Pazer (1985) further point out that measuring timeliness is relatively straightforward if the measure is the current (correct) real world value versus the system value; if the values match, the information is timely and vice versa. This measurement, however, does not take into account distortion of information in input or processing, which also cause inaccuracy of values. Moreover, the measurement comparing correct real world value to the system value is essentially the same as the definition of accuracy, which does not necessarily capture the timeliness dimension in the most exact way.

The following measurements have been proposed to measure timeliness:

- Time in which data are stored in the system –time in which data are updated in the real world (Batini et al. 2009)
- Time of last update (Batini et al. 2009)
- Request time – last update (Batini et al. 2009)
- The age of an information object (Stvilia et al. 2007)
- Up-to-date, refresh time (for data quality), degree to which the currency of information is suitable to use (for information quality) (Todoran et al. 2015)
- Percentage of process executions able to be performed within the required time frame (Batini et al. 2009)

- The difference of time points of information generation and patient commitment in comparison to a pre-set threshold value (Amjad et al. 2014)
- The correspondence of the real value and the value in the system; if they are not the same, the data is untimely (Ballou & Pazer 1985)
- Survey questions to measure accuracy in Lee et al. (2002)
    - This information is sufficiently current for our work.
    - This information is not sufficiently current for our work.
    - This information is sufficiently timely.
    - This information is sufficiently up-to-date for our work.

3.4. Consistency

Consistency means the conformance of all values in the database (Fisher & Kingma 2001) and consistent representation of the data value across the data (Ballou & Pazer 1985, Wang & Strong 1996). Four core elements of consistency can be detected in the literature; information elements describing the same item having same values within the system or in different systems (Ballou & Pazer 1985, Batini et al. 2009, Fisher & Kingma 2001, Stvilia et al. 2007, Weiskopf & Weng 2013), lack of redundancy (Falge et al. 2011, Fisher & Kingma 2001, Todoran et al. 2015), semantic consistency (Batini et al. 2009, Madnick & Zhu 2006, Stvilia et al. 2007), and syntactic consistency (Borek et al. 2011, Strong et al. 1997, Stvilia et al. 2007).

The differences in values within the system or between the systems is fairly evident; the data cannot be of high quality if it shows different values for the same element. Weiskopf & Weng (2013) present an interesting thought that consistency is, in fact, not its own dimension but is in fact a proxy to accuracy and completeness. This stems from the observation that if data is inconsistent, it is due to the data being incomplete or inaccurate; for the data to be inconsistent, either some values are missing, which makes the data incomplete, or some values are incorrect, which makes the data inaccurate. The second element of consistency, redundancy, can refer to information with no use such as irrelevant details in the data (Miller 1995, Orr 1998) or to duplication of information elements like in the definition of consistency of Falge et al. (2011, p. 4317); “The extent to which data in a database corresponds to data in a redundant or distributed database”.

Semantic consistency has to do with the clarity of the meaning of the information elements (Madnick & Zhu 2006) and the elements making sense individually and together (Batini et al. 2009). Stvilia et al. (2007 p. 1729) divide also semantic consistency to intrinsic level, "The extent of consistency in using the same values (vocabulary control) and elements to convey the same concepts and meanings of an information object", and contextual level, "The extent of consistency in using the same values (vocabulary control) and elements required or suggested by some external standards and recommended practice guides to convey the same concepts and meanings in an information object". Fisher and Kingma (2001) also link consistency to preserving the referential integrity between elements. Understanding the meaning of the information element and the form in which it is presented are essential to the dimensions of interpretability and ease of understanding presented in the original framework of Wang & Strong (1996) and ease of interpretation mentioned by Redman (1996). Looking at the current definitions, it seems that these dimensions have been engulfed in the term consistency, which could be explained by the difficulty of drawing a line of separation between the concepts of understandability and interpretability. For syntactic consistency, Stvilia et al. (2007) use the term structural consistency on intrinsic level to cover syntactic features such as the structure, format, and precision, and on contextual level to cover the structure, format, and precision required or endorsed by some external standards or recommended practice guidelines.

The measures of consistency can roughly be divided into three types; there is the approach where data from different sources or within the same source is compared and the differences are interpreted as inconsistencies (Ballou & Pazer 1985, Stvilia et al. 2007, Weiskopf & Weng 2013). This is the so-called gold standard approach, where one source or standards guideline is used as a reference point and a gold standard. The gold standard approach can be used to assess all four consistency elements. Second approach is to check the integrity within the elements, which is typically done by assigning some limits to the assessed value; for instance, the person's age must be between 0 and 120 (Batini et al. 2009). Weiskopf & Weng (2013) call this the plausibility of the information, which primarily assesses the semantic and syntactic issues. Third, the interrelations of the data can be assessed to see if they make sense together (Batini et al. 2009, Weiskopf & Weng 2013); for instance assigning gynaecological operations to a person whose gender is male points to an inconsistency in the data. Weiskopf & Weng (2013) call this concordance, and it focuses on the semantic aspects of consistency.

Since different sets of interrelations are connected in different ways and since the interrelations can be deduced for each dataset from general knowledge, no specific measures for interrelations are proposed here.

The following measurements have been proposed to measure consistency:

- Number of consistent values per number of total values (Batini et al. 2009)
- Count of instances of the same elements having different values (intrinsic semantic, Stvilia et al. 2007)
- Count of instances of the same elements using different formatting (intrinsic syntactic, Stvilia et al. 2007)
- Comparison of format types, redundancies (for data quality, Todoran et al. 2015)
- Comparing the distribution of data in the system with distributions of the same information from different sources such as similar business units or similar companies (Weiskopf & Weng 2013)
- Counts of instances containing inappropriate values according to a standard (relational semantic, Stvilia et al. 2007)
- Counts of instances of element formatting not matching recommended guidelines (relational structural, Stvilia et al. 2007)
- Number of data items violating constraints, number of coding differences (Batini et al. 2009)
- Number of pages with style guide deviation (Batini et al. 2009)
- Survey questions to measure accuracy in Lee et al. (2002)
    - This information is consistently presented in the same format.
    - This information is not presented consistently.
    - This information is presented consistently.
    - This information is presented in a consistent format.

4. Mobile devices

Less than a decade ago the Apple iPhone was launched, followed by the iPad a few years later (Zimmerman 2015). These events can be viewed as an initiation of the modern mobile device era as these devices brought about new computing and usability features, the numbers of devices starting a rapid incline to reach almost 8 billion in 2015 (Cisco Visual Networking Index 2016, Kavanagh 2016, Zimmerman 2015).

The proliferation of mobile devices is a vital part of digital ubiquity, allowing access to digital resources anytime, anywhere, both for leisure and business purposes (Fleischmann 2015, International Data Group 2014, iPass 2014, Lukyanenko 2016). The change of this omnipresent digital is so significant that Lukyanenko (2016 p. 3) feels the need to introduce the term Ubiquitous Digital Intermediation, "the expanding practice of relying on digital information for representing, accessing, and manipulating human mental states and physical and social objects as opposed to directly interacting with the states and objects in reality". Regardless of the vast changes the mobile devices are a part of, this section will be limited to examining features related to human-mediated data input, thus not discussing e.g. social media, content consumption or location-based data or applications.

This section outlines what mobile devices are and how they differ from PCs with regard to data input, and closes by examining the mobile device prevalence and its drivers.

4.1. Definition

The concept of mobile device is not exact, and whilst qualities such a mobility and computing are commonly agreed on, it is for instance unclear whether laptops should belong under the term. The Cambridge online dictionary (2016) includes small computers in their definition of mobile device, "any piece of electronic equipment such as a mobile phone or small computer that you can use in different places". On the other hand, Wikipedia (2016) defines mobile device as "a small computing device, typically small enough to be handheld (and hence also commonly known as a handheld computer or simply handheld), having a display screen with touch input and/or a miniature keyboard and weighing less than 2 pounds (0.91 kg)". For instance Lugtig & Toepoel (2015) and Yurish & Canete (2013) seem to agree with the Wikipedia definition. Leung & Zhang (2016) characterise tablets as having "all the functionality and connectivity of a laptop, and the mobility and portability of a smartphone" (p. 331).

In addition to the terminological confusion, the boundaries between phones, tablets and computers are blurring (Odell 2015); the computing power of the smaller devices is growing, while laptops are equipped with a touchscreen and have become lighter. Moreover, some laptops sport a detachable touchscreen, which functions as a tablet on its own.

In the context of this thesis, the term mobile device is used to describe touch-screen tablets and smartphones that connect to the internet, therefore excluding e.g. early PDAs operated with a stylus and laptops. The mobile devices sport a set of features allowing use on the go; they can be carried around freely, they are lightweight, and they do not have bulky external accessories such as keyboards or pointing devices but are operated via finger touches on the screen. The thesis does not distinguish between large smartphones and tablets, since the differences are rather insignificant and no exact screen size can be determined to meaningfully tell apart the two. Even though some studies like Struminskaya et al. (2015) point towards possible differences between tablet and smartphone performance in error and non-response rates, the similarity of the devices and their applications and uses does not allow separating the two clearly (Mickan et al. 2013). Yet it is useful to distinguish between small-screened smartphones and tablets, since the large screen of the tablet is one of the essential features of a tablet mobile device (Leung & Zhang 2016), and perhaps the differences found by Struminskaya et al. (2015) refer to the difference between these two.

4.2. Differences between mobile devices and PCs

This sub-section investigates the differences between mobile devices and PCs with regard to data input. PCs are without a doubt the most prevalent device for human-mediated data entry, but the use of mobile devices for information collection has been increasing over the past years (Kim et al. 2013). Similar to Lugtig & Toepoel (2015), the study does not distinguish between a laptop and a desktop computer, and defines PCs as large-screened (>6 inches) computers without a touch screen.

There are three key differences between the two technologies. The first major difference is obviously the mobility of these devices, as the name of mobile device already suggests. Secondly the screen size and thirdly the control method, especially text input, are distinctly different between PCs and mobile devices (Lugtig & Toepoel 2015). The differing characteristics suggest that the devices could support different types of data entry, complementing each other. This thesis argues that mobile devices are primarily not a substitute of laptops but a complement; they have a different profile of features and are suited for certain purposes. International Data Group (2012) supports this view, their survey suggesting parallel use of laptops and tablets. While some tasks can be effortlessly performed with either type of device, tasks requiring true mobility are remarkably better supported by tablets or smartphones and tasks requiring extensive amount of text editing, such as writing a master's thesis, benefit immensely from physical keyboards and larger displays provided by laptops or desktop computers. However, the modern mobile devices have emerged more recently, and to some extent mobile devices seem to act as a substitute to PCs since earlier there were few other digital data entry possibilities (iPass 2014).

4.2.1. Mobility

Perhaps the most distinct feature of mobile devices is their radical mobility; the devices are lightweight and compact and do not require any external accessories, enabling freedom of place on an unprecedented level (Prgomet et al. 2009). The devices are extensively used on the go (iPass 2014, Sessions & Havens 2012), and users appreciate the increased mobility (Ozok et al. 2008).

Laptops were a clear improvement on the path from stationary desktop computers to portability, but their design does have some obvious drawbacks hindering the mobile usability in certain environments. Laptop and desktop computers require the use of keyboard and a pointing device such as a mouse or touch pad, and at least earlier more functional laptops have had the tendency to be on the heavy or bulky side (Bogossian et al. 2009, Ozok et al. 2008, Zhai et al. 2005). These factors mean that the laptop could be inconvenient to carry around and difficult and cumbersome to use without a surface to rest it on; thus a better term for laptop is portable rather than mobile.

For mobility, the compactness is an important factor (Zhai et al. 2005), and mobile devices are more compact and require no accessories for use. Adiguzel (2008) compares personal digital assistants, early forms of tablets without touch interfaces, to laptops and notes they are smaller and lighter. The development of mobile devices also trends towards smaller size (Kim et al. 2013, Yurish & Canete 2013). These features make mobile devices very usable in deskless mobile environments and for mobile workers (Adiguzel 2008, Sessions & Havens 2012, Wetzlinger 2014).

The inherent mobility of the devices has a number of further implications for use. For instance, the environment in which the devices are used is likely to be cluttered with distractions and the time and attention reserved for the device are compressed (Sessions & Havens 2012). Moreover, connectivity is a key issue for mobile devices. PCs are often used in an environment where network connection is stable and provided, but mobile devices are present in a number of places where the connection might be slow or unreliable. The users perceive the connectivity difficulties as a major issue for productivity and user experience (iPass 2014). For example Mavletova (2013) and Lugtig & Toepoel (2015) hypothesise that slower Internet connection prolongs the time that mobile users need to enter the requested data. The connectivity issues need to be acknowledged since a significant part of the value of a smartphone or a tablet comes from being connected to the Internet and thus to a large body of information, systems, acquaintances, and entertainment. Also security issues are widely discussed with the transportability and information access capabilities of smartphones and tablets. Mosleh (2013) claims that digital resources are at least as secure as the paper equivalent, both in the sense of safely storing the information as well as in preventing unauthorized access.

Additionally, the mobility of these devices and their constant presence in different circumstances enables benefiting from sensors, which enable effortless information capture in any location the mobile device carrier enters. Consequently the mobile devices are equipped with a number of sensors, such as accelerometer, gyroscope, magnetic sensors, light sensors, and pressure sensors (Yurish & Canete 2013). Moreover, Yurish & Canete (2013) acknowledge the consumer demand for gas, temperature, humidity, altitude, ultra-violet, radiation, and glucose sensors as well as for air quality detectors, fire alarms, alcohol detectors, and breath analysers. PCs are not traditionally equipped with such sensors since their static use does not warrant much benefit from such sensors.

A major benefit of sensors is that they are capable of collecting information without active user effort for text input, which could enable radically eased collection of certain types of data. Moreover, as the automated data collection via sensors spreads, the need for human input of data decreases. This suggests that the need for mobile devices in remote data collection might decrease for e.g. the above mentioned physical phenomena, but there are some applications where sensor solutions are unlikely to take over for a while. These are for instance applications involving large extent of human complexity, like understanding the human experience and perception involving for instance emotions, social factors, and sense of pain. Moreover, the human presence is vital for some processes where the human understanding and compassion are irreplaceable; for instance healthcare environments have these characteristics. Currently also a large number of variables and variation in the data to be collected pose challenges for automation, and might require human-mediation.

4.2.2. Screen size

To achieve the higher level of mobility, the size of the mobile device screen is significantly smaller compared to PCs. While the smallest smartphone screens start at only 4 inches, the largest desktop computer screen sizes can be 27 inches (Lugtig & Toepoel 2015). According to Lugtig & Toepoel (2015), this is perhaps of the defining features between mobile devices and more stationary computers.

Moreover, there is evidence that the screen size might be the most significant factor causing inferior use efficiency; when comparing survey response times on smartphones, tablets, and PCs, only smartphones recorded slower response times (Lugtig & Toepoel 2015). The smaller screen size is obviously able to show less than the larger screen sizes, and thus mobile users can fit less content on the screen and usually see the content smaller and might require zoom (Beaulieu 2013, Lugtig & Toepoel 2015). Struminskaya et al. (2015) however find evidence that tablet-sized screens do not inconvenience the user more than PC screens, and that the difference between a smartphone screen and a tablet screen is a critical one. The smaller screen size of smartphones leads also ability to present only smaller on-screen keyboards, which could further affect the user experience.

The smaller screen of tablets and especially of smaller smartphones does pose limitations to what can be fit on the screen, and the implications on the user interaction have to be taken into account (Goldstien & Bove 2011, Ray 2011). Not seeing all the options for the field at once, or not seeing the title of the field being filled, might affect the quality of the input information. Sessions & Havens (2012) also strongly encourage designing consistent and simple interface to achieve better data quality, so that complex data representation or inattention to missing fields does not deteriorate data quality.

4.2.3. Control

The mobile devices are navigated via a touch-screen (Wetzlinger et al. 2014), whereas PCs feature a display, a pointing device, and a physical keyboard (Ozok et al. 2008, Zhai et al. 2005). This difference is perhaps most influential when entering text into the device; Lugtig & Toepoel (2015) propose the method of text entry as the one of the most defining features between mobile devices and PCs.

On one hand, the touch interface might be intuitive and easy to use. Lehnbom (2014) characterises the tablet devices as responsive, which could be interpreted to refer to the intuitive tapping of screen that takes place when using a mobile device. Lin et al. (2013) note that the mobile device interface seems to provide quicker information access compared to the stationary computers, and they hypothesise that it is partly due to the touch-screen interface of mobile devices. Also when entering information to a mobile device, the keyboard and the screen where the typed words appear are closer, allowing easier inspection of what has been written and whether it has been written correctly (Odell 2015).

On the other hand, entering information into the mobile device and managing the interface can be difficult. Compared to PCs and QWERTY keyboards, text entry on mobile devices with an on-screen keyboard is notoriously inferior to PCs with regard to speed and accuracy (Odell 2015). The study of Berkowitz et al. (2014) exemplifies this, finding that test subjects were reluctant to use tablets for editing or creating lengthy notes due to the slow typing speeds and proneness to errors. This is due to a few factors; finger navigation is less precise than mouse navigation (Lugtig & Toepoel 2015), the small screens allow smaller keyboards which adversely affect typing performance (Kim et al. 2013, Odell 2015), the on-screen keyboards provide little feedback such a feeling the edges of the keys or feeling the keys press down when typing (Odell 2015), and the on-screen keyboards do not allow resting fingers on the keyboard like physical keyboards (Odell 2015). Kaka et al. (2015) detect that experience with tablets also seems to be an influential factor, since the younger tablet users had faster data entry times than the older users.

The text entry is especially problematic since majority of the mobile device use as well as computer use, from document writing the electronic messages to social media, currently relies on text entry (Clawson et al. 2015, Zhai et al. 2005). Moreover, Wetzlinger et al. (2014) studied the usability of tablets versus laptops in mundane office tasks like sending emails and creating calendar entries, and found that laptops were 4-35% faster in all tasks, in addition to which the users felt the tasks were easier when performed on laptop.

Mobile text entry has been the subject of extensive research since late nineties (Reyal et al. 2015), and there are a number of ways to work around the limitations of mobile device data entry. Perhaps the most important is "designing for touch" (Sessions & Havens 2012); allowing the users to select ready options by utilising icons, boxes, and dropdown menus as opposed to users typing all the information themselves. In addition to reducing the amount of typing, this also leverages the intuitive touch interface (Lehnbom 2014). Nevertheless, this type on information entry does not seem to fully resolve the problem; in surveys with multi-choice questions and open questions, Mavletova (2013) and Struminskaya et al. (2015) observed significantly longer response times for mobile users than PC users. Additionally, it might also lead to "close enough" choosing, where the user is forced or opts to choose an option that is somewhat correct but not quite. Moreover, the usability of the system could suffer if the software does not for some reason allow choosing the right option, leading to frustrating situations for the user.

There are a number of options besides the currently widely used on-screen keyboards; for instance, mobile physical keyboard, handwriting recognition, speech recognition, gesture input, and stylus keyboards as alternative mobile text input options (Zhai et al. 2005). Taking into account the distraction-filled environment where mobile devices are operated (Sessions & Havens 2012), Poirier & Sad (2007) emphasise the importance of minimised mental load imposed by the text entry method. For instance speech recognition software has evolved considerably after the study of Zhai et al. (2005), and speech recognition could potentially be an easy way to make notes.

Despite the evident shortcomings of mobile devices, the users often regard them with positive perception and intrigue. Assessing usability, Wetzlinger et al. (2014) found that the tablet received higher overall score than the PC and was perceived less complex, easier to learn, and more consistent than the laptop, even though the users consumed more time on the tasks on tablets and rated the tasks more difficult. Also Ozok et al. (2008) were told their tablet PCs were fun to use, even if more difficult than PCs. Leung & Zhang (2016) recognise the fashion and status element embedded in tablets as a significant reason to engage in using a tablet, and Ficek (2014) also recognise the increased buy-in with tablets when collecting answers for surveys. Ficek (2014) proposes two explanations for this; first, the value add of the novel technology, and secondly, the signal of increased legitimation and importance sent by the use of relatively expensive devices.

4.3. Prevalence & drivers

The ubiquity of smartphones and tablets does not go unnoticed. Phrases such as “unprecedented growth of smartphones and tablets” (iPass 2014, p. 7) and “high growth and potentially huge market” (Yurish & Canete 2013, p. 107) are common, backed up by figures like the Cisco Visual Networking Index (2016) report; in 2020 they expect there to be 5.5 billion mobile users globally, compared to 4.8 billion in 2015. Similarly, the number of mobile-ready devices is expected to grow by nearly 4 billion devices to 11.6 billion.

The fast adoption of mobile device has been supported by technological advances; the devices have become smaller, faster, and more durable with regard to battery life (Wetzlinger et al. 2014, Yurish & Canete 2013). Additionally the benefits such as radical mobility and Internet connectivity enabling leisure and work activities anywhere, anytime coupled with the ease of use (Leung & Zhang 2016) have contributed to the widespread use of devices and partial replacement of laptop as the device of choice. International Data Group (2012) noticed that nearly three quarters of the users say that they carry their laptops around less now that they have the tablet, and over 50 percent say that the tablet has partly replaced their laptop; 12 percent say the tablet has fully replaced it.

Originally aimed at the consumer market, the mobile devices have also found their place in business context (Sessions & Havens 2012, Wetzlinger et al. 2014). IT and business professionals are utilising tablets at work, especially in tasks requiring true mobility like sales and management and customer relations (Wetzlinger et al. 2014). On average, business travellers have three connected devices with them while traveling (iPass 2014); perhaps a smartphone, tablet and a laptop. The iPass survey also notes that 70 percent of business travellers reported to traveling with a tablet, and 36 percent do not “even use a desktop computer anymore” (p. 5).

The discussion around tablets and data tends to focus on the location data provided and its applications, like location-based marketing and assessing people or customer flows. Moreover, the capability of mobile devices to supply different sensor data combined with the prevalence and consequent coverage of mobile devices presents interesting opportunities like usage and behaviour based fees and distributed sensing (Händel et al. 2014). While these applications are of utmost interest and provide fascination opportunities, they are outside the scope of this study. Similarly, the content consumption enabled by radically improved accessibility and consumer content generation via mobile devices are interesting and widely researched topics (e.g. Williams et al. 2014: Consumers' intentions to use e-readers, Chan-Olmsted & Shay 2014: The emerging mobile media market: Exploring the potential of tablets for media content consumption, Händel et al. 2014: Insurance telematics: Opportunities and challenges with the smartphone solution) which seem to be the primary use of tablets (International Data Group 2012), but are not within the scope of this thesis.

The area of interest for this thesis is the purposeful human-mediated information collection. It seems that in circumstances when both PCs and mobile device are available for information entry, PCs are often chosen. However, mobile devices have different usage scenarios than PCs (Wetzlinger et al. 2014); they strongly support working in a truly mobile environment, and are thus well suited for people whose jobs require much mobility. In environments where there is no opportunity to rest the laptop on a surface but the devices have to be used standing, the compactness of mobile is valuable. Ozok et al. (2008) mention retail and services such as restaurants and wine-tasting places as examples of places where tablet PC was used actively. Sessions & Havens (2012) mention increasing use of tablets where data collection in the field is needed – at a potential customer's site, at a crime scene, or at a patient's bedside. Houston (2010) lists a number of construction applications which allow capturing data onsite as well as performing calculations for costs and material needs, and Byass et al. (2008) utilised mobile devices in collecting population data in rural Burkina Faso. Adiguzel (2010) suggests that portable devices are suitable for observations and assessments taking place in research and classroom settings. Moreover, information collection at warehouses or repair shops are potential applications where mobile devices could be utilised.

Particular interest towards mobile device mediated data collection has been shown in healthcare, where there are great potential benefits to achieve from mobile device use due to the high mobility and information intensity, necessitated by both medicinal and legal reasons (Carroll et al. 2004). Moreover, data needs to be collected for clinical research, which requires quite high quality of data (Kaka et al. 2015). The impact of handheld devices, including early

PDAs, on healthcare efficiency and patient care has been widely studied, but the results have been mixed; Gann et al. (2014) summarise that there are a number of studies suggesting both improved workflow and obstructed workflow. For instance Mickan (2013) found evidence that mobile devices support efficient workflows, whereas Perez et al. (2013) found the devices too cumbersome to use and the connection too poor to enable smoother workflows. However, recently there have been a number of studies showing improved efficiency (Crowson et al. 2016, Fleishmann et al. 2015, Mickan et al. 2013, Schooley et al. 2016), giving reason for cautious optimism. With regard to information collection, Stephens et al. (2010) noticed that the PDAs in their study were used to access information but not to produce it. Beaulieu (2013) concurs with this, stating mobile devices are more suitable for information consumption than information creation with regard to electronic health records. However, this might be due to the difficulty of using the PDAs, whose usability is not comparable to modern touch-screened devices.

Another field where the mobile devices have received attention are surveys, where e.g. Lugtig & Toepoel (2015), Mavletova (2013), and Struminskaya et al. (2015) have noticed the increasing number of mobile devices used and consequently examined how surveys filled with mobile devices or PCs differ. Also there the findings are not unanimous; Lugtig & Toepoel (2015) suggest that the devices themselves do not seem to contribute to larger measurement errors or nonresponse in online panel surveys, whereas Struminskaya et al. (2015) unveil contradicting evidence, suggesting that mobile devices lead to reduced answering of open answers and especially for smartphones higher levels of nonresponse and measurement error. In surveys, also paper has commonly been used for information collection. Byass et al. (2008) used personal digital assistants to conduct a large-scale community survey in rural Burkina Faso, and found them a suitable replacement for paper-based surveys with similar rates of inaccuracies. Ficek et al. (2014) also comments on using mobile devices for surveying in place of paper, and notes that tablets yield “cleaner” data; less missing answers and data entry errors.

5. Theoretical implications of mobility on information quality in collection

This section combines the mobile device characteristics found in the previous section to the information quality characteristics present at data input, and examines how mobility, screen size, and control might affect the accuracy, completeness, timeliness, and consistency of the information collected. The identified mechanisms are two-fold; on one hand, the information collection happens at the source of information, eliminating any delay or intermediate notes between obtaining the information from the source and putting it into the system. On the other hand, the mobile interface is more difficult to navigate and the small letters on the on-screen keyboard could cause a number of unintended characters or missed characters, or cause user reluctance to make notes.

The comparison is made to the prevalent computer technology used for documentation, the PC, and for the period between the event to be documented and the computer entry two kinds of strategies are assumed; either producing intermediate notes on a notepad, form, or other paper-based medium, or making no notes at all and relying on memory until a computer is available. Achieving more mobile computing solutions has been attempted for instance in healthcare by placing computers on wheels (COW), but the shortcomings of these devices, for example practical immobility and difficulty of use, have caused failures in adoption (Tang & Carpendale 2008). Similarly the tablet ancestors, personal digital assistants (PDAs), have often been perceived so cumbersome to use that they have been an obstruction to workflow, making it preferable to utilise other methods such as pen and paper instead (Berkowitz et al. 2014).

Since the human-mediated purposeful information collection is of interest, the sensor data and the applications there-of are not further discussed, even though the thesis acknowledges their impact on enabling collection of entirely new types of information as well as more widespread collection of information altogether, affecting the volume and completeness of obtainable data.

5.1. Capture at the source

The high mobility of mobile devices enables information collection directly at the source, without intermediate steps such as paper or memorising. The first dimensions affected are accuracy and completeness; if the data is recorded at the place of observation, the time lapse between observation and entry decreases and the data collector's recall increases (Adiguzel 2010). This applies for both memory-based techniques as well as transferring the paper-based notes to the system. As a result of the enhanced recall, the values entered are more likely to correspond to the true values, and less data is lost on the way to the system, producing richer information. Mickan et al. (2013) find evidence of enhanced accuracy and completeness in their literature review, and also Lutes et al. (2012) detect that the data review at the point of collection yielded "more accurate offsite data", even though the materials accessible for this thesis did not provide a specification of what more accurate data meant in this context and what the magnitude of improvement was. While instant capture of the information presumably improves the accuracy, the environment with more distractions could erode some of this benefit (Sessions & Havens 2012).

The format of the information produced might also be affected by the mobile devices. Since the mobile device is constantly present at the situation where information is collected, it is easier to document the information as it comes, which entails that there would be more data entries with less content per each entry. The alternative is writing a longer piece on a PC in one sitting after returning to work station after the occasion where the information to be collected was observed. This naturally applies only to situations where pieces of information are collected over a period of time, and the effect would not concern for instance having a respondent fill in a pre-made survey at once.

Lutes et al. (2012) noticed that in the setting of indoor air studies, team members located offsite could access the data faster with tablet computers, in addition to which reports and data tables could be produced faster. The earlier input times led to improved timeliness since the data was sooner available to other stakeholders who might need it. The mobile device capability to share the information in real time is regarded an important feature (EY 2014), and timely input of data is a crucial enabler for benefiting from real-time information, especially in time-compressed situations. Thus the timeliness – accuracy trade-off might be alleviated by the mobile devices due to the quick input and access to data (Sessions & Havens 2012). Moreover, Tang & Carpendale (2008) emphasise the importance of information sharing in professions and tasks that are distributed across time and location and specialised teams. For instance healthcare is one of these industries where mobile devices might have a significant effect due to their portability and accessibility.

Additionally, the elimination of the possible paper phase between data collection and data input reduces the work since there is no need for the double entry of first writing the notes on the paper and then again on the computer (Lutes et al. 2012). This points towards increased process efficiency, which Lutes et al. (2012) also observed.

5.2. Entry support

Since the mobile devices are present at the point of information collection, they are able to support the collector in their endeavour. This could lead to more complete, more consistent, and more accurate information.

First, the mobile device can provide a checklist-like view about the necessary information for the collector, which helps the collector to produce complete data. This is especially significant if the previous collection method has been based on memory or unformatted notes. For instance, Ficek (2014) observed that tablets in comparison to paper forms resulted in better "data integrity" in surveys; there were less missing responses and data entry errors. In particular, she attributes improved completeness to the ability to ensure key data extraction through required fields. Similarly Kaka et al. (2015) find mobile device collection to produce less missing data; on average there were 3.3 missing fields per paper form, of which 2.2 would have been detected with an iPad text entry support. Also Sessions & Havens (2012) propose that entry support such as error displays and highlighting missing required fields could improve information quality.

Secondly, the electronic device can be programmed to help with navigating the input interface. For instance question skips, i.e. questions that need not be answered after a certain answer in a form, can be programmed into the device, making the process clearer and more effortless for the user (Ficek 2014). Thirdly, the mobile device can aid with the entry via syntactic and semantic support and predictive answers, improving accuracy as well as consistency and making the process easier for the user. In addition to certain formats of data required to certain fields and sanity checking the data interrelations, for instance probabilistic models can be employed to predict the user's responses to the remaining questions based on earlier answers (Chen et al. 2010). Effective symbol interface design can also aid in producing correctly formatted data as well as providing user with a selection of options to choose from. Moreover, clearly interlinked fields could autopopulate; for instance, if city field is chosen as Helsinki, the country field should autopopulate Finland as the country (Sessions & Havens 2012). Excessive use of autopopulation and rigid format requirements could, however, have adverse effects on the information quality as well as user experience.

Moreover, data entry into specified fields or through symbol interface could also produce more structured data, which would enable immediate analysis of the data (Lutes et al. 2012, Mendes & Rodrigues 2011). Additionally, structured data seems to improve the accuracy of the documentation (Häyrinen et al. 2008), in addition to which Häyrinen et al. (2008) find evidence from literature that structured notes could lead to easier information retrieval. Batini et al. (2009) remark that structuredness of information might have two kinds of effects. On one hand, the usability of information will increase as the percentage of information in free-form decreases. Thus creating summaries and reports becomes easier, and the information can be more easily refined into graphs in a feasible manner, not involving coding the information which would be more cumbersome. Free-form text is currently quite difficult to process, due to e.g. misspellings, synonyms, homonyms, negations, and the sheer complexity of language (Mendes & Rodrigues 2011).

On the other hand, the structure might limit the richness of the information by forcing it to predefined categories. Mendes & Rodrigues (2011) hypothesise that this shift from free-form to certain fields required by the direct data entry system might result in reduced accuracy and completeness, and Strong et al. (1997) note forms with checkboxes for procedure codes leading to a narrowed range of procedures performed according to the data, compared to doctors entering the procedures in free form. Moreover, having to choose from a range of options might cause "close enough" choosing. Structuredness is, of course, not solely tied to mobile devices and can certainly be achieved also with a PC, but the mobile interface and documentation utilising symbols provide a natural platform to execute a shift towards more structured notes.

5.3. Difficulty of input

Whereas capturing the information at the source and provision of entry support mainly point towards enhanced information quality, the method of text input as well as the small screen of the mobile device are factors that could degrade the dimensions of accuracy, consistency, and completeness.

First, operating on the smaller screen with the on-screen keyboard might lead to accidentally pressing unintended keys or other symbols. This might manifest itself as typing errors (Lugtig & Toepoel 2015, Odell 2015), which reduce the accuracy of the information, especially if these inaccuracies occur in critical information. Another possible effect is that the more challenging navigation might lead to submitting empty documentation, sending the same piece of information twice, or perhaps sending a half-finished documentation, affecting the consistency of the information. Even if the design for touch approach recommended by Sessions & Havens (2012) is utilised, the less precise finger navigation (Lugtig & Toepoel 2015) might cause inaccuracy or inconsistency issues when unintended symbols are pressed. Also Kaka et al. (2015) denote the possibility that the user might accidentally select a nearby option instead of the intended option. However, in the context of measurement errors in surveys, Lugtig & Toepoel (2015) conclude that mobile phones seem to not produce any larger errors compared to desktop computers.

Secondly, due to the difficulty of typing with mobile devices, the amount of text entered is likely reduced. Mavletova (2013) and Struminskaya et al. (2015) find evidence of this; Mavletova (2013) observes the mean number of characters for open fields to decline by approximately one third between PC users and mobile users. Struminskaya et al. (2015) detect significant drops in answering open questions when switching from PC to mobile device, and suggest that this could be explained by the lack of keyboard or the longer response durations of mobile devices. Similarly, Mavletova (2013) notices many mobile users skipping open answers. Lugtig & Toepoel (2015) observe missing answers percentage to rise from 4.1 for PC users to 7.4 for tablet users and 12.2 for smartphone users. Moreover, the time needed for the input indeed seems considerably longer for mobile devices than PCs (Mavletova 2013, Struminskaya et al. 2015). For instance Mavletova (2013) observed surveys taking three times longer on mobile phone than on computer. As a result, especially in time-compressed environments, the input requiring more effort and time might show as further reduced amount of text. The findings of Mavletova (2013) provide support for the alleged difficulty of input and its consequences; in comparison to PCs, more people found smartphone questionnaires difficult to fill. Over 40 percentage points less survey invitees participated in the survey, and almost 20 percentage points more participants broke off in the middle of the survey (Mavletova 2013).

The reduced amount of text could lead to less rich notes as well as reduced completeness altogether. However, reduced amount of text alone does not necessarily mean reduced completeness; the form of the information might just become more condensed. The sentence structures could omit non-vital parts of the sentences, and abbreviations might become more common. The question is then whether the users are able to include all the relevant information to the reduced amount of text in an understandable format, or whether the completeness of the information will suffer. Pointing towards the first option, VanDenKerkhof et al. (2003) found in their study that the content-richness of the data in healthcare setting did not suffer from PDA use as opposed to collection by paper. Considering how much the handheld devices have advanced over the past decade, the observations of VanDenKerkhof et al. (2003) encourage to believe that mobile devices are capable of producing as rich data as the pen and paper method. Also Byass et al. (2008) found mobile devices suitable replacement for paper-based surveys with similar rates of inaccuracies, and Abernethy et al. (2008) found that tablets can gather data of comparable validity. Also the constant presence of the device and provided entry support may aid in collecting equally as rich data.

Thirdly, in the context where multiple media of data input are available, the difficulty of input with mobile devices suggests that they might be used for standard, recurring items that either require little specifying or low amount of text input, or can effectively leverage a symbol interface. The kind of data that requires extensive explanations and text production might be preferred to be entered with a more text production friendly medium such as PC.

6. Study design

Empirical studies of information quality often utilise a survey to capture the information's fitness for use (Arazy & Kopak 2010), which was for instance the method chosen by the influential Strong & Wang (1998) study and which is also recommended as information quality assessment tool by e.g. Lee et al. (2002). The surveys are particularly good for capturing the contextual and subjective factors on the information consumption side. On the mobile side the usefulness of mobile devices is often conducted in the form of time-motion studies, which are able to assess the input process and the related time and/or accuracy (e.g. Crowson et al. 2016, Fleischmann et al. 2015, Lin et al. 2013, VanDenKerkhof 2003, Wetzlinger et al. 2014). Similarly to information quality research and loyal to the 'fitness for use' understanding of data quality, another stream of studies have assessed the perceived usefulness and time saved through surveying users (e.g. Crowson et al. 2016, Gann et al 2014, Ozok et al. 2008, Schooley et al. 2016, Sola et al. 2007, Stephens et al. 2010). Alternatively in the setting of online surveying, laptops and mobile devices are compared in panel surveys, where e.g. response rates and faulty answers are studied (e.g. Mavletova 2013, Lugtig & Toepoel 2016, Struminskaya et al. 2015).

This study assumes a slightly different approach, measuring intrinsic properties directly from real operational data instead of attempting to capture the user perceptions or create its own data in a laboratory setting. Since no studies examining the quality of mobile data itself in comparison to PC generated data were found, the study synthesises an approach from the information quality and mobile literature. The approach is primarily quantitative, but contains also a qualitative element due to the nature of the data. The study is conducted in the area of healthcare, where an elderly care facility recently adopted mobile devices to facilitate recording of patient data. Two sets of data are obtained from the facility; one prior to the inclusion of mobile devices, when all the notes were produced with desktop computers, and one after the inclusion of mobile devices when both desktop computers and mobile devices were used. As remarked in 3.3, healthcare is widely recognised as an area that might substantially benefit from mobile technology; the industry is very information intensive (Byrd & Byrd 2013) and the nature of work is highly mobile as the healthcare professionals in wards and hospitals conduct rounds and work where the patient is (Prgomet et al. 2009). Byrd & Byrd (2012) further underline the importance of information quality in the medical setting, where false or delayed information can directly cause adverse health effects or even terminal events.

This section will first introduce the chosen methodology, then give an overview of the dataset, and finally derive the measures and hypotheses used for the analysis.

6.1. Methodology

Since no studies examining the quality of live mobile data itself in comparison to desktop computer generated data were found, the study synthesises an approach from the information quality and mobile literature. The approach leverages quantitative methods.

The study focuses on the information collection and consequently on the information quality dimensions relevant in collection, i.e. accuracy, completeness, timeliness, and currency. Drawing from the measures and assessment techniques used in the information quality literature, a set of eleven measures is constructed to capture the possible effects of mobile device use. Furthermore, based on the mechanisms found in section 5, hypotheses on the possible effects are formulated. The aim of the measures is to capture the level of quality in an objective manner (Stvilia et al. 2007) and establish comparable units of quality. The measures do not generate any absolute compound measure, but produce an objective understanding of the level of data quality produced with the different selections of technology which lends itself to comparison. The approach compares the two sample datasets, i.e. the dataset produced with only desktop computers and the hybrid dataset produced with desktop computers and mobile devices in parallel. The approach is based on the logical induction that any substantial changes on information quality inflicted by use of mobile devices will be present in the whole dataset, affecting the total values. Thus the data produced in the two settings can be compared and the effects of including mobile devices in the data production can be examined.

The obtained measures are then evaluated in relation to each other utilising t-tests, testing whether the means of the measures differ. These tests will be used to support or reject the formulated hypotheses regarding the effects mobile devices have on data quality in comparison to purely desktop produced data. Statistical approach was assumed because statistical analysis is widely employed in information quality research and thus proven to be suitable for the purposes of information quality study (Madnick et al. 2009), and it enables observing differences in the means of the data. The sample is large enough to utilise t-test, and a t-test assuming unequal variances is employed since there is no reason to assume similar variances. Moreover, observation independence is assumed. In reality full independence cannot be assumed, and thus the standard t-tests might produce biased results. However, the t-test gives a good understanding of the direction and magnitude of the change, and highly significant results are very likely to remain significant also in methods accounting for the dependencies. This approach is assumed for practical reasons here, but in subsequent analysis, to ensure full reliability of the results, these dependencies should be controlled for.

To achieve further confirmation and richer understanding of the obtained results, box plots are drawn to gain understanding of the distribution of the data. Box plots are a statistical technique which allows concise summarising of median, mean, quartiles, and lowest and highest data points in an easily understandable visual way, and which are often employed in data analysis of exploratory nature (Williamson et al. 1989). In the box plots of this analysis, the limits of the central box denote the limits of the second and the third quartile, a cross denotes mean, the solid line denotes median, the whiskers denote the minimum and maximum value excluding outlier values, and the dots denote outlier values, i.e. values that are more than 1.5 times the value of the upper or lower quartile. Since a number of hypotheses are tested, the multiple t-tests subject the analysis to alpha inflation; the multiple tests could mean that the actual alpha of the whole set, the experimentwise error rate, would inflate considerably. Consequently the reliability of the results would be much lower than the intended alpha. To avoid the uncertainty caused by alpha inflation, the study will set the alpha as 0.01. This means that the experimentwise error rate will be $1-(1-0.01)^{11} = 0.105$. While this is not ideal, it does give reasonable indication of the changes.

In addition to the above presented formal statistical testing between the two sample datasets, i.e. the dataset produced with only desktop computers and the hybrid dataset produced with desktop computers and mobile devices in parallel, a descriptive analysis will be conducted within the hybrid data set to examine the particular characteristics of mobile device use versus desktop computer use.

6.2. Data

The dataset consists of nurses' notes from a Finnish healthcare organisation's residential elderly care unit. The notes are daily documentations of the residents' health and wellbeing status produced by nurses, ranging from mundane bodily functions and daily activities to recreational activities and the visits of next of kin (see Table 7 on page 74 for full set of categories). The data originates from an environment of high mobility where capturing the data about the state of health and wellbeing of the resident is crucial for ensuring high level of care. Since the data attempts to capture the health and wellbeing of the resident as well as any other information of importance related to the resident, there is not any rigid predefined format for the documentation. Moreover, the nurses may enter the data whenever they like, but due to the busy high mobility environment of attending to the residents anywhere in the facility, the notes have usually been entered only at the end of the nurse's shift.

The notes received for this study contain the following elements; resident identification number, nurse identification number (only some of the data), date and time of the note, optional categorisation of the data, and the main note. The data is subject to strict patient information laws and measures and anonymised to protect patient privacy. While the data cannot be linked to any residents in the organisation, the case organisation shall not be introduced in more detail to prevent any possibility of identification.

In addition to these notes, a personal care plan (PCP) was received for each resident. The PCP is a care plan personalised for each resident's needs, preferences, and condition. It contains daily activities like hygiene activities, meal times, leisure preferences, and social activities, weekly items like medication or sauna, and when needed or monthly activities like change of bedsheets, visitation of animals, or manicure (the aforementioned are isolated examples and form no care plan). The PCPs are created in collaboration by healthcare professionals and next of kin, to ensure personalised and effective care for each resident. The number of items they contain vary, but in the sample the number was typically around fifteen.

The organisation recently adopted mobile devices for the purposes of creating notes, aiding in directing the nurses' work, and creating a smoother workflow. This thesis grasped the opportunity to obtain two sets of data; data prior to the introduction of mobile devices and data after the introduction of mobile devices (Table 5). Before mobile devices, all the electronic notes were entered via desktop computers, whereas after the introduction of mobile devices both mobile devices and desktop computers have been used. The type of computer technology used to make the note has been specified in the data, and thus the second set of data can be divided into mobile and desktop notes. The first set will be called '*non-mobile data'*, and the latter in its entirety will be called *'mobile data'*. The two sub-sets of mobile data will be called *'new system desktop data'* and *'new system mobile data'*, to distinguish them from the two main sets and to avoid terminological confusion. This terminology is used through the rest of the thesis, and the reader is encouraged to pay close attention to the names of the datasets and data subsets to avoid any terminological misunderstanding.

Table 5 The two periods in the data and their differences

	Non-mobile data	**Mobile data**
Time	Before introduction of mobile devices	After introduction of mobile devices
Computer technology used	Only desktop computers	Desktop computers (called 'new system desktop data' in the thesis) and mobile devices (called 'new system mobile data' in the thesis)

The introduction of mobile devices was accompanied by a new system. The new system has different interfaces for desktop use and mobile devices, with the mobile device utilising symbols in its interface (Figure 9). By clicking the corresponding symbol, the symbol creates a structured note regarding the topic, with possibility to supplement the note with an evaluation or free text. For instance, a symbol generated note could be of form 'GETTING DRESSED: Getting dressed (aided)'. 'GETTING DRESSED' would be the category, 'Getting dressed' the pre-programmed note and 'aided' an optional addition that can be chosen from a pre-specified list. After that, the user may input what they wish into an open text field. While this example contains a lot of repetition, there are also categories which do not, such as minor complaints or hygiene. This solution is temporary, and eventually the categorisations and notes will be separated from each other. Moreover, currently only 77 mobile notes or 30 percent utilised these symbol notes in the sample data.

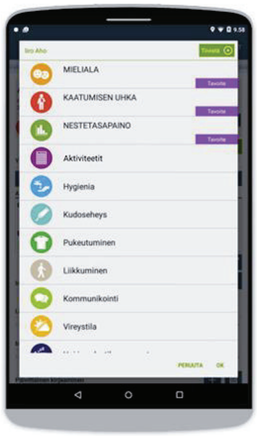

Figure 9 The mobile interface with symbols

The type of device used is a large-screened smartphone, following the recommendations of the system vendor of 5 inch screened devices. The system does not have autocorrect, automated correction of text, but should the user choose to turn on the phone's own autocorrect it will also be applied to the application. The new system also affected the desktop system, but it has been described as quite similar to the old system.

A sample of ten residents were chosen from the full set of data based on three factors; first, the number of days the notes covered during the examination period, secondly a meaningfully broad personal care plan, and thirdly no major updates to the personal care plan over the time period. The datasets are 31 day consecutive periods from both sides of the system cut-off point to control for other factors affecting the notes and consequently to maximise their comparability, however leaving a short period before and after the system change to exclude the most drastic change environment and e.g. the effect of technical difficulties. In spite of this, as Figure 10 shows, there are relatively few mobile device produced notes in the beginning of the observation period due to the early phases of the adoption, but the chosen period was decided to be kept due to the utmost importance of temporal proximity of the two time periods. Furthermore, there is nothing to infer that the quality of the notes should differ of those produced in later time periods, and they are considered to be representative of the nature of mobile notes.

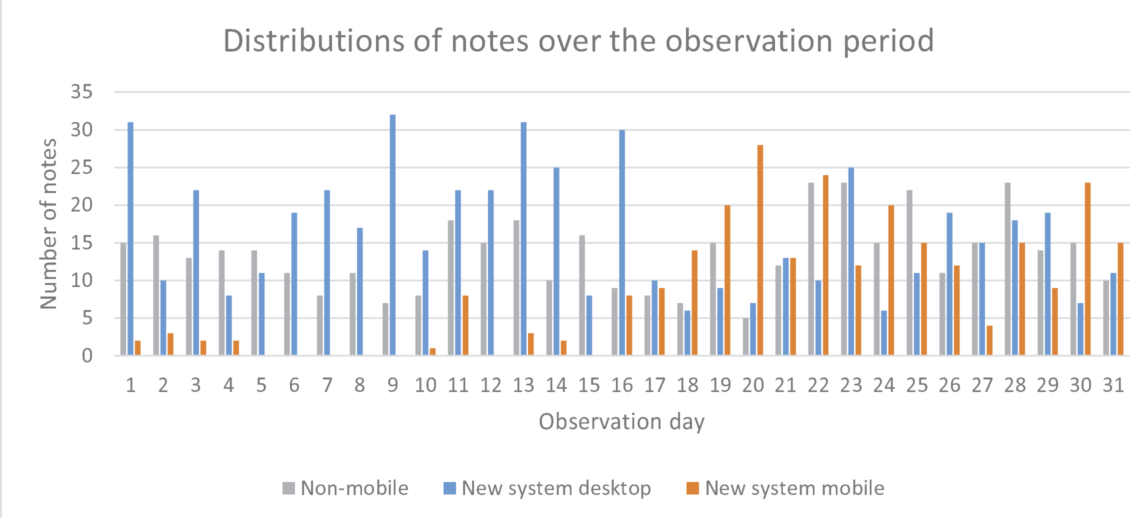

Figure 10 Distributions of notes over the observation periods

Over the one month long period, there were altogether 1195 notes, of which 1183 were non-null, non-duplicate and non-outliers (see Table 6). In this case, outlier notes were notes clearly copy-pasted from a doctor's report and containing more than 1000 characters. Over the 31 day period, there were 421 notes from the non-mobile period and 774 from the mobile period.

Table 6 Summary of the dataset

	Residents	Days covered	Total notes	Empty notes	Duplicate notes	Outlier notes
Mobile data	10	31	774	6	1	3
Non-mobile data	10	31	421	0	2	0
	10	31	1195	6	3	3

The comparison of the same ten residents on both time periods is designed to mitigate the patient-related and nurse-related dependencies; thus the observations are in this study treated as independent. This is of course assuming that the caring for the patients have remained the same, and that patient-specific factors have not undergone significant change. Moreover, the residents are from the same facility, which controls for organisational level variables (Karahanna & Straub 1999). However, strictly speaking observing the same residents over both time periods does cause a dependence between the observations.

6.3. Hypotheses and measures

This sub-section will combine the information quality dimensions present at input (section 3) and the theoretical implications of using mobile devices for data collection (section 5) to produce a set of measures and corresponding hypotheses to assess the effect of mobile technology utilisation on information quality in human-mediated data collection. First, a set of hypotheses and measurements are developed to assess the differences between the solely PC-produced data and the data produced with both PCs and mobile devices. Secondly, the approach to analyse data produced solely on mobile devices to data produced solely on PCs is presented.

For the comparison of the non-mobile dataset, i.e. the dataset produced only with desktop computers, and the mobile dataset, i.e. the hybrid dataset produced with desktop computers and mobile devices in parallel, the first dimension considered is accuracy, which stands for the correctness of the data. As noted in section 3, theoretically accuracy is extremely easy to measure as the difference between the system value and the true value, but in practice such true value often is not readily available or even known. When studying electronic health records, it is often measured by gold standard approach (Weiskopf & Weng 2013), where the values in the system are compared to a gold standard source such as paper record, which is considered "the truth". Unfortunately this kind of double records keeping does not systematically exist in the case organisation, in addition to which it is somewhat dubious whether the paper records in fact contain gold standard worthy data. Another approach mentioned by Weiskopf & Weng (2013) is comparing distributions of data between similar facilities, which is not feasible when data from only one facility is obtained. Another test for accuracy can be conducted through dimension Weiskopf & Weng call plausibility, which is comparison of the element against common knowledge – in the light of general knowledge, is it possible the value is true. For instance, a person with age of 200 is an implausible value. However, with regard to the data, a person would require extensive medical knowledge as well as understanding of the facility, its practices, and patients, to conduct such evaluation on this data. This information is not available in this study, and consequently the approach cannot be employed.

It seems that the common ways of measuring accuracy are inapplicable, but the study would like to include a measure for accuracy since the importance of this dimension cannot be overlooked. Thus it adopts an accuracy measure mentioned by Borek et al. (2011), Eppler & Helfert (2004), and Stvilia et al. (2007); number of spelling errors. While this measure is not optimal and does not capture the most interesting aspects of accuracy, it is enabled by the data and acts as a proxy for accuracy capturing the possible difficulty of writing with a mobile device. Since the mobile interface is more difficult to operate, it could be that the data includes more spelling errors.

The accuracy dimension is also affected by two contradictory mechanisms that suggest mobile devices could improve the quality of collected data. The first is the constant presence enabling capture of more accurate information, but the effect of this mechanism is not present in the measure of spelling errors. Secondly, theory suggests that entry support could also have a positive effect on the information accuracy through syntactic and semantic support, but this software does not provide accuracy supporting features. Additionally, the nurses writing the notes are extremely careful to produce correct notes knowing the tremendous importance of notes, and in this setting the mobile device use is likely not to have a remarkable impact on the correctness of the data through these mechanisms. Alternatively, or perhaps additionally, the cumbersome text entry could affect typing times, but that topic is left to the realm of time-motion studies.

Hypothesis 1: Mobile data contains more spelling inaccuracies than non-mobile data.

Measure: Average number of spelling errors per note

The second dimension is completeness, which measures the extent to which values are present in the data. Popular ways to measure this is comparing the number of actual produced values to the intended number of collected values (Amjad et al. 2014, Ballou & Pazer 1985, Batini et al. 2009, Hogan & Wagner 1997, Weiskopf & Weng 2013), but this approach is only viable when there is a clear number of intended data items to be collected, for instance a survey or a standard assessment with predefined fields. The data in this study is created on needs basis, where the notes are written as necessary or when the nurse feels they want to add something. Moreover, there are days when there are no notes, presumably because the resident has e.g. been visiting their relatives or has resided in a hospital, which do not provide indication of the quality of data collected. In addition to the presence or absence of elements approach, Weiskopf & Weng (2013) list gold standard method and a review by a patient as possible completeness assessment methods, neither of which are suited to this dataset.

Since no readily applicable measures for completeness were found, a set needs to be tailored based on the definitions. As the extent of information collected seems to be central to the definition of completeness, the thesis assesses completeness in the mobile context by first looking at the amount of information produced. This will be conducted by comparing the amount of daily notes between the time periods as well as assessing the average length of a note. Since mobile devices are easier to carry around and are present with the nurses a considerable portion of their time if not all the time, it is hypothesised that more notes will be produced when also mobile devices are in use. The study of Mickan et al. (2013) also points towards expecting increased completeness from mobile devices. However, it could also be that the difficulty of writing or operating the new technology altogether could reduce the number of notes, supported by the observations of Struminskaya et al. (2015) about declined answer rates for open fields on mobile devices.

Hypothesis 2: Mobile data contains more notes over the time period than non-mobile data.

Measure: Average number of notes produced per day

The second measure is the length of the notes, which is assumed to shorten due to the difficulty of producing text with mobile devices, similarly to what Mavletova (2013) observed. Other options would be that it is not more difficult to produce information with the mobile devices e.g. due to the symbol interface, or that the nurses determinedly produce the same data regardless of the difficulty, taking just more time with the mobile device. Alternatively it could also be possible that there is reduced data loss between the point of care and documentation point (Adiguzel 2010) and that the mobile notes would in fact contain more information and therefore have more characters.

Hypothesis 3: Mobile data notes contain less characters than the non-mobile data.

Measure: Average characters per note

Hypothesis 2 expects more notes, but hypothesis 3 expects them to be shorter; these hypotheses have opposite effects on the total number of characters produced. To gain an understanding of the total effect on the number of characters produced, an additional measure of characters per day is also calculated.

With the previous completeness hypotheses, only the amount and length of information are measured, not the quality of the content. It could be that the inclusion of mobile devices would flatten the information collection to bare necessities, producing less rich information. On the other hand, the hypothesised shorter notes do not necessarily mean that there is any less content in the note, it could be that the nurses are able to condense the information into a smaller number of characters. To measure the richness of the content, the data is reflected on the personal care plans, in addition to which the topics covered in the note will be analysed through two note topic categorisations.

The data on each resident is coded based on the PCP; for each note, it is examined which items in the PCP are covered. Since the PCP items are determined by healthcare professionals and next of kin to ensure good care, they are viewed as a meaningful set of items that are important to the care; thus they function well as a definition of completeness of the data. Initially the measure was planned to be percentage of PCP items covered but a number of PCP items are more like guidelines for care and communication between care personnel than items that can be completed at the determined interval. Moreover, the assigned frequencies of PCP items seemed non-standard and a number were assigned to be conducted when needed. Thus instead of rates of documentation completeness, the study chose to evaluate the total sums of PCP items covered, which are comparable for the same resident over the two time periods. It is important to note this is not an evaluation of the care and whether the planned care actions have been carried out, but this study examines how the PCP items have been documented and what information of the resident's health and wellbeing status exists. Moreover, the system is clearly not used to document all data such as detailed medication data.

Following the reasoning for hypotheses 2 and 3 and considering the guiding effect the mobile symbol interface present at the point of care, more care plan items are expected to be present in the mobile data. However, there are examples from literature which could be interpreted to suggest reduced content, like the findings of Mavletova (2013) and Struminskaya et al. (2015) who both witnessed mobile device using questionnaire respondents' answer rate to open questions declining by over a third compared to PC users. Also Lugtig & Toepoel (2015) noted missing answers to increase considerably for mobile devices.

Hypothesis 4: More PCP items are covered in mobile data than in the non-mobile data.

Measure: Total number of PCP items covered

The content of the information produced will be further analysed by categorising the data into types mentioned in the original data, slightly modified to be better suited for the study (Table 7). For the purposes of this study, the categories were simplified and the number of categories reduced. The categories defined by the organisation, utilising their expertise in the area, were considered meaningful groupings representing subjects of interest to the organisation. The notes in their original state did not use categories extensively; most were either marked as 'report note' or 'general'. However, the mobile system will be developed to utilise categorisation more extensively, and currently there are a number of categories defined but so far little used. The notes were coded in a similar manner to PCP items but one note could have up to five categories, depending on the content. Not all the categories were present in the data; there were no notes regarding falls and no cancelled tasks or reminders occurred in the data (Table 7).

No specific hypotheses will be formulated for each category. Generally, due to the mobility and the difficulty to produce text, it is expected that the mobile devices will capture more mundane, recurring items, like hygiene, nourishment, and sleeping, which benefit from the easy access to documentation device but do not require extensive specifying. It seems these criteria describe physiology-related activities. In addition to the topical categorisation, the data is also categorised based on the notion of human as physio-psycho-social entity within the discipline of psychology. It divides the notes in either physiology-related, psychology-related or socially related categories (PPS categories). One note could be assigned to all three of these categories if the elements were present in the note. Similar to the topical categories, it is expected that the physiological category is more pronounced in the mobile data.

Hypothesis 5: Mobile data contains more notes related to physiological activities than non-mobile data.

Measure: Average count of physiological category notes per day

In addition to the average count of physiological category notes per day, also the frequencies of items in strongly physiology-related categories of bodily discharge, hygiene, measurements, medication, minor complaints, moving, nourishment, and sleeping, in topical categories are used. The assigning of both topical and PPS categories is entirely based on the researcher's judgement; however consistent criteria has been applied across the whole data.

Table 7 Topical categories

Topical categories	
Bodily discharge	Notes related to bodily discharge
*Cancelled task**	A planned task set in the future that was cancelled e.g. due to incorrect resident or changes in care plan
Doctor	Notes on doctor's visits or other consultation of doctor
*Falls**	Notes on any falls experienced by residents
General	Notes on general state of the resident such as "feels well", "feels ok" or other generic notes
Hygiene	Notes on hygiene-related events such as showers or tooth brushing
Measurements	Notes on measuring health items such as blood sugar, blood pressure, weight, or tracked bodily functions
Medication	Notes on the planned and administered medication
Minor complaints	Notes on non-acute physical issues such as wounds, sores, and aches
Moving	Notes on the resident's mobility such as walking about unsupported, supported, or in different kinds of wheelchairs
Nourishment	Notes on nourishment such as eating meals or the lack thereof
Psychosocial	Notes on non-physical states of residents, such as emotions, social behaviour, or memory or lucidness
Recreational activity	Notes on leisurely activities such as listening to music or watching televisions, or participating in organised group activities
Relatives and friends	Notes on the visits, calls or other communication with family and other close people
*Reminder**	A reminder that has been set to do a task such as measuring of blood sugar, typically within short time of the creation of the note
Sleeping	Notes on the times of sleep, quality of sleep, or sleeping in general
Special circumstances	Notes on uncommon occasions such as sudden health complaints or accidents
	* category not found in the data

Combining the tendency to produce shorter notes on mobile devices and the expected nature of notes produced on mobile devices to the constant note making enabled by mobile devices, the data produced in the system utilising also the mobile devices might have less categories per note for both topical and PPS items. In other words, the notes are more likely to concern fewer topics per note, whereas on the whole they are expected to produce a more comprehensive set of data.

Hypothesis 6: Less topical categories are covered per note in mobile data than in non-mobile data.

Measure: Average number of topical categories per note

Hypothesis 7: Less PPS categories are covered per note in mobile data than in non-mobile data.

Measure: Average number of PPS categories per note

The third dimension measured is the timeliness of the information. Considering timeliness as an intrinsic quality, without relating it to any contextual perspective, rules out the commonly used approach of assessing data entry time stamps to set time limit (Weiskopf & Weng 2013). The study does not comment on whether the data is sufficiently timely for its purpose, but on the absolute time when the data has been entered into the system; thus the measure time of last update is adopted from the currency measures listed by Batini et al. (2009). Since the mobile devices can be carried about anywhere and the nurses are able to document the information on the spot instead of having to wait to document it on the desktop computer, it is hypothesised that the mobile data is produced earlier and thus timelier. If the notes are consistently documented earlier, the average input time of the notes will become earlier. In other words, the study aggregates all the note entry times and assesses the differences of these aggregate figures. The difficulty of mobile device data input could give reason to believe that the typing itself might take more time, but on the whole the effect of this is expected to be quite insignificant.

Hypothesis 8: Mobile data is produced earlier than non-mobile data.

Measure: Average time of day of data input

Finally, the study will address some measures of consistency. Weiskopf & Weng (2013) suggest measuring concordance, similar concept to consistency, by comparing values within and across systems to see if the same information has the same values or that the values make sense together. Also Batini et al. (2009) and Stvilia et al. (2007) list a similar measure. Since there are no elements measuring the same exact same object in the data, varying in time and topic, and since there is only one source of data, the study has to rely on other measures of consistency. Also syntactic and semantics measures popular in literature cannot be meaningfully used as such since the user input data elements do not have a strict structure for either and e.g. time and date are automatically created and presumed correct. However, the number of abbreviations can be understood as a syntactic factor, which in addition may affect the understandability of the data. Since the text production on mobile devices is more cumbersome, it could be that the mobile device users use shortened versions of words to reduce the typing effort.

Hypothesis 9: Mobile data contains more abbreviations than non-mobile data.

Measure: Average number of abbreviations per note

Another component of consistency is redundancy (Falge et al. 2011, Fisher & Kingma 2001, Todoran et al. 2015), meaning the duplication of information elements in the data. The thesis presumes that mobile devices are more prone to sending the note twice by accident due to the less precise finger navigation (Lugtig & Toepoel 2015), and thus more redundant notes are observed in the mobile data. Here, redundancy refers to either duplicate notes or empty notes.

Hypothesis 10: Mobile data contains more redundancy than non-mobile data.

Measure: Average number of duplicate values per day

Similarly, the number of submitted null values is considered to interfere with the consistency of the data. Using similar reasoning as for H10, the hypothesis is that mobile data will contain more empty notes.

Hypothesis 11: Mobile data contains more empty notes than non-mobile data.

Measure: Average number of empty values per day

The eleven hypotheses are collected to Table 8.

Table 8 Summary of hypotheses

Hypothesis #	Hypothesis (Measure)
H1	Mobile data contains more spelling inaccuracies than non-mobile data. (Average number of spelling errors per note)
H2	Mobile data contains more notes over the time period than non-mobile data. (Average number of notes produced per day)
H3	Mobile data notes contain less characters than non-mobile data. (Average characters per note)
H4	More PCP items are covered in mobile data than non-mobile data. (Average number of PCP items covered daily)
H5	Mobile data contains more notes related to physiological activities than non-mobile data. (Average count of physiological category notes per day)
H6	Less topical categories are covered per note in mobile data than in non-mobile data. (Average number of topical categories per note)
H7	Less PPS categories are covered per note in mobile data than in non-mobile data. (Average number of PPS categories per note)
H8	Mobile data is produced earlier than non-mobile data. (Average time of day of data input)
H9	Mobile data contains more abbreviations than non-mobile data. (Average number of abbreviations per note)
H10	Mobile data contains more redundancy than non-mobile data. (Average number of duplicate values per day)
H11	Mobile data contains more empty notes than non-mobile data. (Average number of null value notes per day)

The differences between the non-mobile dataset and the mobile dataset as a whole are assessed first to understand the differences between the old and the new system as a whole (H1-H11). In addition to the formal testing between the data produced solely on desktop computers and the data produced with both desktop computers and mobile devices, the differences between the new system desktop data and the new system mobile data will be assessed in a descriptive manner. In other words, the differences within the hybrid dataset produced with both desktop computers and mobile devices are examined. This subset of data does not lend itself to any formal statistical analysis since the nurses have had the freedom to produce the notes with either technology and at any time they prefer. Consequently the means and variances for the same measures are calculated within new system desktop data and new system mobile data. Also the distributions of categorical items within the two subsets of mobile data are examined. Additionally, descriptive figures for new system desktop data and new system mobile data can be compared to those of the non-mobile data set, which facilitates better understanding of the presence of other system related changes, such as different usability of the system, different attitudes towards the system, or different data collection culture induced by the new system.

7. Results

The results yielded by the analysis between non-mobile and mobile data are presented in Table 9 (covering H1-H4 and H8-H11) and Table 10 (covering H5-H7); the column non-mobile denotes the period prior to introduction of mobile devices, and mobile denotes the period incorporating mobile devices in data collection. The variances are in brackets and statistically significant differences at the 0.01 level are marked with an asterisk in the column on the left.

Table 9 Differences in data quality measures between non-mobile and mobile data

	Non-mobile	***Mobile***	***p-value***
Accuracy			
Spelling errors per note	0,08 (0,1)	0,09 (0,11)	0,3655
Total spelling errors	35	69	
Completeness			
*Notes per day**	13,52 (23,59)	24,65 (64,04)	0,0000
Characters per note	104 (12 034)	98 (8 397)	0,1407
*Characters per day**	1 410 (246 966)	2 404 (1 029 844)	0,0000
Total characters	43 723	74 534	
*PCP items covered per day**	13,61 (34,78)	21,68 (57,89)	0,0000
Timeliness			
*Time of input**	14:23 (1:29)	12:52 (1:28)	0,0000
Consistency			
*Abbreviations per note**	0,02 (0,02)	0,06 (0,08)	0,0003
Duplicate values per day	0,06 (0,06)	0,03 (0,03)	0,2809
Empty values per day	0 (0)	0,19 (0,29)	0,0282
Measures are **averages**, variance is in brackets, and statistically significant items at the 0.01 level are marked with an asterisk			

Table 10 Differences in categories between non-mobile and mobile data

	Non-mobile	**Mobile**	**p-value**
Topical categories			
*Bodily discharge**	1,84 (1,47)	4,39 (7,38)	0,0000
Cancelled task	0	0	-
Doctor	0,06 (0,06)	0,29 (0,41)	0,0379
Falls	0	0	-
General	2,1 (3,49)	2,58 (5,92)	0,1918
*Hygiene**	6,81 (11,43)	11,52 (21,12)	0,0000
*Measurements**	0,26 (0,33)	1,81 (4,03)	0,0001
Medication	2,23 (2,38)	3,19 (17,89)	0,1194
*Minor complaints**	2,81 (3,89)	5,45 (9,46)	0,0001
Moving	1,61 (2,58)	2,26 (2,13)	0,0516
*Nourishment**	3,68 (3,29)	5,55 (10,19)	0,0033
Psychosocial	3,32 (7,69)	4,61 (4,85)	0,0236
Recreational activity	1,23 (1,58)	1,65 (1,97)	0,1101
Relatives and friends	1,39 (1,11)	0,94 (1,2)	0,0515
Reminder	0	0	-
*Sleeping**	3 (3,2)	5,58 (12,78)	0,0004
Special circumstances	0,13 (0,12)	0,03 (0,03)	0,0844
*Categories per note**	2,25 (1,1)	2,02 (1,04)	0,0001
PPS categories			
*Physiology related**	12,03 (15,63)	22,68 (55,63)	0,0000
Psychology related	4,26 (9,66)	5,42 (5,18)	0,0495
Social related	3,39 (7,71)	3,45 (3,06)	0,4566
*Categories per note**	1,49 (0,47)	1,31 (0,35)	0,0000

Measures are **averages**, variance is in brackets, and statistically significant items at the 0.01 level are marked with an asterisk

The number of spelling errors per note (H1) is similar in both the non-mobile and mobile data. Additionally, few spelling errors were present in the data in the first place, on average approximately one per every ten notes. Thus the first hypothesis is rejected; this is also confirmed by Figure 11, the box plot of the number of spelling errors per note, where not much difference can be observed between the two time periods. The box of the box plot has been flattened to a line near the zero line, and the observed spelling errors are shown as outlier dots. The results support the notion that nurses are careful in documenting patient data, even when making non-numerical notes.

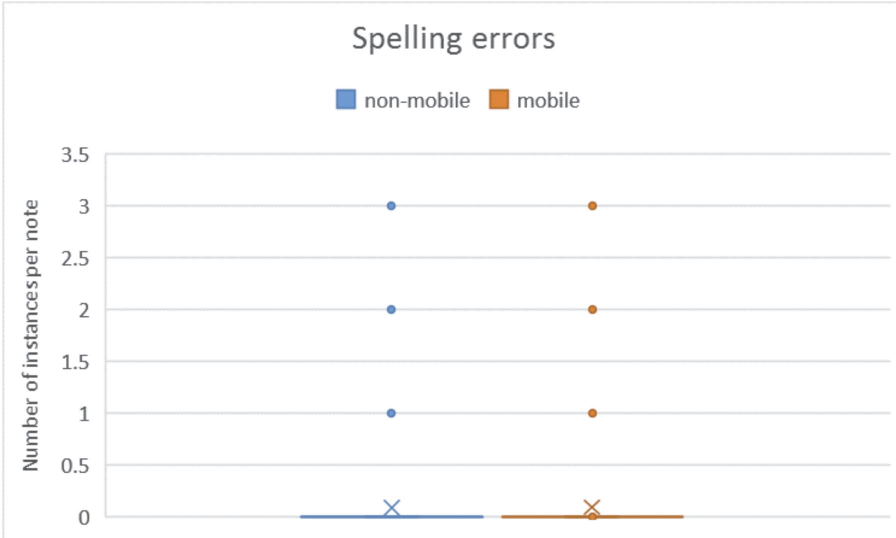

Figure 11 Box plot of spelling errors per note

The number of daily notes (H2) shows a very significant difference (<0,001) between the data; in the non-mobile dataset there were on average 13.5 notes, where as in the mobile data there were 24.7. Also the box plot (Figure 12) shows a clear shift in the numbers produced; not only have the average and the median shifted, but also the bulk of observations is more numerous in the mobile period. It seems that the new system indeed produces more notes, and consequently also significantly more characters per day (1410 VS 2404), as illustrated by the box plot (Figure 13). Moreover, the length of the notes (H3) is on average slightly shorter (104 VS 98) as was hypothesised, but the difference is not significant; the variances are quite high. Assessing the box plot (Figure 14), it can be seen that the limit of the fourth quartile is slightly lower, but that there are nevertheless many unusually long notes in both data. The hypothesis is thus rejected.

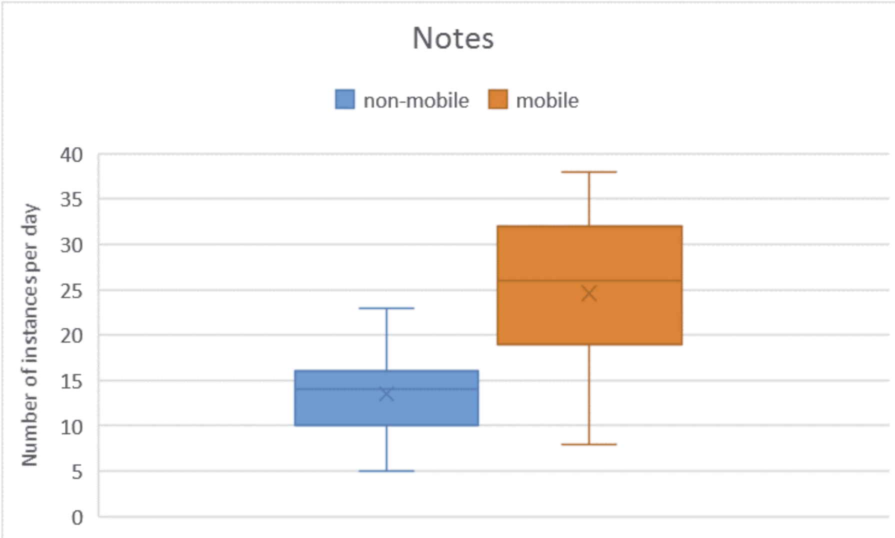

Figure 12 Box plot of notes per day

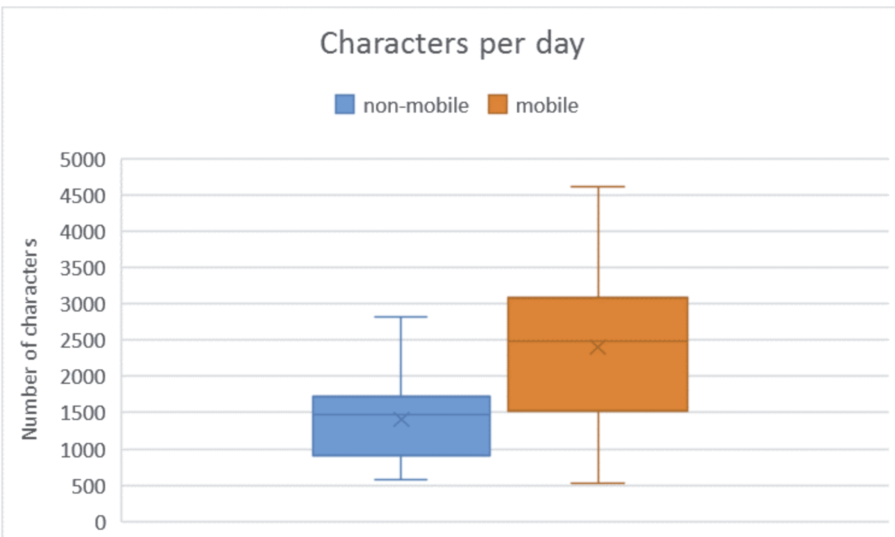

Figure 13 Box plot of characters per day

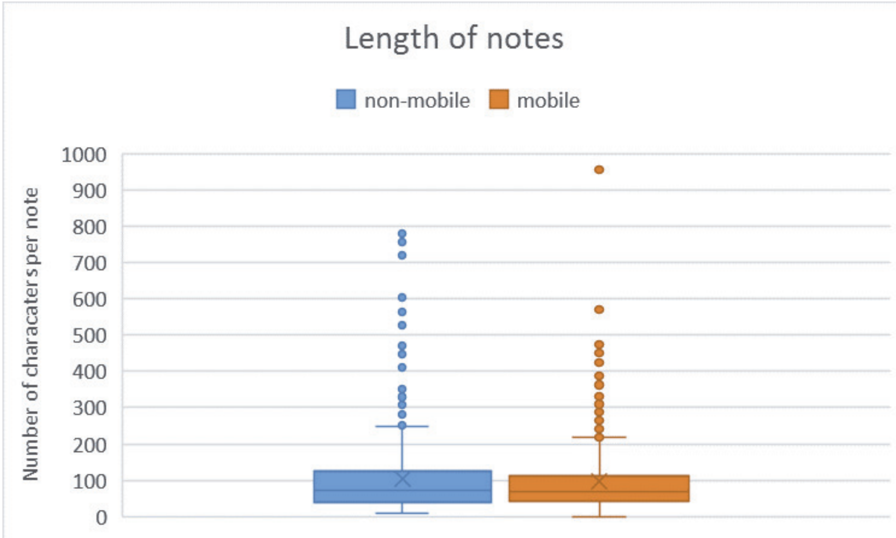

Figure 14 Box plot of characters per note

On the content side of the completeness analysis, the results point towards increased content collected. The daily PCP items covered (H4) also shows significant increase (p-value <0.00005) in the latter data, with on average eight more items covered per day (Figure 15). Support is also found for H5, the increase in physiology-related notes; the box plot (Figure 16) shows radical increase in notes related to physiology However, the topical categorisations only provide partial support; as expected, notes related to bodily discharge, hygiene, measurements, minor complaints, nourishment, and sleeping show significant increase (Figure 17). Due to their similar nature, medication and moving were also expected to show increase in the mobile system, but while there was an increase for both, it was not significant. Category psychosocial is very close to showing significant increase with p-value of 0.02, which is similar to the PPS category psychology related notes. The psychology related notes also show some increase and the observed difference would be significant on 0.05 significance level (p-value 0.0495). However, the box plots for both psychology items do not show tremendous difference. Moreover, all categories except for the non-present categories and relatives and friends and special circumstances show added volume on the whole over the observed periods. However, changing the perspective from daily figures to categories per note, it can be observed that per note there are in fact significantly less categories assigned. Thus H6 and H7 also receive support.

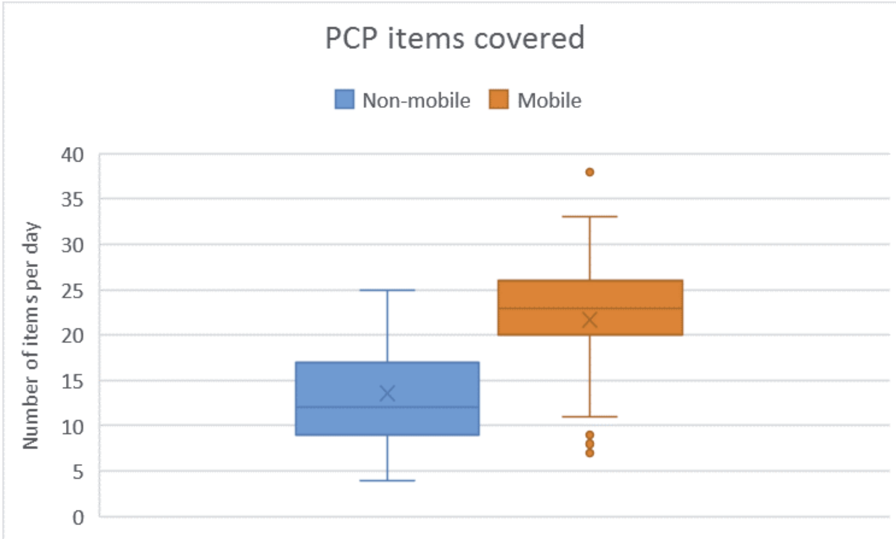

Figure 15 Box plot of PCP items covered per day

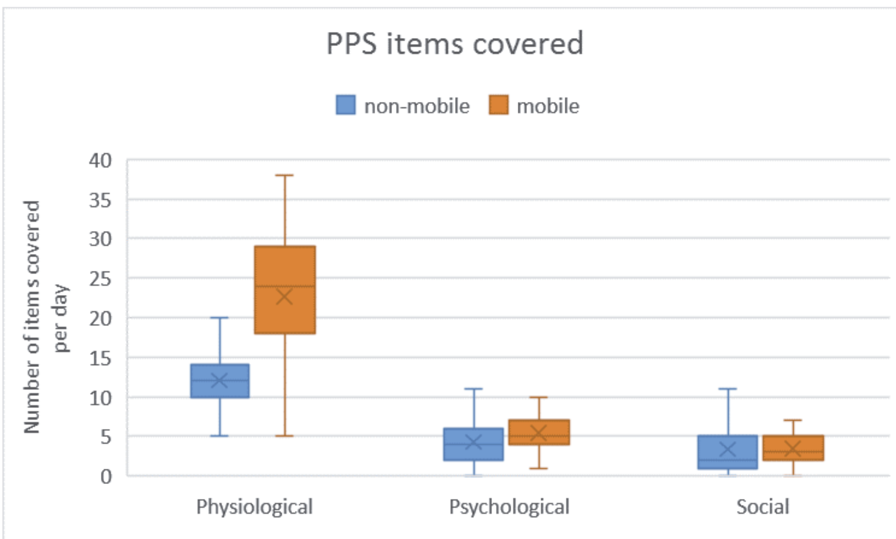

Figure 16 Box plot of PPS items covered per day

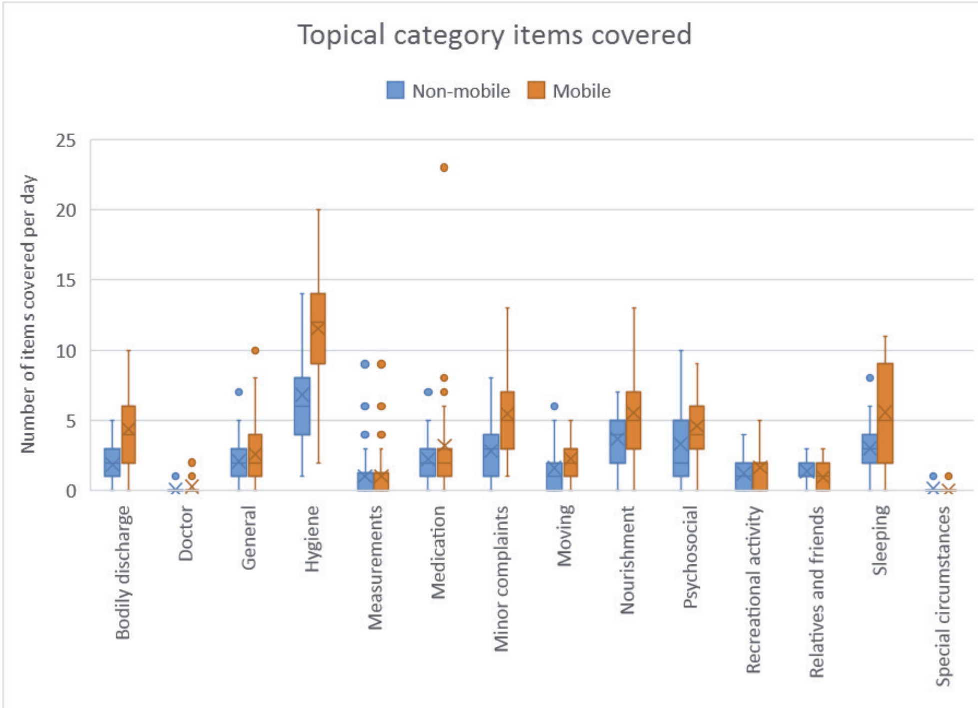

Figure 17 Box plot of topical category items covered per day

Regarding H8, the mobile data has been documented into the system significantly earlier than the non-mobile. However, the box plot in Figure 18 does not show such drastic difference in the grand scheme of things; the bulk of the observations within the second and the third quartiles are on quite similar levels, even though the mean and the median in the mobile set are earlier. The compression of 24 hours into the y axis has to be taken into account, though; it could have a belittling effect on the difference.

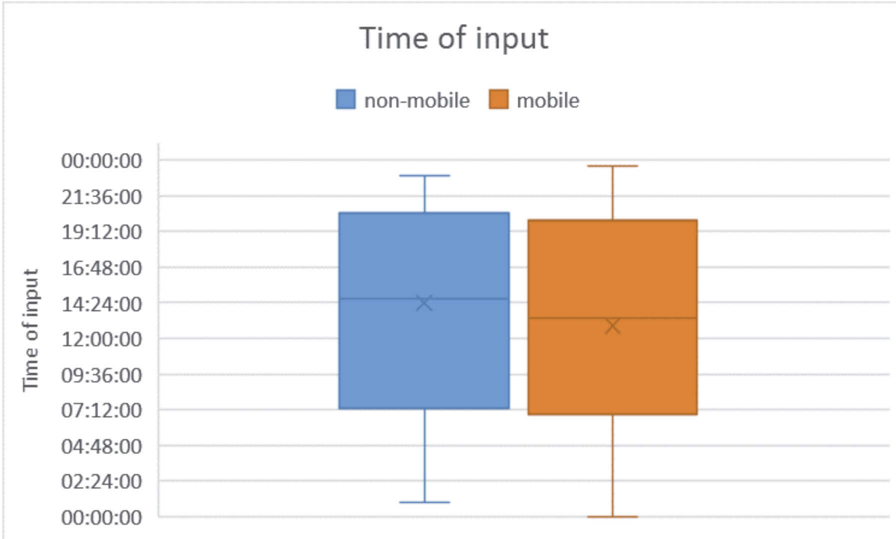

Figure 18 Box plot of times of input

Of the consistency measures, abbreviations, duplicate values, and empty values (H9, H10, and H11), only abbreviations shows statistically significant increase. Also the number of empty values has increased, and the difference would be significant on a 0.05 significance level (p-value 0.03). However, considering the box plots (Figure 19 and Figure 20), it seems that there is no detectable change visible. Regarding abbreviations, it seems that all the occurrences are, in fact, atypical values outside the bulk of observations. Similarly to Figure 11, the boxes of the plots have flattened to lines on the zero level. Also the number of duplicate and empty values is very small. It seems that the difficulty of operating on-screen keyboard on the smaller screen might induce abbreviations, whereas the allegedly difficult navigation of mobile device does not result in accidental empty notes or double entries.

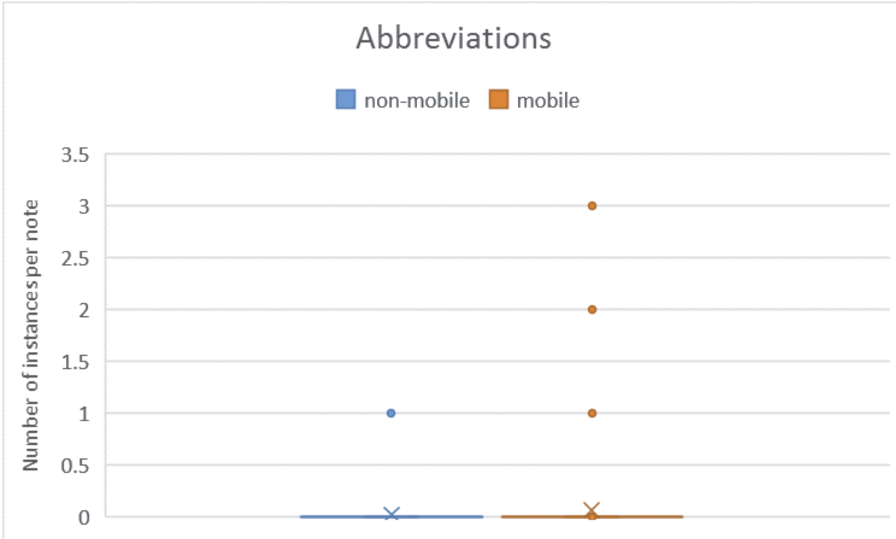

Figure 19 Box plot of abbreviations

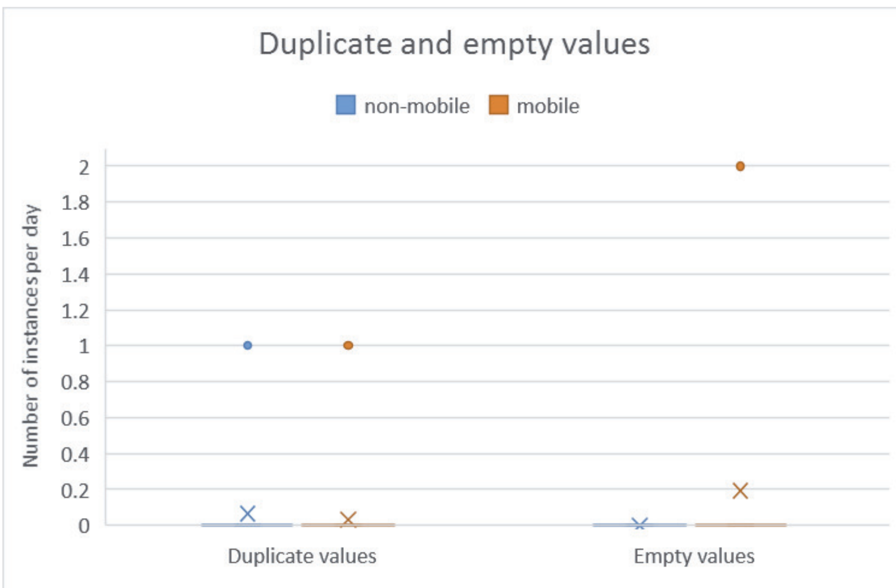

Figure 20 Box plot of duplicate and empty values

The results of the hypotheses testing are collected to Table 11.

Table 11 Summary of the results of hypotheses testing

Hypothesis #	Hypothesis (Measure)
H1	Mobile data contains more spelling inaccuracies than non-mobile data. *Rejected at 0.01 significance level*
H2	Mobile data contains more notes over the time period than non-mobile data. *Supported at 0.01 significance level*
H3	Mobile data notes contain less characters than non-mobile data. *Rejected at 0.01 significance level*
H4	More PCP items are covered in mobile data than non-mobile data. *Supported at 0.01 significance level*
H5	Mobile data contains more notes related to physiological activities than non-mobile data. *Partially supported at 0.01 significance level*
H6	Less topical categories are covered per note in mobile data than in non-mobile data. *Supported at 0.01 significance level*
H7	Less PPS categories are covered per note in mobile data than in non-mobile data. *Supported at 0.01 significance level*
H8	Mobile data is produced earlier than non-mobile data. *Supported at 0.01 significance level*
H9	Mobile data contains more abbreviations than non-mobile data. *Supported at 0.01 significance level*
H10	Mobile data contains more redundancy than non-mobile data. *Rejected at 0.01 significance level*
H11	Mobile data contains more empty notes than non-mobile data. *Rejected at 0.01 significance level (supported at 0.05 significance level)*

The results presented above are the differences between the full sample datasets and capture the difference between a desktop-only system and mobile and desktop in parallel system. To shed further light on the possible effect of the system as well as to characterise data produced on mobile devices alone, the following descriptive statistics were created within the mobile dataset between the new system desktop data and new system mobile data. The averages and variances were calculated separately for the new system desktop and new system mobile data (Table 12).

Interestingly, the mobile notes have more spelling mistakes per note, lending support to the hypothesis regarding higher numbers of spelling errors produced by mobile devices, even though the hypothesis was rejected for the parallel device data. There are also on average ten percent less characters in mobile device produced notes, suggesting that mobile devices might actually produce shorter notes, or the users might choose the devices for notes that are shorter.

Table 12 Descriptive statistics for new system desktop and new system mobile data

	New system desktop	New system mobile
Accuracy		
Spelling errors per note	0,07 (0,08)	0,12 (0,17)
Total spelling errors	37	32
Completeness		
Notes per day	16,23 (63,51)	8,42 (69,52)
Total notes	503	261
Total days covered	31	31
Characters per note	101 (9 283)	91 (6 655)
Characters per day	1 638 (954 081)	767 (677 148)
Total characters	50 770	23 764
PCP items covered per day	13,74 (77,93)	7,94 (64,33)
Timeliness		
Time of input	12:48 (1:31)	12:58 (1:21)
Consistency		
Abbreviations per day	0,06 (0,07)	0,07 (0,09)
Duplicate values per day	0 (0)	0,03 (0,03)
Empty values per day	0,13 (0,18)	0,06 (0,06)

Measures are **averages** and variance is in brackets.

Curiously, the mobile devices seem not to produce timelier notes than the desktop computers, but on the contrary the time of input is slightly later for mobile devices. This seems to point toward the more timely information in the new system stemming from factors outside the technology itself, such as change in the system, changes in the process, or changes in attitudes. Other changes are further supported by the notion that even if the mobile device produced notes are excluded, the new system has produced 503 desktop notes compared to 419 notes in the old system data; the amount of notes produced on desktop only has increased. The consistency measures look quite similar for both technologies, and they seem quite rare altogether. One noteworthy remark is that the desktop data has, in fact, more empty values than the mobile data, which indicates that the assumption of more accidental touches and submissions in mobile data seems false.

Table 13 Distribution categories in the new system desktop and new system mobile data

	new system desktop		new system mobile	
	#	%	#	%
Topical categories				
Bodily discharge	96	9,6	40	7,4
Cancelled task	0	0,0	0	0,0
Doctor	9	0,9	0	0,0
Falls	0	0,0	0	0,0
General	49	4,9	31	5,7
Hygiene	199	19,8	158	29,2
Measurements	51	5,1	5	0,9
Medication	85	8,5	14	2,6
Minor complaints	110	11,0	59	10,9
Moving	39	3,9	31	5,7
Nourishment	93	9,3	79	14,6
Psychosocial	113	11,3	30	5,5
Recreational activity	32	3,2	19	3,5
Relatives and friends	22	2,2	7	1,3
Reminder	0	0,0	0	0,0
Sleeping	104	10,4	69	12,7
Special circumstances	1	0,1	0	0,0
Categories per note	2,0		2,1	
PPS categories				
Physiology related	458	68,0	245	80,6
Psychology related	127	18,8	41	13,5
Social related	89	13,2	18	5,9
Categories per note	1,3		1,2	

*Measures in the left-side column are **counts of category items** in the data and in the right-side column frequencies in percent, except for the categories per note measures which are averages.*

Moreover, the contents of the new system data are described in Table 13 and in the corresponding Figure 21 and Figure 22. They show the proportion of notes that discuss the category; it should be noted that one note can contain multiple categories. It should be noted that contrary to previous results tables, the measures are not averages but full counts of items in the data and derived percentagewise frequencies, with the exception of categories per note measure which are averages.

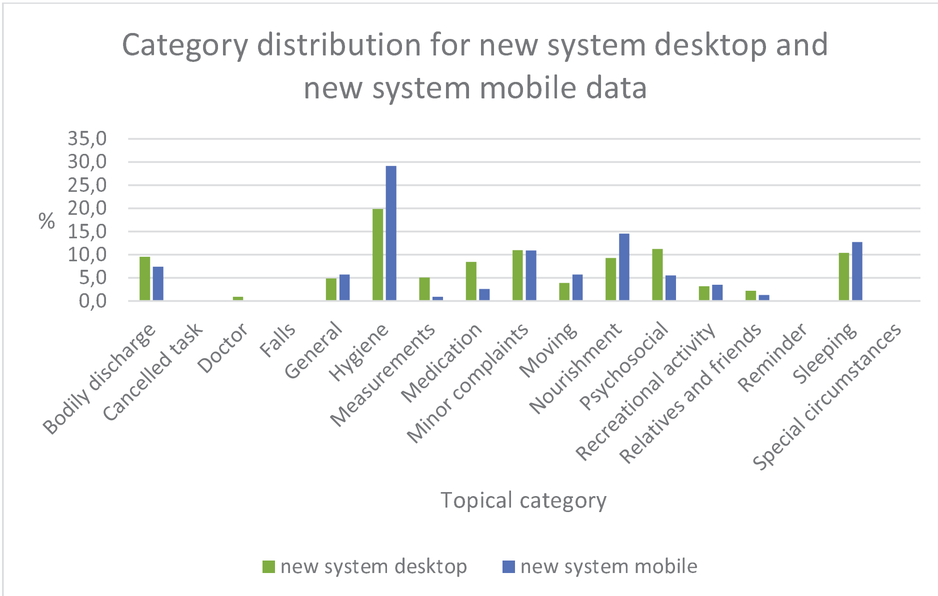

Figure 21 Distribution of topical categories in the new system desktop and mobile data

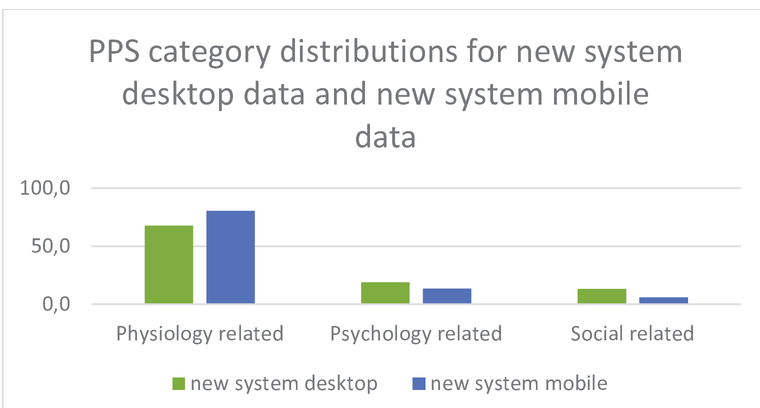

Figure 22 Distribution of PPS categories in the new system desktop and mobile data

Percentage-wise, these confirm that mobile devices are used in particular for hygiene, moving, nourishment, and sleeping, whereas rather surprisingly desktop computers are used proportionally more for bodily discharge, doctor, measurements, medication, psychosocial, and relatives and friends. The physical items bodily discharge, measurements, and medication in particular differ from the hypothesis of mobile devices use for documenting of physical, recurring items. Perhaps the notes relating to doctor, measurements, and mediation are always handled in the office where a desktop computer is readily available; information regarding doctor and medication is likely received in the office setting via computer or on the phone, and the equipment needed to produce measurements like blood pressure and weight might reside next to a desktop computer. It could also be that the categories psychosocial and relatives and friends might require more free form specification, leading to preference for desktop computers. However, considering the PPS categories, it seems that proportionally considerably more mobile device produced notes are in relation to physical notes. The number of categories covered per note seem similar to both technologies suggesting that the mobile device interface does not seem to induce change in this area as expected. It should also be noted that mobile devices seem to be used less for social related categories as well as for topical categories doctor, measurements, medication, and psychosocial.

8. Discussion

The introduction of mobile devices to the information collection process in a Finnish elderly care facility seems to have some significant positive implications on the quality of information, despite the contradictory mechanisms through which mobile devices could affect the information collection. This section starts by discussing the results and their implications in the light of earlier literature and summarising the key insights first for theory and then for management. Finally, the section assesses the limitations of the study and outlines avenues for further research.

8.1. Theoretical implications

The effect of mobile devices on information collection is discussed in the frame set by the hypotheses, starting with accuracy and then proceeding to completeness, timeliness, and consistency. Also the validity of the identified mechanisms is examined in the light of the empirical results, and the implications of these on theory and practice are drawn.

Accuracy

Starting with the accuracy dimension, the measure of accuracy used found no difference between the data, which is contrary to the assumption of more errors due to mobile device input difficulty. However, assessing the differences within the dataset produced with both mobile and PCs, the mobile devices did produce more spelling errors, even though there were altogether rather few spelling errors. The finding of no significant difference between the datasets is in accordance with the assumption that nurses take great care of supplying the right message and values on e.g. vitals and medication dosages in their notes. Also looking at the differences in topical categories in the new system data between the desktop and mobile produced notes, it is observed that mobile devices are used particularly little for notes regarding doctor, measurements, and medication; it could be that the nurses avoid using mobile devices for this kind of particularly accuracy sensitive data precisely due to the increased possibility of error. These results cannot as such be extrapolated to apply for wider mobile device use; with a user-base less committed to error-free data the problem might be different, as the high mobile device typing error rates observed by Reyal et al. (2015) suggest. Mobile device users for information collection in, say, warehouses, might not be as careful as slight errors do not have as dire consequences.

The study recognises the narrow view of accuracy given by using only spelling errors as a measure. Consequently, the study refrains from making extensive conclusion about the mobile devices' effect on accuracy, only noting that in these circumstances the presumed difficulty of text production with mobile devices did not show in the spelling errors. Additionally, the study agrees with literature (e.g. Fisher & Kingma 2001, Laine & Lee 2015, Michnik & Lo 2009) about the great importance of the accuracy dimension and encourages further investigation of the dimension in relation to mobile devices. Ideas for research are presented in 8.4 Further research.

Completeness

Perhaps the most exciting findings of the study are with regard to completeness, where the most striking difference is the sheer volume of notes. In the system with mobile devices and desktop computers in parallel use, 80 percent more notes and 70 percent more characters were produced in comparison to desktop computer only system. This magnitude of increase suggests radical improvement in completeness, which is in harmony with the study of Mickan et al. (2013). These are, however, not alone attributable to mobile device use, since during the sample period approximately a third of the notes were produced with a mobile device and the rest with a desktop system. Comparing only the desktop notes between the two periods, the new system has produced approximately 20% more notes. It seems that along the introduction of the mobile technology some other change has taken place; perhaps the system is overall more usable, or perhaps the new system has been received as a signal from management about the importance of thorough note making, alike to what Ficek (2014) suggests. Nevertheless, the organisation feels that the two systems are quite similar, and the considerable number of notes also hints towards the anticipated usefulness of having the mobile device handy. Similar to International Data Group (2012) noticing reduced need for laptops due to tablets, it seems that mobile devices can aid in the data collection.

Moreover, the third hypothesis anticipated that including mobile devices in information collection would lead to shorter notes. Between the two full samples no statistically significant difference was observed, even though the average length of note reduced from 104 to 98. Moreover, average length reduced from 101 to 91 between the new system desktop and mobile sets. No definitive answer is found, but it can be concluded that the data points towards shorter notes from mobile devices, which would be logical considering the difficulty and slowness of mobile entry (Odell 2015). Additionally, in the analysis of mobile device produced notes the full text of the note is included, even though currently also the category is written within the note, possibly causing some repetition and adding to the number of characters (i.e. 'GETTING DRESSED: Getting dressed (aided)'). While only a third of the mobile device produced notes utilised this type of symbol documentation, the repetition means that the length of content only in mobile notes is in fact slightly shorter than 91 characters on average.

Compared to the approximately 35 percent reduction in the length of open answers observed by Mavletova (2013), the shortening effect of mobile device use on the length of documentation seems more modest. However, there are some fundamental differences between the setting of this study and the survey responses studied by Mavletova (2013), which mean that those results are not expected to be observed in this study as such. The studies of Mavletova (2013) as well as those of Lugtig & Toepoel (2015) and Struminskaya et al. (2015) consider the effect of mobile devices on the quality of answers in surveys, and consequently the motivation of the text producers is quite different. In work-related information capture the data collector is bound by duty and the documenter presumably feels a strong sense of purpose, which shows as more diligent documentation. Meanwhile, survey respondents do not have the same commitment to filling in the data, likely not on personal nor on any other level of responsibility, since the answers are anonymised and the answerer will not be held responsible. Even though this difference is likely to alter the results noticeably, these studies provide interesting references for comparison.

Like Sessions & Havens (2012) encourage, the mobile system does utilise design for touch and allows choosing options through symbol interface, easing the difficulty of mobile device facilitated documentation. However, during the study period the symbol note feature was not used very actively; this might be due to the relative newness of the system, but hints that the positive impact on information quality might increase as this feature becomes more widely used and the strengths of the mobile interface more comprehensively harnessed. Positive effects from the learning curve are likely to show here strongly.

One of the aims of the study was to assess whether the richness of the information would suffer, drawing on the thought that the difficulty of capturing information might lead to flattened content. Also the measures aiming to capture this qualitative richness and completeness of the notes show enhanced information quality with introduction on mobile devices, despite some evidence from the literature finding contrary evidence (Lugtig & Toepoel 2015, Mavletova 2013, Struminskaya et al. 2015). The number of average PCP items covered per day increased significantly, from 13.6 to 21.7 notes per day. On average, 13.7 of the 21.7 came from desktop notes, and 7.9 from mobile devices. In the case facility, the care plans were not yet programmed to show the daily items for each patient, but this was still waiting for implementation. Utilising the presence of the mobile device in this way would not only aid the nurses in directing their work and ensuring covering of all care plan items, but it also enables easy documentation with the ready-made symbol interface. Observing the effect of this kind of guided information collection would be interesting, and might have considerable effects on the completeness of information in healthcare as well as other industries.

In addition to the PCP items, topical and PPS categorisations were used to measure the richness of the collected data. In both categorisations, all items except relatives and friends and special circumstances showed increased frequencies, with a number of items showing statistically significant differences; also these support the hypothesised richer data collection. The increased completeness is in line with the findings of VanDenKerkhof (2003). What is, however, noteworthy, is that for both categorical measures there are significantly less categories recorded per note, telling that the individual completeness of each note has in fact decreased. While it seems that the new system encourages more robust information capture overall, the information content is distributed over a larger quantity of notes. This hints towards dividing the collected information into more granular pieces, which could be interpreted as a step towards more structured information and e.g. automated reports. It is also in concordance with the case organisation reporting observations of documenting the information in smaller pieces along the day, as opposed to the pre-mobile practice of entering large amounts of information at once.

The significant increases in the amount of categorisations only partially followed the hypothesis of physical items having stronger presence in the new system data. Between the desktop only data and desktop and mobile data, there was a significant increase in the PPS category physiology related notes, from 12 to almost 22.7 items daily. Moreover, in the new system 68 percent of desktop produced notes covered physiological aspects, while for new system mobile notes the same figure is 80.6 percent; it seems that mobile devices indeed are useful for capturing these recurring, mobility-requiring items. Similarly, mobile device produced notes seem to have particularly little social-related notes. Considering the individual topical categories, the results are not as straightforward to interpret. The statistically significantly increased topical items were in the hypothesised set, but some of the expected items like medication and moving showed no significant difference. Moreover, within the system with both mobile and PC technology, only categories hygiene, nourishment, and sleeping were proportionately more pronounced. For instance bodily discharge was expected to be present in this category because the identified mobile device characteristics support it well.

While there are no obvious common denominators or differentiators to explain all observed preferences, one explanation could be that the three categories mobile devices are particularly used for require less additional information, thus making them more suitable for mobile documentation. In addition, there is the possibility of nurses preferring desktop computers for accuracy-sensitive notes as speculated before. Alternatively, the physical related items measurements and medication might not be produced on the go but in circumstances where a desktop computer is readily available. The measurements like blood pressure and weight need equipment which might be located next to a desktop computer, and updates to medication are likely to be received via desktop computer or by phone close to a work station with a desktop computer.

The increased content can primarily be understood as a positive development, and upon employing the new system the case organisation was hoping that it would aid in producing more complete documentation. In this sense, the system with mobile devices has fulfilled its purpose. However, the implications of more documentation should also be considered with regard to efficiency. A key question is the effect of the mobile device on the time and effort spent on the recording; do the users find the mobile device an effortless way to record data, and what is the efficiency effect - how long does the recording take in comparison to purely PC-based systems. This process efficiency is of utmost interest for business entities, in addition to which in this setting less time spent taking notes contributes towards the holy grail of care industry, nurses' ability to spend more time on the direct care instead of administrative or other supportive work. This kind of efficiency gains and reduced administrative burden are naturally extremely desirable across industries.

The case organisation reports that the mobile information collection is perceived as a faster option among the nurses, which implies improvement also in this area. However, no rigorous study was conducted to support this. The works of Mavletova (2013), Struminskaya et al. (2015), and Wetzlinger et al. (2014) point in the opposite direction, towards slower input times when comparing PCs and mobile devices directly, but they do not account for the effect of high mobility environments and the consequent inconvenience of locating a PC and keeping the data in memory or on a paper for the intermediate time. While Gann et al. (2014) conclude mixed results from healthcare mobile device studies with regard to effects on workflow, the recent studies such as Crowson et al. (2016), Fleischmann et al. (2015), Mickan et al. (2013), and Schooley et al. (2016) find evidence supporting enhanced workflows. Also Beaulieu (2013) supports this, stating that considerable improvements to workflow are achieved when mobile devices can be used for data input in addition to its retrieval. The findings by Gann et al. (2014) could be explained by the studies assessing earlier generations of mobile devices, which did not have all the usability features of the modern mobile devices. The evidence from the case organisation suggests that in addition to enhanced completeness, the time spent taking notes did not increase but possibly decreased, rejecting the anticipated quality – time spent trade-off. However, the perceptual and non-quantitative nature of the efficiency observation is emphasised.

In addition to possible temporal benefit in note making, the use of mobile devices could also be preferred by the users. For a modern person, using mobile devices and especially smartphones comes naturally, in addition to which Wetzlinger et al. (2014) and Ozok et al. (2008) claim that this technology has a certain "fun factor". It is however, not clear how long this effect lasts and whether it is permanent enough to be considered an actual benefit. Similarly to what Kaka et al. (2015) observed, the case organisation notes eagerness to use mobile devices seems to depend on the age and the digital proficiency. The younger staff members adopt the use of devices eagerly, where as in general the older age group of nurses use desktop computers more.

Timeliness

The timeliness measure yielded unexpected results; while the grand difference between the non-mobile and mobile dataset was significant and approximately one and a half hours in difference, examining the new system datasets reveals that both desktop and mobile produced notes have experienced this difference. Also this points towards a change in the note taking habits induced by the new system and its implications. The case organisation has noticed a shift to more notes made over the course of the day, which they notice helps with the mental load; the events of the day can be documented as they happen, instead of having to keep them in memory until the moment of documentation at the end of the shift. This also contributes towards more complete information, as it is not forgotten or lost (Adiguzel 2010). Documenting along the day also helps to reduce the administrative burden from end of the shift, which is likely perceived positively by the nurses. This is well in line with the benefits of information collection at the source found from the literature.

Outside the setting of the study, an important benefit from the enhanced timeliness would be the instant information sharing between collaborators and thus smoother processes with less waiting (Lutes et al. 2012). In healthcare, the timelier information input might be very valuable for instance in a busy emergency room environment, where an ambulance on the way to the hospital would be able to brief the hospital on the status of the incoming patient. Moreover, in geographically distributed operations direct input of information into the system streamlines the operation (Tang & Carpendale 2008). Nevertheless, in this particular setting it seems that the timeliness of the information itself is not a very valuable dimension as the information usually is not instantly needed by anyone else. Here timeliness is rather a by-product of more frequent documentation, which mainly produces more complete information and reduces the nurses' mental burden.

Consistency

While the hypotheses expected the consistency to reduce in mobile data, only significant change was found in the measure of abbreviations. What is more, the abbreviations seem to reside equally in the new system desktop data and the new system mobile data, suggesting that the mobile device use does not harm consistency. The information quality implications of increased use of abbreviations can further be questioned; while abbreviations could make understanding the text could become more difficult, among professionals sharing the same trade-related lingo they are unlikely to cause issues. The empty values were very close to significant at the 0.01 significance level, and would have been significant on 0.05 significance level. Increased empty values would point towards reduced data quality in consistency, but the number of observations of empty values is so small, one in five days, that it further undermines confidence it the difference. The comparison of the parallel device data also shows that the empty values are produced with both desktop computers and mobile devices.

In these circumstances the benefits of mobile devices experienced by Ficek (2014) and Kaka et al. (2015) and suggested by Sessions and Havens (2012) in guiding in the data input and forcing the collection of certain fields are not relevant as the process is designed to be very simple and it does not have a number of fields to fill. Moreover, in certain circumstances the forms enforced by the interface might be very helpful in obtaining the right format data, and the desired categorisation may be aided with prepared categories. The entry support provided by mobile devices could also aid in structuring the data (Mendes & Rodrigues 2011), which enables aggregative, automated statistics to be produced giving enhanced view to the wellbeing and health status as well as timely reactions to abnormalities. In an open-formatted note system these reactions are more tied to the nurses' alertness. Structure is not, of course, solely tied to mobile devices and can certainly be implemented on a PC also; however, the mobile interface supports symbols notes and provides a natural platform to execute more structured notes.

Mobile device mechanisms of affecting information quality

The empirical study also enables validation of the mechanisms regarding how use of mobile devices might affect information quality in comparison to PCs. First, the positive effect of capturing data directly at the source is supported by the evidence with regard to completeness and timeliness, in addition to which the organisation has noticed improvements in both. The effect on accuracy in the sense that the data would be more correct could not be evaluated in this study. The logical reasoning behind the benefits of capturing the data at the source is quite strong, which points towards the finding being generalizable. However, the empirical testing of the mechanism is still very limited, and also due to the diligence in producing accurate notes in healthcare, this finding should not be generalized without great caution.

Moreover, the mobile interface did not yet employ many entry support features, and consequently the mechanism cannot be comprehensively evaluated. Having said that, the mobile interface still shows possible items to be collected and provides opportunity to categorise with the symbol interface. The more complete information could be interpreted as supportive of the existence of the mechanism, and also the categories provided in the symbols were used for a third of the notes, providing more structured entries. Thirdly, the effects of the difficult input are chiefly rejected; the mobile devices do not seem to induce more accidental presses in form of spelling errors, empty values, or duplicates or curb the willingness to write with mobile devices. There were more abbreviations in the data produced with both mobile devices and desktop computers, but the increase was not attributable to mobile devices. The shortened notes and use for standard, recurring items received partial support.

Theoretical contributions

All in all, the study finds interesting results for mobile device use within high mobility environment information collection, building the study on an amalgam framework merged from cross-disciplinary sources. The mechanisms fused from information quality and mobile device literature receive partial support from the empirical evidence, and these mechanisms and the ideas behind them can be utilised in further studies to better understand the mobile device information collection. Moreover, the study builds a custom set of measures, suitable for intrinsic data assessment and testing for the anticipated changes provoked by mobile device use. These measures are also adaptable for future studies, enrichening the body of available information quality measures.

Moreover, the study also contributes to theory by executing an analysis based on these measures on a live field dataset. The analysis evaluates the information quality changes in an inpatient setting, seizing the opportunity to gain data from a transition from PC documentation only to inclusion of mobile devices. The measures, mechanisms, and results are pioneering in their own niche within the discipline of information quality research, contributing towards tools and understanding of the constantly evolving technology used to produce, store, manipulate, and utilise information. On a societal level, contributions towards finding and validating means of producing better quality information have their effect in our world powered by data, also this study contributing in its miniscule scale towards better information and better decisions. On a more concrete level, the improved information quality achieved by involving mobile devices in data collection could for example be utilised to produce better patient care in healthcare.

8.2. Managerial implications

From practical perspective, the evidence supports the notion that mobile devices are useful for information capture in high-mobility environments; the information quality experienced some remarkable enhancements, while the suspected negative effects of the devices did not manifest in data except for slightly elevated number of abbreviations. Thus no major disadvantages for parallel mobile device use were detected in this study. Seizing the opportunity to improve the information quality right at the impactful point of data entry, the mobile devices seem to be able to contribute towards enhanced information quality and reduced costs stemming from low quality information. In particular, the mobile devices have a positive effect on the completeness of information, and thus the study recommends them for circumstances where rich information needs to be collected.

The thesis also aimed to produce a recommendation about the kind of information that would particularly benefit from the mobile device utilisation, but unfortunately the results do not warrant a firm recommendation. While the literature suggests more difficulty in text entry with mobile devices and encourages use of non-typing entries, the hypothesis of recurring, standard items without need for extensive specifications only received partial support. Within one categorisation support was found, but within the other the results were mixed. On one hand, the areas where there was significant increase did suit this description and the categories with (statistically non-significant) reductions had opposite characteristics, but on the other hand all the categories with these characteristics did not experience significant increases in frequencies. Based on these findings it seems that the mobile devices are used for documentation benefiting from the mobility, but there are clearly other influential factors yet to be discovered.

The study shows that high mobility environments seem to benefit from this kind of technology. Considering the range of high mobility environments, the results are most likely generalizable within healthcare since the study was conducted within healthcare and since mobile device characteristics seem to support features typical to healthcare; the care delivery in healthcare is inherently mobile and improving quality of care and reducing errors are central targets of information technology (Mendes & Rodrigues 2011, Prgomet et al. 2009). Furthermore, the importance of a sufficiently high quality data cannot be overstated with respect to other technological trends within healthcare such as the decision support systems; no decision support system can function optimally if the source data it uses is e.g. outdated, incorrect or if there are important values missing.

It should be noted that in this study only the implications of mobile devices on the inherent data quality are discussed. Already there the effect on data collection seems convincing, but outside information quality there are a number of other benefits supporting the utility of mobile devices. For instance, within healthcare the availability of patient information and guidance and other medical resources anywhere is found a considerable benefit (Beaulieu 2013, Gann et al. 2014, Lehnbom 2014, Mickan et al. 2013, Stephens et al. 2010). The devices can also be utilised to discuss medical information with patients (Fleischmann et al. 2015), and in the case organisation the mobile device system also functions as a work management tool, optimising the task division between nurses in real time. Data collection for clinical research is also another application of interest (Abernethy et al. 2008), and Prgomet et al. (2009) suggest mobile devices might alleviate the issue of inadequate number of desktop computers for information input. Schooley et al. (2016) also observe patients' enhanced perception of the provider due to the use of modern technology. Combining these uses of mobile devices to the positive effects it seems to have on information quality, the study recommends use of mobile devices for human-mediated information collection. The thesis does not discuss the costs of implementation, only denotes without disclosing any exact figures that the organisation describes them as reasonable. The mobile devices used did not have to be from the more expensive end of the range, and the system costs did not undergo a large change. Of course the cost of implementation including also time and effort has to be included in the expenses but all in all, the required investment was not tremendously large.

8.3. Limitations

The study is not without limitations. First of all, studying the phenomenon through field data means that the study was conducted at a single institution, over a limited time period, and in one setting only. The study also assumes the setup of the study, acquiring notes of the same set of residents before and after a new system, neutralises the effect of the facility, the resident, and nurses, leading to independent observations. Nevertheless, strictly speaking the observations are very unlikely to be perfectly independent, and these interrelations, regardless of the measures taken to mitigate them, might affect the obtained results. Additionally, the mobile dataset is from very early on in the system adoption, and the system might not yet be in full use and the learning curve could alter the results. However, temporal proximity of the two time periods is of utmost importance to minimise external factors affecting the observations.

Also the source of the data poses some limitations to the generalisability of the results. The setup from which the data of the thesis was acquired is a residential care unit which emphasises personal touch in the care and aims to have assigned nurses to each patient, so that the nurses would know the patient and could develop a relationship to the resident. This kind of personal familiarity de-emphasises the importance of data for these nurses as they know the resident more personally, and similar circumstances might not be present in other environments. The setup is not observed in many facilities even within healthcare environment; these kinds of facilities focused on co-living drastically differ from operations oriented facilities such as hospital environments, where the reliance on information might be greater and the utility greater with the dynamic patient flow and nurse rotation.

Also some of the dimensions, particularly accuracy, could have been assessed in more depth. With the available resources, a thorough assessment of accuracy was unfortunately not possible. In addition, the obtained results with regard to accuracy are likely strongly shaped by the healthcare setting and the associated emphasis on producing accurate notes. While the study presents promising results, noticeable decrease in accuracy would render them meaningless; inaccurate data can rarely be tolerated. The findings should be read with this in mind.

Furthermore, the thesis discusses the mobile system in isolation. While this is meaningful considering the purposes of the study, it also assumes that the environment with human, organisational and social elements has remained the same between the observation periods. The periods were set very close to each other to mitigate these effects, but it is still possible that some circumstances may have changed between or during the periods of observations. The study also observes only one type of mobile device user interface; even though many studies have only focused on the size of the screen and the layout and type of on-screen keyboard, the usability of the user interface and all the associated solutions are certainly not without consequences.

The author declares no conflicting interests with respect to the research.

8.4. Further research

Thorough understanding of the effect of mobile devices on the quality of produced information is still in its infancy, and also this study captures only a limited aspect of the matter; thus the study beckons a number of related and subsequent research.

First, the study has its limitations, and studies transcending these limitations would give further confidence in the obtained results. As discussed in methodology, a certain dependence between the two samples exists due to the same subjects being observed over both periods, even though it seems unlikely to radically influence the results. Either a rigorous panel data method could be employed to mitigate this effect, or a study with a treated group - control group design could be conducted, so that the between-sample dependence could be mitigated.

One of the most important limitations the study has is with regard to generalisability, since the study is a case study with a relatively modest sample size. Thus the study invites more research both within industry as well as across industries in high mobility environments, from healthcare to construction and crime scenes. Especially healthcare could benefit from further research as Byrd & Byrd (2013), Carroll et al. (2004), Mendes & Rodrigues (2011), and Prgomet et al. (2009) suggest; in addition to being inherently mobile, it also has a high dependence on quality information. Moreover, capturing the complexity of the human experience in health and wellbeing is at least currently non-automatable with sensor technology, which implies that the need for human-mediated information collection will persist in the setting. However, the current mobile device data collection literature seems to be strongly focused on healthcare, and research should expand beyond healthcare to assess if and how the technology can be utilised in other settings.

The time period studied was also somewhat brief and in the very early phases of mobile device use for information collection. A study spanning over a longer period of time or taking place in an already stabilised setting, say after a year of the device introduction, would create understanding of the longer term effects and bring insight to the effects of the learning curve and the possible novelty attraction of the technology (Ozok et al. 2008, Wetzlinger et al. 2014). Also utilising the entry support enabled by the mobile devices was not fully in use during the study, and the setting of this study would provide a great opportunity to later assess the effect of implementing symbol notes to the full extent or having the device show PCP items prioritised.

Secondly, this study focuses only on the intrinsic information quality of the data produced by mobile devices. Even though the topic is very exciting in itself, in practice it is inseparable from the usability of the device and the related effects on the processes; does the mobile device documentation increase or decrease the total time dedicated to note taking? The efficiency perspective is extremely interesting for its practical utility, and study should indeed be directed towards understanding the effects on processes. For instance a time-motion study could help unravel the implications of mobile device use. More specifically, these studies should consider the current technology as opposed to the majority of existing studies focusing on outdated technology such as PDAs. Having said that, it is clear that studies have difficulty keeping up with such fast-developing technology, in addition to which it might be replaced by entirely new disruptive technology in a matter of years.

The usability aspect deserves further attention beyond merely considering the time savings. The data collectors' perception about the device should be assessed with regard to whether the mobile devices aid or obstruct the information collection. As Strong et al. (1997) point out, data collection might be viewed as an additional burden that intervenes with the "real work", and thus the collection should be made as easy as possible. Moreover, difficulty of use is likely to lead to reduced adoption, thus mitigating the possible benefits. The usability could be assessed drawing from the broad body of literature on the topic of usability, perhaps collecting experiences via a usability survey.

On a related note, this study has been discussing mobile devices as one homogenous entity, but the characteristics of the hardware as well as software surely have an effect of the usefulness and usability as well as quality of information. Studying how these elements affect the information quality, and perhaps isolating the most significant factors for information quality, would be tremendously interesting and would yield very practical results. Both elements have so far relatively limited study and narrow confirmation. Berkowitz et al (2014), Kim et al. (2013), and Odell (2015) also suggest that a significant source of the difficulty of input associated with mobile devices is due to the text input. Here, alternative methods of feeding human-generated data to mobile devices should be studied. For instance, speech transcription has evolved considerably over the past few years, and it has been mentioned as an alternative to text input (Zhai et al. 2005).

Thirdly, similar study with focus on richer study on the accuracy dimension would be fruitful; the current approach reduced accuracy to mere spelling errors, even though the dimension is perhaps the most important (Fisher & Kingma 2001) and has a number of sub-components. For instance, experts assessing impossible values or contradictory statements within the data would yield more expressive measure of accuracy, or having some gold standard source to compare the values to. Moreover, the study supposes that nurses are very aware of the importance of accurate information and thus extremely careful to enter correct data. Thus it would be interesting to test for accuracy in different settings and in different industries and see how mobile devices affect accuracy there. Additionally the study assumes better accessibility granted by mobile devices, but also this assumption and its magnitude warrant investigation in themselves.

Finally, studying the nature of mobile device use could bring insight into the tasks which it is best suitable for. Studying the parallel use of mobile devices and PCs, this study finds partial support for the hypothesis of mobile device use to record recurring, standard items. However, some of the expected items were not recorded considerably more with mobile devices, which urges the question of the types of documentation mobile devices are the preferred technology for. As the parallel use scenario is presumably typical due to the complementary qualities of PC and mobile, understanding the user behaviour and preferences would aid in designing optimal systems and utilising the different technologies in an optimal manner. Considering that mobile device produced notes seem slightly shorter, it would be interesting to understand whether the mobile device notes are written in a more concise way, or if perhaps mobile devices are only used for notes that would be on the short side anyway and the longer notes are saved for different technologies. On the other hand, assessing samples consisting purely of mobile produced information and PC produced information would also be interesting, should the circumstances allow this kind of study.

9. Conclusions

Assessing the effects of mobile device use in human-mediated information collection on information quality through a healthcare case study, the thesis obtains results supporting the usefulness of mobile devices in information collection. From the literature, the thesis identified the information quality dimensions of accuracy, completeness, consistency, and timeliness relevant for the information collection phase and the mechanisms of capturing information at the source, provided entry support, and the difficulty of input possibly affecting the information quality dimensions. The thesis developed a set of eleven suitable measures to capture these anticipated differences, and then tested the hypotheses on a live field dataset consisting of data solely produced with desktop computers and data produced with desktop computers and mobile devices in parallel.

The obtained results seem encouraging, even during the initiation phase. The study concludes that parallel use of desktop computers and mobile devices seems to improve the quality of information in human-mediated information capture, particularly with regard to the completeness of the information. There was approximately 80 percent more notes and 70 percent more characters in the data collected utilising also mobile devices, in addition to which the measures assessing the richness of the data showed positively results. The coverage of personal care plan items increased significantly and, with exception of two categories, all topical categories as well as physio-psycho-socio-related categories showed increase. Significant increase was in particular found in data related to physiology, but also the psychology related items showed nearly significant increase. Also the timeliness of the data improved significantly, with an average of one and a half hours.

The study interprets the increased documentation to be at least partially attributable to the convenience of constant mobile device access, which decreases the amount of information lost between the event and the documentation and decreases the documenters' burden of intermediate information storage. Moreover, each individual piece of documentation seems to contain less categorical content, meaning that more notes are made with shorter intervals. This supports the reduced burden of keeping the information in intermediate storage such as memory, and furthermore is a step toward more structured documentation. It is also noteworthy that the increased documentation was not perceived to increase the time spent on information collection, but the information collectors on the contrary felt that the mobile devices enabled faster documentation. Even though the entry times and process implications were not studied in any rigorous manner, this supports the recent studies in healthcare mobile device use suggesting positive impact on workflow and efficiency.

Considering the literature reporting difficulty of controlling mobile devices and especially feeding in text, the study surprisingly finds no considerable negative effects on the data, only significant difference being increased use of abbreviations. Negative effects in spelling errors (accuracy) and consistency (abbreviations, duplicate values, and empty values) were expected based on the literature. Also the empty values measure would have been significant on the 0.05 significance level, but the very small number of empty values combined with box plot facilitated assessment imply there is no real difference. It should, however, be noted that the accuracy dimension was measured only rather narrowly, and given its fundamental importance for information quality the results should be interpreted with this caution in mind.

The results of the study also give some insight into the types of information collection tasks mobile devices are preferably used for and types of documentation for which desktop computers were chosen for over the mobile devices. The mobile devices were hypothesised to be used in particular for repeating, standard events, for which the strengths of the touch interface can be harnessed. These items, in this setting items related to physiology, received partial support; the significantly increased items belonged into this category, but not all items belonging to this category increased significantly. Therefore there seems to be an additional underlying factor unknown to this study influencing the use. Moreover, it seems that the mobile devices were used particularly little for documentation requiring considerable accuracy, in this case doctor, medication, and measurements, indicating that perhaps the documenters associate mobile devices with error proneness and consequently prefer to use desktop computers for particularly accuracy sensitive documentation. Alternatively it could be that this kind of information is obtained in circumstances where a desktop computer is readily available for documentation. Further support for mobile device use for standard, recurring items is found in the length of mobile device notes, which seem slightly shorter in comparison to desktop produced notes.

The empirical results can also be reflected on the mobile device effect mechanisms combined from the literature; the positive effect of capture at the source was supported by the findings regarding completeness and timeliness. However, the study was unable to comment on the accuracy perspective, which is in general assumed to improve due to immediate documentation. The hypotheses regarding difficulty of input were mainly rejected; it seems that the difficulties either are much less significant than expected, or alternatively the mobile device interface has been successfully designed to overcome these difficulties for instance via design for touch. The second identified mechanism, the mobile devices providing support at the source of collected data, could not be thoroughly assessed since the mobile device system did not extensively utilise entry support. Nevertheless, the obtained results such as increased completeness and added structure provide some support for the mechanism.

While the study features a limited set of data of 1195 observations and draws its conclusions from one residential elderly care unit, the results give reason to believe that inclusion of mobile devices in information collection can lead to improved information quality and yield the associated advantages in both business and societal context, enabling enhanced decisions. Based on the results, mobile devices can be recommended to complement information collection in high mobility environments, especially when the target is to achieve robust data. The study as well as previous literature identify healthcare as an industry where mobile devices seem to provide particular value and potential.

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