Norwegian School of Economics
Bergen, Spring 2017

Micro-Moments: New Context in Information System Success Theory

Marina Snegirjova

&

Fanni Tuomisto

Supervisor: Herbjørn Nysveen

Master thesis, Economics and Business Administration,

Marketing and Brand Management profile / CEMS

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

Recent technological advancements, such as smartphones and mobile internet, are changing the consumer behaviour. One of such changes is the emergence of micro-moments concept: the moments of high intent and engagement on mobile device that happen rapidly. This study investigates whether the micro-moments context moderates the effect of information quality on customer satisfaction, as the measure of information system success. Results of quasi-experiment show that relevancy, amount of data and ease of understanding are still important to achieve customer satisfaction in traditional context. Yet, lack of significant findings in micro-moments situation leads to a conclusion that information systems success theory needs adjustment based on individual user characteristics, as well as individual contexts. Based on the results, conceptual, methodological and managerial implications are provided.

Table of Contents

Table of Figures

Table of Tables

1. Introduction

Recent technological advancements had brought multiple changes into modern marketing. For example, the Internet facilitated and quickened access to information, social networks created new channels of communication with customers, as well as provided marketing managers with unprecedented amount of consumer data. The introduction of mobile devices with access to the Internet further spread these developments, leading to the discussion the of ubiquity of mobile services, as well as the development of m-commerce and u-commerce concepts (Watson, Pitt, Berthon & Zinkhan, 2002, p. 332).

But not only marketing strategists and theorists started adjusting to these technology-driven changes: consumer behaviour has altered as well, which has led to the emergence of *micro-moments* concept (Google, 2015, p. 3). McTigue (2015) defines micro-moments as the moments of high intent and engagement which happen rapidly in customer's spare time: commuting, waiting or being bored. These moments are part of everyday life and are becoming the new battleground for brands (Legault, 2015).

This thesis aims to expand the theoretical understanding of micro-moments and their implications for marketing practitioners that work within the mobile environment or use mobile services for marketing activities.

1.1. Study Context

Often consumers are not looking to engage with brands, so distracting or irrelevant message can trigger negative attitude. However, at other times customers might be open to brand communication, seeking information and help in their decision-making moment, and the brand has to be there (Google, 2015, p. 4). In academic literature, these two situations are denoted as “push” advertising and “pull” or response communication (Okazaki and Barwise, 2011, p. 60), and the present study is focusing on the “pull” case where information is readily present on customer's voluntary request.

The concept of micro-moments brings marketing practice to a new level, allowing for a more detailed analysis of consumer behaviour. Marketing managers are able to communicate with the customers in their specific moment of need while knowing customer interests, location and other personal data. As a concept pioneer, Google (2015, p. 5) has developed several marketing strategies for companies to leverage micro-moments and win customers' attention.

The concept of micro-moments has not been widely researched from the academic perspective yet, so there is still room for theoretical research on the differences in consumer behaviour and customer satisfaction in traditional decision situations versus those in micro-moments.

Since micro-moments concept originates from the mobile environment, this study aims to investigate whether the factors influencing the success of mobile services change in the micro-moments setting. However, the focus on just mobile services would limit the practical use of this study in the future, as research of particular mobile technology could become quickly outdated at the present pace of technological development (Okazaki & Barwise, 2011, p. 68) as, for example, short-text messaging did. We, therefore, interpret mobile services as information systems in general, i.e. a way to structure and organise the information, as well as deliver it to the user or customer, focusing more on the marketing content rather than technological setup. In the next sections, we establish the research questions and possible contributions of this study in the marketing field.

1.2. Research Questions

This study aims to find what makes mobile services succeed; yet, mobile service success is an abstract concept and as such rather hard to measure. Therefore, we use customer satisfaction, a more readily observable construct, as a proxy for mobile service success. Prior research shows customer satisfaction has a direct positive effect on company revenues, the ultimate indicator of a product or service success (Westbrook & Oliver, 1991, p. 84; Fornell, 1992, p. 6; Anderson, Fornell & Lehman, 1994, p. 63). By definition of Churchill and Surprenant (1982, p. 493), product and service performance exceeding consumer expectations lead to consumer satisfaction.

As mentioned previously, in the context of this study any mobile service is viewed as an information system, i.e. a way to structure and organise the information. Being interested in the antecedents of the information system success, defined as customer satisfaction, we adopt DeLone & McLean information system (IS) success model (2003). In this model, user satisfaction is a key determinant of IS success and is dependent on the information quality among other factors.

This study is therefore focused on two research questions. First, we study available academic literature on customer satisfaction in the mobile and digital environments in general in order to develop an underlying theoretical framework and answer the first research question:

RQ1: What are the antecedents of customer satisfaction with mobile services?

Based on the developed framework, we then seek to understand whether these antecedents have a different effect on customer satisfaction in the micro-moments situations. The difference in effects might stem from limitations of human information processing, since micro-moments imply a very short time frame and thus imposes restrictions on the time available to perceive and process the information. This, in turn, might influence the perceived importance of various information quality attributes. In addition, the initial intentions of the customer differ: practitioners characterise micro-moments as brief, but intense engagement or curiosity (McTigue, 2015) versus a comprehensive information research in a traditional search situation. This might affect both the initial, pre-purchase expectation of mobile service performance and the actual perceived one, which are both components of customer satisfaction concept. The second research question is therefore defined as follows:

RQ2: Does the significance of the antecedents of customer satisfaction with mobile services vary across micro-moments compared to traditional situations?

We expect for the general direction of the effects to remain the same, as information quality should be still positively correlated with the success of the information system. However, some of the discussed antecedents might gain more significance (i.e. display stronger influence on the customer satisfaction) due to the ubiquitous nature of the micro-moments situation.

1.3. Contributions

1.3.1. Academic Contribution

First, the paper elaborates on the current theories of consumer satisfaction by studying them in the novel context of micro-moments. Due to its novelty, the concept of micro-moments has enjoyed limited attention from academia to this date. It proposes an interesting research setting by incorporating the recent development of mobile services as a potentially moderating influence on customer satisfaction.

Second, as the micro-moments concept is closely related to that of the ubiquity, the present study will add to the ever-growing body of research on the topics such as ubiquity per se, m-commerce and u-commerce, to which ubiquity forms one of the dimensions. Given the ongoing integration of mobile services into our everyday lives, it is crucial that theoretical research follows closely this observed consumer behaviour trend.

Okazaki and Barwise (2011, p. 68) state that there is a time lag between published academic research and recent technological development. The literature review presented in Appendix 1 further supports this statement. Okazaki and Barwise (2011, p. 68) then identify three directions for further research based on “push” or “pull” advertising mode and the level of ubiquity. In our view, the micro-moments setting represents both high level of ubiquity and “pull” mode of advertising, which, in line with Okazaki and Barwise (2011, p. 68), is an important area for further academic research in mobile marketing.

1.3.2. Managerial Contribution

Finally, there is still a lot for marketing practitioners to learn about micro-moments and factors affecting consumer satisfaction in this setting. In their case presentations, Google (2015) provides evidence that companies gain tangible benefits (e.g. increased ROI in mobile marketing) from managing micro-moments. However, the steps leading to the mobile service success in the micro-moments settings are unknown for the majority of companies. Only 34% of businesses feel they have the will and the capacity to reach consumers in their moments of need (Forrester Consulting, 2015, p. 3). Therefore, we will draw managerial implications from the research, outlining which marketing practices should be adopted in order to increase customer satisfaction and, respectively, drive the success of mobile services within the micro-moments setting.

1.4. Study Outline

The rest of the paper is structured as follows. In Chapter 2 we describe the context of mobile services and how they are different from the traditional online services, as well as define the micro-moments and point out related concepts in existing theory on mobile commerce. In Chapter 3 we dig into the main underlying theories regarding antecedents of customer satisfaction with mobile services and discuss the concept of information quality. We then develop a synthesised framework and hypotheses that build on both existing theories and available empirical knowledge about micro-moments in Chapter 4. Chapter 5 describes the methodology behind the present study, as well as discusses its reliability, validity and limitations. Next, we describe the empirical results and state the evidence for or against each of hypotheses in Chapter 6. Finally, in Chapter 7 we draw conclusions from our analysis, develop managerial implications and propose suggestions for further research.

2. Study Background

2.1. Mobile Services

Already in the beginning of 2000's it was clear that interaction with customers and the delivery of services in electronic environments were important for the success of companies (e.g. Parasuraman & Zinkhan, 2002, Watson et al, 2002). However, further development of mobile services and specifically the introduction of smartphones in 2007 brought multiple changes to the technology world, such as new paradigms of software distribution, hardware requirements and understanding of copyright laws.

The most crucial of those changes, strengthened by the introduction of tablet computers in 2010, is 24/7 mobile connectivity that smartphones brought to consumers. Mobile changed how and when people access the Internet, search for information and make purchase decisions. The number of mobile Internet users surpassed that of desktop in 2014, revealing the importance of consumer research targeted towards the mobile use of electronic devices (comScore, 2014). Recent statistics show that the mobile media consumption keeps growing compared to the one conducted on the desktop (Chaffey, 2013).

Yet, despite the growth in mobile media time, businesses are missing out opportunities by not spending enough on mobile advertising, not having websites optimised for mobile browsing or, in other words, just not being “there” when a consumer is searching for them (Chaffey, 2013). The same was highlighted in a study by Google and Nielsen (2013, p. 18), suggesting that mobile site optimisation and mobile-tailored advertising play an important role in modern consumers' mobile path to purchase.

According to Watson et al (2002, p. 333), mobile services are different from other online services because of their ubiquitous, universal and unison access to information. They allow for more personalisation based on the individual usage patterns and features such as e.g. location tracking. Further developing the concept of u-commerce, Watson et al (2002, p. 339) state that information is becoming the core of marketing and both marketing academics and practitioners need to account for the superabundance of information and limited processing capabilities of humans.

On the one hand, continuous connectedness and access to the vast amount of information through mobile services overload consumers; yet, at the same time, mobile services facilitate information processing by arranging, systematising and structuring it (Loeb & Panagos, 2011, p. 393). While all channels matter, mobile services are of key importance among other digital media as they have become the connector between online and offline world (Google, 2015, p.

22). The new consumer behaviour patterns that emerged from the use of mobile devices, such as continuous engagement with the brand and time investment in a deeper research, have implications beyond mobile marketing, affecting the entire consumer journey across screens, devices, channels and media types (Google, 2015, p. 22).

In the next section, we address the phenomenon of micro-moments and related concepts in existing mobile commerce and marketing theory.

2.2. Micro-Moments

2.2.1. Definition and Types of Micro-Moments

The changes in consumer information technology and especially the rapid development of mobile have lead to the emergence of the *micro-moments* concept. Micro-moment is defined as "an intent-rich moment when a person turns to a device to act on a need: to know, go, do or buy" (Google, 2016a). The consumer journey is now changing, but the changes come not only as growing mobile usage. Due to the omnipresent and unique nature of mobile services, the customer journey has been fractured into hundreds of tiny decision-making moments. These moments are a part of our everyday lives, and consumers stay open to the brand communication in these moments as long as it provides help in decision-making (Google, 2015, p. 4).

The micro-moments concept was introduced by Google in 2015, but has already attracted a lot of attention from marketing practitioners. It builds on an earlier research by Google and the concept of "moments of truth" (Lecinski, 2011), yet, brings more depth and detail into consumer behaviour insight by breaking consumer activities into smaller, more manageable and consequently winnable scenarios (Google, 2016a), as presented in Figure 1.

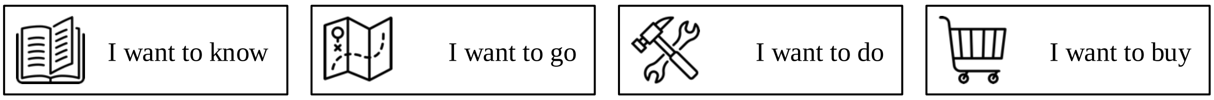

Figure 1. Types of Micro-Moments Scenarios. Adapted from Google (2016a).

"I want to know" scenario relates to users exploring or researching information without necessarily aiming to purchase anything. This random spark of curiosity, if not satisfied immediately at that particular moment, is lost due to the ubiquitous nature of micro-moments. The information search is usually triggered by some external stimuli: for example, according to a study conducted by Google (2016a) 66% of United States smartphone users state they had researched something they had seen during a TV commercial.

In "I want to go" scenario, a potential customer is looking for a local business or is considering buying a product at a nearby store. These micro-moments emerged with the development of location-based technologies that help to identify businesses located near the customer. Given the portability and mobility of smartphone users, an immediate access to information is crucial, as within minutes the customer could move away from the close proximity of the business in question.

Google (2016a) describes situations when users need help in completing a task or trying something new as “I want to do” moments. Due to the portability of mobile devices, 91% of smartphone users turn to mobile search for ideas while completing a task. In fact, the number of mobile searches conducted in general is rapidly growing (Google, 2015, p. 4). YouTube, the video platform developed by Google, provides consumers with new ideas for things to do with more than 100 million hours of “how-to” guides watched annually (Google, 2015, p. 14). Being useful and helpful for the customer in “I want to do” moment presents a unique branding opportunity for companies.

Finally, the “I want to buy” moment is the closest to the conversion from random interest to an actual purchase decision. In that scenario a customer is ready to make a purchase and just needs extra help in deciding what to buy or how to buy it. This may involve checking for additional information about a product, while being at the store, or choosing online or mobile purchase options instead of physical ones. The mobile conversion rates grew by 29% from 2014 to 2015 (Google 2015, p. 4), thus it is becoming increasingly important for companies to be present in these “I want to buy” moments.

2.2.2. Related Concepts in Mobile Commerce

As previously mentioned, a prominent feature of mobile services is their ubiquity. Pioneering research by Watson et al (2002, p. 332) describes ubiquity as a synonym to omnipresence: “not only that they are everywhere but also that they are, in a sense, ‘nowhere,' for they become invisible as we no longer notice them”. Within the context of mobile commerce, ubiquity has been widely researched by Balasubramanian, Peterson and Jarvenpaa (2002), Okazaki, Li and Hirose (2009) Okazaki and Barwise (2011), as well as Okazaki and Mendez (2013b).

A subsequent body of research adopted a more current definition of ubiquity that develops further in two dimensions: the anywhere and anytime nature of mobile services (Balasubramanian et al, 2002, p. 350) and the combined flexibility of space and time (e.g. Okazaki et al, 2009, p. 64). Okazaki and Mendez (2013b) developed a measure for perceived ubiquity of mobile services that comprises of the following aspects: continuity and simultaneity, immediacy and speed, portability and mobility, as well as searchability and reachability. As authors outline, there are two main views on ubiquity: time and location flexibility, and interactivity that provides consumers with an unprecedented control and customisation of the content that they see. Yet, very few studies incorporate the construct of ubiquity in their models (Okazaki & Barwise, 2011, p. 66).

We propose that micro-moments are advancement on the ubiquity concept, since micro-moments by definition incorporate both views on ubiquity. First, micro-moments happen anytime during the customer's free or idle periods. Second, due to the widespread mobile Internet availability and permanent online connection, the location becomes flexible as well. Finally, linking to the second view on ubiquity, a high level of information personalisation and customisation allows for interactivity within the context of micro-moments.

Micro-moments can be also linked to an earlier concept of nexus marketing, which implies that companies act to reduce the necessity for conscious interaction in specific contexts (Fischetti, 2001, p. 92). Nexus marketing uses available data about consumers' location and time to deliver tailored information, freeing the consumer from providing additional details. These time-space specific connections or nexuses are used to facilitate information processing and reduce the number of actions required from the customer. The idea of a nexus is similar to that of micro-moments in a sense that customer expects information to be tailored to his particular situation. However, marketing in micro-moments needs to go further, since only a fraction of micro-moments depends on a particular location ("I want to go" and, partially, "I want to buy"). Most of them are not location-specific ("I want to do", "I want to know" and "I want to buy" related to online purchases), but rather depend on a need or a purpose. In addition, due to the narrow time frame of the micro-moments situation, the attention span of a customer is much shorter, so the task of personalising the information becomes more complex than is viewed in nexus marketing.

Micro-moments are a novel, overarching concept, which not only relates to several existing concepts in mobile marketing, but also accommodates the most recent technological development. In addition, micro-moments are not measurable with traditional performance indicators; it is not just a branding issue or a digital presence issue (Google, 2015, p. 26). Each micro-moment is a critical touch-point within the customer journey, which makes the understanding of micro-moments' specifics so crucial for marketing managers.

2.2.3. Marketing Strategies to Leverage Micro-Moments

If marketing is to succeed in a society characterised by attention deficit, it needs to give time back to consumers so that they could attend to multiple stimuli (Watson et al, 2002, p.

338). Therefore, to aid customers in their decision-making process and leverage aforementioned moments, Google (2015, p. 5) suggests three marketing strategies (see Table 1) that go in line with the ubiquity aspects, as described by Okazaki & Mendez (2013b).

Be there	Be useful	Be quick
Anticipate the micro-moments for target audience and commit to being there to help when those moments occur.	Provide a digital experience that is relevant to consumers' needs in the moment, and quickly connect people to the answers they are looking for.	Provide a fast and frictionless mobile experience, since mobile users want to know, go, and buy swiftly.

Table 1. Marketing Strategies to Leverage Micro-moments. Adapted from Google (2015).

With these strategies Google (2015) highlights several changes in consumer behaviour associated with micro-moments. First, user intent plays a crucial role and is typically deeply embedded in the context, i.e. consumer's needs might change significantly depending on their situation. Therefore, marketing managers are encouraged to adapt to these various situations in an attempt to make their content, ad message or app functionality most useful for their customer. Next, the information usefulness is mentioned as the key determinant of a customer's purchase decision or brand choice: 69% of online consumers agree that the quality, timing, or relevance of a company's message influences their perception of a brand (Google, 2015, p 11). Finally, time and speed are also important: increasing speed of access to information and decreasing attention span bring engagement from extended sessions down to spurts, thus adding importance to the immediacy property of the ubiquitous mobile services (Watson et al, 2002, p. 338). Modern consumers have heightened expectations for speed in general, as they are often in a hurry to accomplish their tasks: e.g. 40% of shoppers will wait no more than three seconds before abandoning a retail or travel site (Google, 2015, p. 20).

The research by Google (2015) presents the practitioners’ view on the observed changes in the consumer behaviour. Yet, as stated by Watson et al (2002, p. 332), the emergence and development of ubiquitous commerce (or u-commerce) and related concepts might challenge the existing marketing theories. Therefore, since the concept of micro-moments has not been widely researched from the academic perspective, we wish to expand the theoretical understanding of micro-moments, relate them to existing theories of customer satisfaction and outline the implications for marketing practitioners. We expect micro-moments setting to alter the effect of antecedents of customer satisfaction, compared to traditional situations of brand exposure and engagement.

3. Theoretical Development

3.1. Customer Satisfaction

This study uses customer satisfaction as an indicator of the mobile service success, as customer satisfaction is closely linked to other business performance indicators. Prior studies show customer satisfaction has a direct positive effect on company revenue streams and profitability through repeated purchase intention, increased loyalty, customer insulation from competitor advancements, reduced failure costs, and reduced customer acquisition costs (Fornell, 1992, p. 6; Anderson, Fornell & Lehmann, 1994, p. 63).

Customer expectancy disconfirmation theory has long been the dominant research paradigm within the area of customer satisfaction (Tse, Nicosia & Wilton, 1990, p. 180). It defines customer satisfaction as a post-purchase evaluation of a product or a service resulting from the comparison between the perceived product or service performance and the pre-purchase expectation (Churchill & Surprenant, 1982, p. 493). There are both direct effects of perceived expectations and perceived performance on customer satisfaction, as well as the effects mediated by the confirmation or disconfirmation of those expectations (Figure 2).

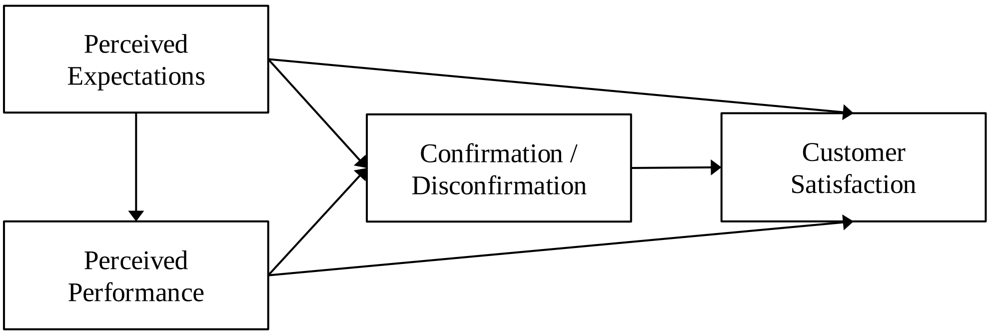

Figure 2. A Causal Model of Satisfaction Formation Process. Adapted from Churchill and Surprenant (1982).

According to Oliver (1980, p. 460-461), once a customer has formed an evaluation of a product's performance, their initial expectation can be confirmed (expectation met), positively disconfirmed (better than expected), or negatively disconfirmed (worse than expected). Positive disconfirmation increases or maintains the satisfaction level, while negative disconfirmation leads to dissatisfaction.

Customer expectancy disconfirmation model explains most variation in customer satisfaction. The rest is explained by direct effect of perceived expectations and product performance. Based on correlational analysis Trawick and Swan (1982, p. 97-101) found product performance to strongly affect customer satisfaction. In his field study Oliver (1977, p.

2-9, 1980, p. 466) found a significant relationship between perceived expectation and customer satisfaction.

Prior research indicates customer satisfaction is more influenced by the negative disconfirmation than the positive one. The prospect theory states that the utility functions of losses and gains differ, thus loss is perceived as greater than gain (Kahneman & Tversky, 1979, p. 279). Anderson and Sullivan (1993, p. 138) empirically proved that the prospect theory is also applicable to the customer satisfaction.

3.2. Drivers of Customer Satisfaction

As outlined in the previous section, in scope of this study, the success of mobile services is measured by customer satisfaction. As this study aims to investigate whether the effects of customer satisfaction antecedents change in the micro-moments setting, we analyse customer satisfaction in the specific context of mobile services.

Yet, a particular mobile service or technology is in danger of becoming quickly outdated at the present rapid pace of technological development, thus limiting the practical application of this study in the future. Therefore, this study adopts a more general view of mobile services as information systems, i.e. a way to structure and organise information. Focus on the content rather than mobile service technology allows us to draw conclusions beyond the current ways of customer communication and sustain the results of this study even when new technologies emerge. A systematic literature review of customer satisfaction in mobile environment (see Appendix 1 for further details) supports this view, as the absolute majority of the reviewed studies focuses on short message services (SMS), the marketing use of and revenue from which is steadily declining in the past years (Bourne, 2016).

The literature review led us to the information systems (IS) success model by DeLone and McLean (2003). The model was first published in 1992 and later revised in 2003 to incorporate a number of modifications proposed by subsequent research. According to the IS success model, five interdependent variables simultaneously affect the success of an information system (Figure 3, dashed lines indicate the research focus of the present study). A comprehensive meta-analysis, conducted by Sabherwal, Jeyaraj and Chowa (2006), provides support for most relationships identified by the model.

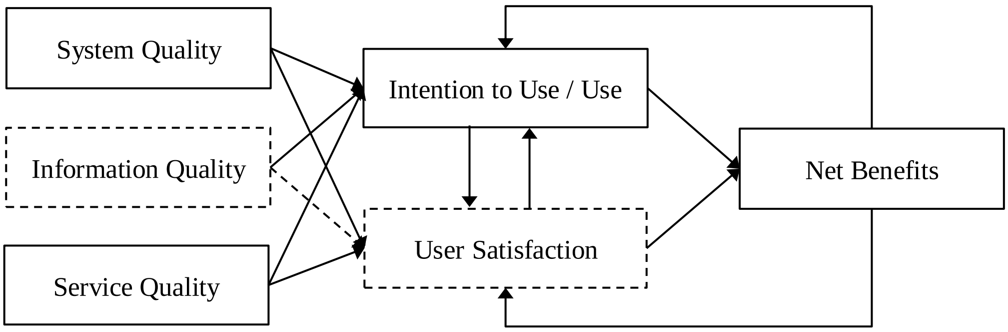

Figure 3. Information System Success Model. Adapted from DeLone and McLean (2003).

The IS success model suggests a causal relationship between information quality, service quality, system quality and customer satisfaction. These relationships have been extensively studies within the areas of customer satisfaction and information management. Substantial share of prior studies confirms a significant, positive relationship between the information, service and system quality and customer satisfaction in a wide variety of settings (e.g. Wixom & Todd, 2005; Kulkarni, Ravindran & Freeze, 2006; Chiu, Chiu & Chang, 2007; Halawi, McCarthy & Aronson, 2007).

High-quality information is a type of information which reaches or exceeds certain pre-acknowledged criteria in its accuracy, timeliness, or relevance (EURIM, 2011). Yet, the perceptions that consumers have of these criteria tend to vary. Attributes that one customer segment highly values might mean very little to another customer segment (Miller, 1996, p. 79; Koivumäki, Ristola & Kesti, 2008, p. 376).

Linking back to information systems, a positive relationship between the information quality and user satisfaction has been found by several empirical studies in mobile context, e.g. Chung and Kwon (2008), Lee and Chung (2008) and Chen (2013). Other studies focused on information quality aspects of websites, such as content or layout, also suggesting that the information quality significantly affects the level of customer satisfaction (Kim, Jung, Han & Lee, 2002; Palmer, 2002). Effective presentation of product information is likely to enhance customers' ability to review product features and product compatibility, yet many retailers are inefficient in the way they deliver information online (Lim, Widdows & Hooker, 2009, p. 841).

3.3. Information Quality

According to Watson et al (2002, p. 339), information plays increasingly important role in modern marketing. Moreover, today's widespread availability of smartphones and mobile Internet make access to this information ubiquitous: omnipresent, independent of time or location, and highly interactive. We, therefore, would like to draw attention to the theoretical construct of the information quality and elaborate on the link between the information quality and user satisfaction as a measure of mobile services success.

The Total Data Quality Management model (further in text, TDQM) is a framework created to help managers improve the quality of their information products. The TDQM is based on the total quality management, which focuses primarily on the physical product quality guidelines and techniques. Indeed, there are similarities between the product management and the data quality management (see Table 2), as product manufacturing turns raw materials into physical products, while information manufacturing turns raw data into information products (Wang, Lee, Pipino & Strong, 1998, p. 59)

	Product Manufacturing	Information Manufacturing
Input	Raw Materials	Raw Data
Process	Assembly Line	Information System
Output	Physical Products	Information Products

Table 2. Comparison of Product and Information Manufacturing. Adapted from Wang et al (1998).

The total quality management helped to deepen the understanding of the data quality management. Quite like physical products can be evaluated on certain quality dimensions, information products are associated with information quality dimensions. The quality of information products reflects the quality of information manufacturing system as well as the quality of the raw data input.

The terms "data" and "information" are often used interchangeably both by managers and researchers. Although there has been no consensus about the distinction between data quality and information quality, the custom in prior research has been to use data quality when referring to technical issues and information quality when referring to nontechnical issues (Zhu, Madnick, Lee & Wang, 2014, p. 1). Since the main focus of current study is non-technical, we will consistently use the term "information quality".

To explore the concept of the information quality, we employ a framework introduced by Wang and Strong (1996) that has become the most prominent theory in the field of information quality research. The framework consists of a comprehensive taxonomy of information quality aspects, grouped into 4 distinct categories and further split in 15 dimensions (see Figure 4).

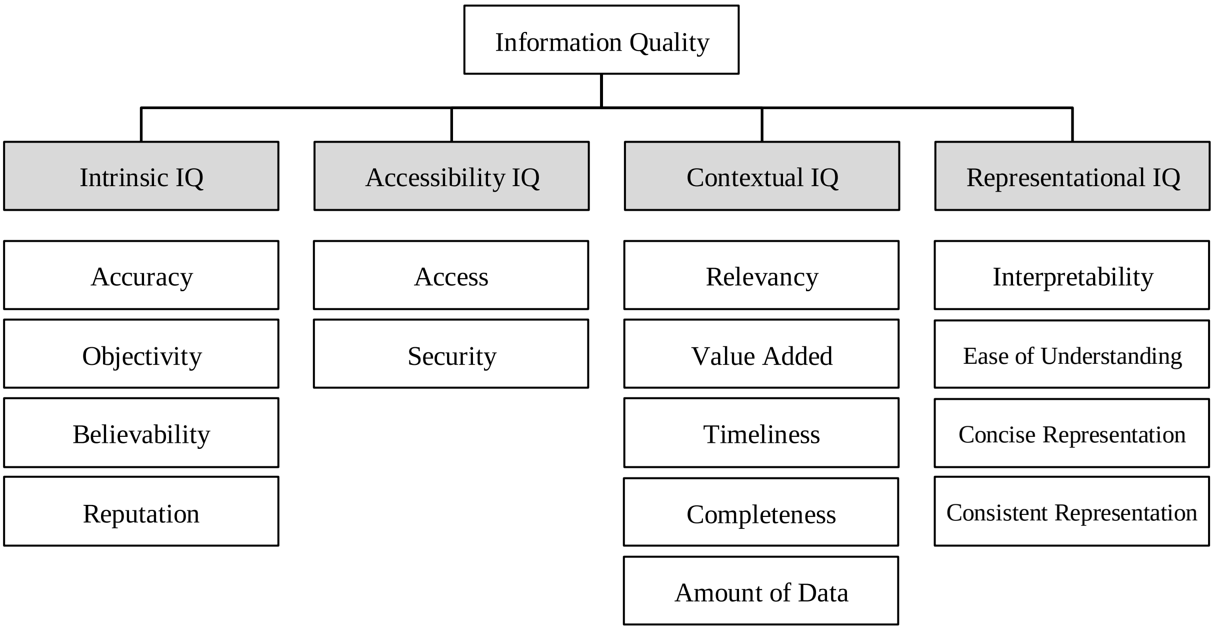

Figure 4. Information Quality Taxonomy. Adapted from Wang and Strong (1996).

Intrinsic information quality refers to information that has quality in its own right. The main dimensions of intrinsic information quality are believability, accuracy, objectivity, and reputation (Wang & Strong, 1996, p. 20). According to recent studies, high levels of intrinsic information result in increased customer trust. Customers are more likely to trust supplier information that satisfies the aforementioned attributes, even if some secondary information has not been provided (Ayadi, Cheikhrouhou & Masmoudi, 2013, p. 255).

Contextual information quality underlines that information quality should be examined within the context of the activities at hand. The main determinants of contextual information quality are value-added, relevancy, timeliness, completeness, and appropriate amount of data (Wang & Strong, 1996, p. 20). The capacity of human short-term working memory is limited, therefore, the information system should attempt to reduce memory overload by absorbing and combining various bits of information (Aidi, 2009, p. 393). According to the theory of cognitive efficiency, the cognitive effort can be minimised, and simultaneously the search performance and user gratification can be maximised when a cognitive task can be completed easily and quickly. Information systems that limit cognitive overload therefore allow for increased knowledge gained with limited time and effort investments (Sweller, 1994, p. 301; lo Storto, 2013, p. 1006).

Representational information quality states that the information should be represented concisely and consistently. The main determinants of representational information quality are interpretability, ease of understanding, representational consistency, and concise representation

(Wang & Strong, 1996, p. 21). According to Palmer (2002, p. 163-164), ease of reading information online produces a desirable image of the website and results in the intention to use it in the future.

Accessibility of information focuses on the ease with which the information pursued is accessed. The main determinants of accessibility are access and security (Wang & Strong, 1996, p. 21). The importance of speedy access to information has been increasing due to recent changes in consumer behaviour (Google, 2015, p. 18-20).

In the following chapter, we analyse the information quality categories and dimensions in more detail. We put information quality theory in the context of micro-moments and build a research model underlying the current study.

4. Research Model

Although positive correlation has been reported between the information quality and customer satisfaction, prior results vary greatly (Ghasemaghaei & Hassanein, 2015, p. 966). Previous studies report correlations between as low as 0.13 (Evanschitzky, Iyer, Hesse, & Ahlert, 2004, p. 244) and as high as 0.82 (Eom, Ashill, Arbaugh & Stapleton, 2012, p. 155). Petter, DeLone and McLean (2013) were the first to suggest that contextual factors may moderate the relationship between the information quality and other variables in the IS success model, thus explaining some of the variance within prior studies.

Since Petter et al (2013) published their study, an area of research has emerged utilising contextualised theory building within the literature on information systems. To this date, several notable studies have used contextualised theory building examining the relationship between the information quality and customer satisfaction. It has been proposed that at least the website type (e.g. e-service or retail), the information quality type, e.g. representational or nonrepresentational (Ghasemaghaei & Hassanein, 2015, p. 977) and the customer thought mode, e.g. conscious or subconscious thought process (Gao, Zhang, Wang & Ba, 2012, p. 775) could possibly moderate the relationship.

There are multiple general benefits to the contextualised theory building. Johns (2006, p. 389) argues that the contextualised theory building diminishes over generalisation by offering explanation for the inconsistencies created by the context and aids in the evaluation of research findings' applicability. Furthermore, Bamberger (2008, p. 840) states that the context helps to be more aware of the potential situational conditions affecting theories.

The present study makes use of the contextualised theory building by introducing the micro-moments context into the existing theory of the information quality as the antecedent of customer satisfaction, where satisfaction is a measure of the information system success. To see which information quality dimensions are the most relevant in the context of micro-moments, in the next section we explore the underlying psychological process of human information processing.

4.1. Underlying Psychological Process

Consumer behaviour within the micro-moments setting essentially differs from the traditional online information search in the time consumers have to interpret, process and respond to the information obtained. The shortage of time largely affects consumer information processing capabilities, making human information processing a relevant topic within the scope this study. In this section we briefly discuss the basic functioning of the human information processing.

The way in which the human brain operates is extremely complex. The human brain, with an estimated hundred billions of neurons and multiple hundreds trillions of synaptic connections, has the ability to process information merely in milliseconds (Marois & Ivanoff, 2005). Yet, despite the human brain's impressive complexity and processing power, it still has some functional shortcomings (see Figure 5). Prior research regarding the human cognitive abilities identified the following three: the time taken to consciously identify and consolidate visual stimuli, the restricted number of stimuli humans are able to hold in their mind at a given time, and stimuli appropriate responses.

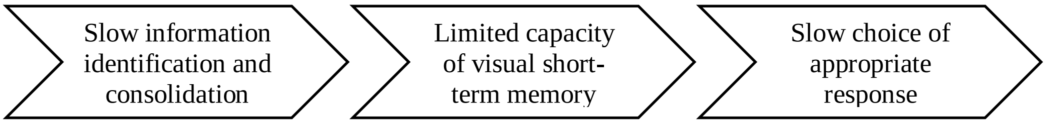

Figure 5. Human Information Processing Bottlenecks. Adapted from Marois and Ivanoff (2005).

These are by no means the only weaknesses of the human brain, but these have the most influence on the human ability to consciously acknowledge, process and appropriately respond to stimuli presented. Thus, these are the most important ones affecting online users' ability to draw meaning from information provided (Marois & Ivanoff, 2005). Identifying the most appropriate response can postpone one's cognitive processing by up to a several hundred milliseconds (Marois et al, 2005, p. 296). The emotional state as well as the context can affect response times and their suitability for stimuli, e.g. negative emotional arousal (e.g. worrying) increases response time for ambiguous stimuli (Vertes, Wilson & Wolpe, 1990, p. 85).

Some researchers state that the limited capacity of the visual short-term memory (VSTM) is closely related to the limitations of human attention (e.g. Cowan, 2001; Rensink, 2002; Becker & Pashler, 2002). VSTM storage limits works rather similar to human ability to pay attention to multiple targets in presence of distracting elements (Marois & Ivanoff, 2005, p. 298). The attention capacity has been studied by numerous researchers, with a wide variation in results. Yet, there is an agreement that a trade-off exists between the object complexity and total number of objects the human brain is able to store (Alvarez & Cavanagh, 2004, p. 109).

It is likely that customers consciously engage in the cognitive information processing to make judgements about information quality and limitations of the human brain play a crucial role in that process. In the following section, the human information processing will be further discussed in the context of information quality and micro-moments. The exclusion of nine information quality dimensions introduced by Wang and Strong (1996) from the current study will be justified. Overview of the discussion is also available in Appendix 2.

4.2. Excluded Information Quality Categories

As previously explained, 15 information dimensions in four categories were prioritised based on their relevance to the human information processing. The following sections justify the exclusion of the entire intrinsic information quality and accessibility categories presented by Wang and Strong (1996).

4.2.1. Intrinsic Information Quality

Intrinsic information quality evaluates whether the information is trusted, free of error, unbiased and credible from the user's viewpoint.

In today's hectic world many consumers do not question information they have been exposed to through online platforms. According to a study by Flanagin and Metzger (2000), few consumers rigorously verify information they have found online. The authors find that most consumers rely on information they have encountered online as much as on any other media, such as magazines, television or radio. Only information obtained from newspapers ranks higher in people's minds than information provided by the Internet, despite the large body of evidence demonstrating that online information is often biased and inaccurate.

Thus, we expect that consumers would not alter their opinions about intrinsic information quality dimensions solely due to the short duration of the micro-moments. It is important to note, however, that the study conducted by Flanagin and Metzger (2000) used as the foundation for this decision is focused on the Western world, thus its results may not reflect the behaviour of customers from other cultures, such as China or Japan.

Based on the arguments above, we exclude intrinsic information quality dimension.

4.2.2. Accessibility of Information

Accessibility of information focuses on the ease to access information. Information access and security form the main determinants of the information accessibility (Wang & Strong, 1996, p. 21). These dimensions strongly relate to the technical aspects of the information system.

The speed of access and the level of security relate to the architecture, tools and processes enabling proper functioning of an online platform. The leading causes for slow access are usually related to unoptimised images, content served without HTTP compression, combinable

CSS images, and images without caching information (Isham, 2013). Online security problems are usually caused by SQL injections, cross-site scripting and forgery, broken authentication, insecure object references and security misconfiguration (Bassi, 2015). Since online security usually follows several standard protocols, such as HTTPS, it enables tech-savvy users to verify the site safety themselves.

We believe that these technical aspects are out of the scope for most marketing managers. Consequently, the present study focuses on the aspects of information quality that marketing practitioners do have an influence on. Based on the aforementioned arguments, we exclude IQ dimensions related to the accessibility of information.

4.3. Included Information Quality Categories

We continue to look at information quality categories and dimensions through the lens of the human information processing theory. The following sections analyse the contextual and representational information quality categories, justifying inclusion and exclusion of relevant dimensions presented by Wang and Strong (1996).

4.3.1. Contextual Information Quality

4.3.1.1. Relevancy (included)

The concept of information relevancy is understood in this paper as the extent to which the information is applicable and helpful for the task at hand (Wang & Strong, 1996, p. 31). The recent advances in the data analysis techniques have enabled providing information tailored to each customer and their unique needs. For example, Netflix, Amazon and Pandora use big data to discover users' watching patterns, suggest shows users might like and, therefore, increase the relevancy and helpfulness of information provided for them (Chen, Chiang & Storey, 2012, p. 1169-1170).

Google (2015, p. 11) states that mobile phones provide a critical insight into the consumer behaviour and help companies be more relevant and useful for users during the moments of need as part of “be useful” strategy of conquering micro-moments.

By testing for this dimension, we hope to find more insights about how helpful the consumers perceive information they are exposed to. Relevancy should mirror any problems with the rest of the information quality dimensions. Irrelevant data will likely slow down the information processing, resulting in lower evaluation of contextual information quality. Thus, we include information relevancy as part of the current study.

4.3.1.2. Completeness (included)

The concept of information completeness refers in this study to a degree to which the information set is presented as whole and with sufficient breadth and depth (Lee et al, 2002, p. 143). We presume that the process of consciously identifying, consolidating and responding to stimuli should largely affect how customers perceive the completeness of information they are presented with.

The human brain is somewhat slow in consciously processing visual stimuli. It takes approximately half a second for the human brain to detect and consolidate stimuli, i.e. transfer a piece of information from the visual short-term memory to the long-term memory. Furthermore, the average response time for visual stimuli has been estimated to be at several hundred milliseconds, meaning that the identification and response alone slow information processing (Marois & Ivanoff, 2005, p. 298). The slower one processes information, the less complete information may seem during a micro-moment. When lacking time to process information, one is more likely to identify the information set as incomplete.

In addition, Google (2015, p. 12) stresses that consumers particularly value brand messages that help them answer their questions, i.e. provide complete information on the search topic. Based on these arguments, we include completeness in the final research model.

4.3.1.3. Amount of Data (included)

The human brain is able to gather huge amounts of information during its lifetime, but despite the impressive long-term memory capacity, the visual short-term memory (VSTM) is only able to bear a limited number of stimuli at any given time. The nature of the VSTM pertains the brain is only able to hold any given piece of information between 20 and 30 seconds before losing it or moving it to the long-term memory (Marois & Ivanoff, 2005, p. 298).

Due to the limited capacity of the VSTM, we assume that large information quantities will slow down the information processing of our subjects. The more information one is exposed to, the more cognitive efforts it requires to complete given task. Therefore, when presented with large quantities of information under a restricted time frame, excessive amount of information may hamper study subjects' information processing by overcrowding their short-term memory. The limited cognitive capabilities of the human brain set restrictions for the appropriate data volumes (Kool, Mcguire, Rosen & Botvinick, 2010, p. 2).

In addition, the amount of data has a technical consequence: the more data is presented, the longer the page will load. While we discussed previously that the speed of access is usually controlled by the technical department, the information itself is produced by the marketing managers. Therefore, following the “be quick” strategy outlined by Google (2015, p. 18-20), companies should aim at reducing the amounts of data customers are exposed to.

Based on the possible effects that the information quantity has on the human information processing and Google (2015, p. 18) research, we include this dimension in the current study.

4.3.1.4. Value Added (excluded)

The concept of value added is understood in this paper as the extent to which information provides advantages for the user (Wang & Strong, 1996, p. 31). Benefits provided should be greater than costs incurred in order for a customer to draw value from the use of the information system. The technical aspects, e.g. navigation and structure, when executed poorly may cause customers to face mental costs causing decline the value drawn from usage (Santosa, 2010, p. 197). Google (2015, p. 12) confirms the importance of value added provided by a mobile service. Their research outlines that customers prefer information that provides not only a direct brand message, but also contains educational value and explicit answers to customers' questions.

In their initial study Wang and Strong (1996) included value added in their information quality taxonomy. Later research, however, discovered that other academics as well as practitioners did not support the value added as a separate dimension (Lee, Strong, Kahn & Wang, 2002, p. 134-136). To be perceived as high-quality and to add value to the task at hand, the contextual information has to be timely, relevant, complete and appropriate. Therefore, value added is rather a consequence of high quality information than the information quality dimension per se (Lee et al, 2002, p. 135).

Thus, we exclude value added from the final research model.

4.3.1.5. Timeliness (excluded)

According to Wang and Strong (1996, p. 7), the information quality should be considered within the context of consumers' current tasks. Yet, current practical knowledge on micro-moments shows that consumer situations vary greatly in their intent (Google 2015, p. 9) and the evaluation of the information quality thus depends on the experiment setting.

In addition to that, the concept of timeliness within contextual information quality is understood as the extent to which the age of the data is appropriate for the task at hand (Wang & Strong, 1996, p. 32). Therefore, we exclude timeliness as the information systems in the scope of this study are constantly updated by automated algorithms and timeliness is unlikely to be an issue in the experiment setting.

4.3.2. Representational Information Quality

4.3.2.1. Interpretability (included)

Interpretability relates to the extent to which information received by the study subjects is in appropriate language and is using clear data units and definitions (Wang & Strong, 1996, p. 31). In the frame of the information processing theory, we may assume that an appropriate language decreases response time, therefore increasing interpretability.

According to the previous studies, the perceived usability of an information system depends on the used language: e.g. users derive more use of the websites in their native language (Nantel & Glaser, 2008, p. 12). When subjects lack time, a foreign language likely has an impact on the information processing speed and, therefore, the number of information points processed and included as the basis for a chosen reaction.

Google (2015, p. 17) further supports this with statistics, stressing the importance of the previously mentioned “be quick” strategy: 40% of the users are usually in a hurry, when looking up something on their smartphone, and 28% of the shoppers are in a rush when buying online. Due to the influence that the information interpretability has on the speed of information processing, we include interpretability in the current study.

4.3.2.2. Ease of Understanding (included)

The concept of ease of understanding is referred to in this paper as the extent to which data is clear, without ambiguity and easily comprehended (Wang & Strong, 1996, p. 32). A number of factors affects users’ ability to understand information provided in the online context. In previous studies, high coherence of a given text has been linked with increased comprehension, especially for low-knowledge users. When given some background knowledge, low coherence of a text has the ability to enforce deeper understanding as it forces the reader to fill in the gaps within the text themselves and to give the text more thought while reading it (McNamara, Kintsch, Songer & Kintsch, 1996, p. 2).

In their “be quick” strategy, Google (2015, p. 18) also implies that optimising information and making it easier to understand is crucial in micro-moments, e.g. eliminating unnecessary steps in forms or using one-click functionality. Based on this discussion, we include ease of understanding in this study.

4.3.2.3. Concise Representation (included)

The information conciseness is the extent to which the information is compactly represented without being overwhelming, i.e. brief in presentation, yet complete and to the point (Wang & Strong, 1996, p. 32). Previous studies have found a positive relationship between online information conciseness and consumer satisfaction (e.g. Bliemel & Hassanein, 2007; Ghasemaghaei & Hassanein, 2015).

According to prior research, information conciseness may facilitate information processing by limiting the total number of items to be processed. In her study, Hathaway (1992, p. 54) found that information conciseness decreases users' mean information reading time by up to 22%. Google (2015, p. 19) further suggests that more prominent presentation of the most important information increases the speed of processing and, thus, leads to better customer feedback. This tip along with the analysis of customers' past behaviour is at the core of “be quick” strategy (Google, 2015, p. 19).

Based on the aforementioned, we expect information conciseness to affect our subjects’ evaluation of the information quality, especially within the micro-moments situations, since it is more likely that the whole body of information will be processed if it is concise. Thus, we include information conciseness in the current study.

4.3.2.4. Consistent Representation (excluded)

The concept of the representational consistency is understood in this paper as the extent to which the information is always presented in the same format and are compatible with previous information (Wang & Strong, 1996). The perception of the representational information quality, i.e. information formatting and meaning, is likely to vary among users (Koivumäki, Ristola & Kesti, 2008, p. 376).

The current study investigates only one type of information within one type of interface due to the setting of the quasi-experiment that ensures the manipulation (see Chapter 5.1.1.). The information the subjects of this study are exposed to is unlikely to vary in the consistency of its representation, as the source of it is the same for all respondents. Thus, we exclude this dimension from the final research model.

4.4. Summarised Research Model

Although multidimensional, the information quality is a single phenomenon and its dimensions are not entirely independent. Their interdependency may present certain difficulties when using the data driven analysis, such as the path analysis for the validation of our survey (Lee et al, 2002, p. 140).

Based on the prior discussion, we draw the final research model (see Figure 6). We focus our study on the six antecedents of the information quality: relevancy, completeness, amount of data, interpretability, ease of understanding and concise representation, as they seem to be most relevant within the context of micro-moments, supported by the human information processing theory. In Figure 6, dashed lines display how each of these information quality dimensions relates to the marketing strategies, introduced by Google (2015, p. 5). Comparing the micro-moments setting with the traditional setting, we expect to find a moderating effect in each relationship.

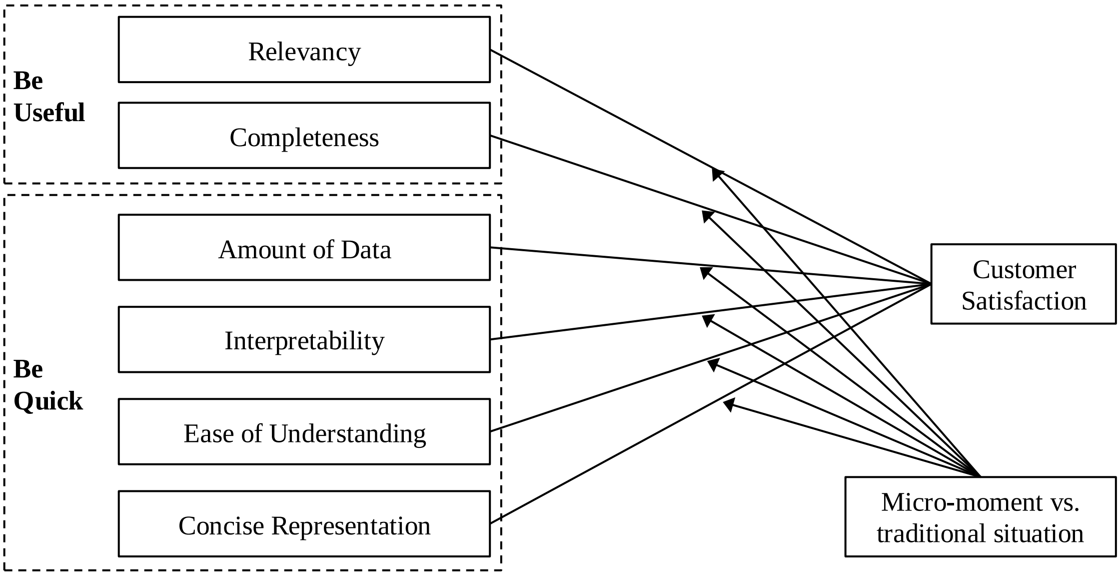

Figure 6. Summarised Research Model. Created by authors.

4.5. Hypotheses

Based on the research model presented above, two sets of hypotheses were generated. The first set concerns direct effects of the information quality dimensions on customer satisfaction, thus answering the first research question ("*What are the antecedents of customer satisfaction with mobile services?"*) within the theoretical premise of the information quality concept.

The second set of hypotheses explores the moderating effect of a micro-moments situation on each of the direct effects mentioned above. This part of the study aims to answer the second research question (*“Does the significance of the antecedents of customer satisfaction with mobile services vary across micro-moments compared to traditional situations?”*).

4.5.1. Direct Effects

The hypotheses in this section relate to the direct effect of selected information quality dimensions on customer satisfaction from using mobile services. It is important to note that the information quality evaluation is subject to users' own perceptions rather than based on a set of objective criteria (Koivumäki, Ristola & Kesti, 2008, p. 376).

The expectation of the direction of these effects, both positive and negative, builds on two studies underlying the final research model. Based on the Information System Success Model by DeLone and McLean (2003), we assume that higher information quality leads directly to higher customer satisfaction with the service. This relationship is further confirmed by multiple empirical studies that analyse antecedents of the information system success based on DeLone and McLean (2003) framework applied specifically to mobile services' context (see Appendix 1 for the summary of the studies). In addition, a study by Ghasemaghaei and Hassanein (2015, p. 974) reveals that, though wide variation exists between different studies of the information quality and its influence on customer satisfaction, the direction of the relationship is still positive. It is just the strength of the effect that changes in the presence of moderating effects, which this study specifically aims to explore in the context of micro-moments.

Next, we analysed how each dimension of the information quality is related to the information quality overall based on Wang and Strong (1996). Again, the theoretical framework is supported by the empirical evidence (e.g. Ayyash, 2015). In addition to the empirical evidence, Ayyash (2015, p. 130) also conducted a meta-analysis of academic literature on the information quality taxonomy, which further confirms that most information quality researchers agree on the importance and positive effect of the four categories and 15 dimensions of information quality as presented by Wang and Strong (1996). We present a more detailed discussion of the hypotheses for each direct effect in Chapter 4.4, Figure 6.

The availability of big data and continuous development of the analysis tools allows to tailor the information to each customer individually and uniquely, as well as suggests that users value increased relevancy of data they are presented with, as it increases the helpfulness of the data (Chen, Chiang & Storey, 2012, p. 1169-1170). Hence, we expect to find a positive relationship between the information relevancy and the user satisfaction with a mobile service.

H1a: *Relevancy has a positive influence on the satisfaction with the use of a mobile service.*

According to Google (2015, p. 12), customers value information containing answers to their questions, thus, filling the gaps in their knowledge. Naturally, the more complete the information, the better it fills the existing information gaps. In addition, information completeness is directly linked to the speed of information processing (Marois & Ivanoff, 2005, p. 298), thus we expect to find a positive relationship between the perceived completeness and satisfaction.

H1b: *Completeness has a positive influence on the satisfaction with the use of a mobile service.*

The perception of the amount of data is closely linked to the concept of the cognitive overload that happens when the data volume reaches the appropriate limit set by the human brain (Kool et al, 2010, p. 2). Yet, information per se and the data available are a good thing as they help users to answer their questions (Google, 2015, p. 12). Therefore, we expect the relationship to be initially positive, but to reach a tipping point when the human cognitive capacity is exceeded, after which extra information will likely have a negative influence on the user satisfaction. Based on the aforementioned, we expect to find a nonlinear relationship between the two variables.

H1c: *The amount of data has a positive influence on the satisfaction with the use of a mobile service up to a point of cognitive overload.*

Interpretability as the information quality dimension strongly relates to the speed of the human information processing. The more interpretable the information is, the quicker users are able to process it and, consequently, derive more value from it.

H1d: *Interpretability has a positive influence on the satisfaction with the use of a mobile service.*

According to McNamara et al (1996, p. 2), high coherence of information is linked to the increased comprehension, which then enhances the user satisfaction with the information system, as the user is able to derive more knowledge from the information provided. From the empirical perspective, the same is stated by Google (2015, p. 18), as they urge marketing managers to make information provided easier to understand.

H1e: *The ease of understanding has a positive influence on the satisfaction with the use of a mobile service.*

The final hypothesis about direct effects is based on the empirical findings by Bliemel and Hassanein (2007) and later, Ghasemaghaei and Hassanein (2015) of is a positive relationship between online information conciseness and the user satisfaction.

H1f: *Concise representation has a positive influence on the satisfaction with the use of a mobile service.*

4.5.2. Moderating Effect of Micro-Moments

In general, the existing practical knowledge about micro-moments (e.g. Google, 2015) does not contradict the information quality theory. Therefore, we expect that in micro-moments situations the direction of the effect that each information quality dimension has on customer satisfaction will remain the same, compared to the traditional search situation.

However, because of the short time that micro-moments last and their ubiquitous nature, as well as the limitations of the human information processing capabilities, outlined in the previous sections, we expect that the observed direct effects might gain more weight or significance due to the moderating effect of the micro-moments situation. We present a more detailed discussion of hypotheses for each indirect effect in Figure 6.

Google (2015, p. 11) confirms that big data generated by mobile phones allows for a deeper analysis of the consumer behaviour and enables companies to provide exceedingly relevant information in user's micro-moments. The time limit imposed by the micro-moments situation adds to the importance of the information relevance, as irrelevant information may slow down the information processing (Marois & Ivanoff, 2005, p. 298).

H2a: *The* **positive effect** *of information relevancy is* ***stronger*** *in the micro-moments situation compared to the traditional information search.*

Based on Marois and Ivanoff (2005, p. 298), we assume that the perception of information as complete or incomplete may indicate whether the user had enough time to process it. The short duration of the micro-moments situation gives even less processing time, thus enhancing the importance of the information completeness even further.

H2b: *The* **positive effect** *of information completeness is* ***stronger*** *in the micro-moments situation compared to the traditional information search.*

We expect to find a non-linear relationship between the amount of data and customer satisfaction similar to the motivation for hypothesis H1c (see Chapter 4.5.1.). Initially, more data is driving satisfaction as it helps to answer customer questions (Google, 2015, p. 12), but afterwards excessive information may cause cognitive overload. What differs, however, is how early the tipping point is reached. More information takes more time to load, which is crucial in micro-moments (Google, 2015, p. 18), as well as takes more of the human processing capacity (Marois & Ivanoff, 2005, p. 298), thus we would expect a nonlinear function to be skewed compared to the original one.

***H2c:** The **initial positive effect** of higher amount of data **remains the same** in the micro-moments situation compared to the traditional information search, while the **negative effect** of cognitive overload is **stronger** in the micro-moments situation.*

The statistics from Google research (2015, p. 17) state that users are usually in a hurry when looking up information online, once again stressing the importance of the short duration of the micro-moments situation. Therefore, it is more important to have highly interpretable information during micro-moments to alleviate the limitations of the human information processing.

***H2d:** The **positive effect** of information interpretability is **stronger** in the micro-moments situation compared to the traditional information search.*

Eliminating unnecessary steps or using one-click functionality is crucial during the micro-moments, as it optimises information for easier understanding (Google, 2015, p. 18). Once again, the practical “be quick” strategy suggested by Google goes in line with Marois and Ivanoff (2005, p. 298) research on the human information processing capabilities. Information that is easier to process alleviates the limitations of the human brain, which is crucial when a user has a limited amount of time for the information processing, as in the case of the micro-moments situations.

***H2e:** The **positive effect** of ease of understanding is **stronger** in the micro-moments situation compared to the traditional information search.*

The empirical evidence from Bliemel and Hassanein (2007) and later, Ghasemaghaei and Hassanein (2015) of the positive relationship between the information conciseness and the user satisfaction can be complemented with the research by Hathaway (1992, p. 54), stating that the information conciseness decreases users' reading time. We believe it helps to reduce the impact of the limitations of the human brain in terms of the information processing capabilities in the micro-moments situations, thus leading to better information processing and, consequently, higher satisfaction with the information system. It is also found by Google (2015, p. 19) that concise presentation of information increases the speed of processing and generated better feedback from the customers.

H2f: *The* ***positive effect*** *of concise representation is* ***stronger*** *in the micro-moments situation compared to the traditional information search.*

4.5.3. Control Variables

In prior studies, the age and the level of education have been linked with the cognitive performance. The information processing speed of younger adults is greater across virtually all information-processing tasks compared to older adults (Tucker-Drob, Johnson & Jones, 2009, p. 439; Myerson, Hale, Chen & Lawrence, 1997, p. 95). Therefore, we believe that subjects' age and the level of education affect their information processing capabilities. The older the subject, the slower are their conscious identification of visual stimuli, VSTM capacity and the response time.

Following the same logic, the more educated is the respondent is, the more efficient their or her information processing is, making it easier for them to understand the information received. The context of micro-moments will likely increase the disparity of the information processing and understanding by the study subjects due to the limited time frame. The less time one has, the more processing speed and, thus, cognitive capabilities are required to digest the same amount of information.

Okazaki and Barwise (2011, p. 65) also agree that age, income and information privacy awareness might have influence on the users' evaluation of a mobile service. Finally, according to the Okazaki and Mendez (2013a, p. 1240), gender plays a significant role in the perception of mobile service, as the ease of use has stronger effects among men compared to women.

Therefore, we consider gender, age and the level of education as the control variables in order to eliminate potential biases and inconsistencies from the evaluation of direct effects of the information quality dimensions on customer satisfaction, as well as from the estimation of moderating effect of micro-moments.

5. Methodology

5.1. Study Setup

5.1.1. Task-based Experiment

In order to address the research questions, a task-based quasi-experiment was conducted. Each subject respondent was asked to use his or her mobile handset to complete the task described in the experiment scenario (see Chapter 5.1.3. and Appendix 3).

Half of the respondents were given 15 minutes to do the research, while the other half was instructed to complete the task in under 3 minutes in order to simulate the micro-moments situation. The two scenarios were randomly assigned to participants and the timing was controlled automatically by survey software.

After the time allocated for the task ran out, respondents filled in a structured questionnaire. The perception of the information quality constructs was evaluated on a 11-point Likert scale ranging from “completely disagree" to ‘‘completely agree". The measurement items for the constructs were adapted from prior research by Lee et al (2002, p. 143) and were adjusted slightly to match the task scenarios. See Appendix 4, Q11-Q37 for the complete list of measurement items.

5.1.2. Dependent Variable

For the dependent variable, i.e. customer satisfaction, a measure used by Evanschitzky, Iyer, Hesse and Ahlert (2004), and earlier by Szymanski and Hise (2000) was adopted. Both studies explored the antecedents for customer satisfaction in an online context based on the examples of online shopping and online banking services. While the experiment setting of the current study does not precisely correspond to the surveys conducted by Evanschitzky et al (2004) and Szymanski and Hise (2000), the dependent variable has been developed and tested in the same field of study, and thus is directly transferrable.

There might be a potential mono-operation bias (Heppner, Wampold & Kivlighan, 2007, p. 99), i.e. bias resulting from the evaluation of the dependent variable based on one question only. However, research demonstrates that a single-item scale might be just as reliable and valid as multi-item scale (Fuchs & Diamantopoulos, 2009, p. 202). Fuchs and Diamantopoulos (2009, p. 203) also found that highly complex and multidimensional concepts are better captured with single measurement, since multi-item scale might miss some of the important aspects of the concept. In addition, in diverse yet limited samples, single-item constructs tend to perform better (Fuchs & Diamantopoulos, 2009, p. 206). Both nature of customer satisfaction and our sample properties confirmed our choice of single-item scale for the dependent variable.

5.1.3. Scenario Development

This study is focused on just one type of micro-moments in Google (2016a) typology, the "I want to know" moment. In contrast to the other three, this type of micro-moments is relatively easy to convincingly replicate in the experimental setting.

For example, "I want to go" moment is tied to the location, so the experience of respondents, unless they are located in the very same geographic area (e.g. laboratory), would not be the same and potentially would lead to biased or inconsistent results. "I want to do" moments in real life occur based on the prior knowledge of the user on the topic (e.g. how to cook something), thus different users would find different level or type of information satisfactory in terms of information quality. It is nearly impossible to sufficiently control for the level of knowledge without exposing respondents to a burden of additional questions. Finally, "I want to buy" moments imply that the respondent should have a purchase intention, which is impossible to imitate or generate upon request for the purpose of the experiment.

Thus, using "I want to know" moment allows creating most realistic situation in the experiment setting and derive results that are independent from respondents' location or prior experiences. The other three scenarios would present an opportunity for further research, as discussed in Chapter 7.3.

All respondents were exposed to one of the two scenarios: one involving traditional information search and another imitating micro-moments situation. We have used imaginary search for flight information on the online service of Flight Search Company[1], which ensures that all participants are exposed to the same information, language (English) and currency (GBP), as it is homepage for United Kingdom. The respondents were asked to search for flights between London and New York in a particular month, as these cities among the most frequently searched destinations (#3 and #1 respectively; Plautz, 2016). Exposing all respondents to identical interface and asking them to lookup the same information leads to consistent results and allows to attribute differences in perception to the experiment manipulation. See Appendix 3 for the complete description of both scenarios.

[1] The actual brand name and web domain are anonymised throughout the paper for confidentiality reasons.

5.1.4. Questionnaire Design

The survey was conducted online using Qualtrics software. The questionnaire contained 41 question distributed across 9 pages (screens). All descriptive texts and complete list of questions are available in Appendices 3 and 4, respectively.

The first page was devoted to introduction, common for all respondents. Next, respondents received scenario-based instructions for task completion and the task itself on two separate pages to allow for preparation (i.e. ensuring Wi-Fi access, opening browser on mobile, loading the website etc). Qualtrics functionality allows the adjustment of scenario flow as well as a random assignment of respondents to either of the two scenarios.

After completing the task, respondents were asked to evaluate their satisfaction with the service to generate data for the dependent variable in our model. We also estimated respondents' familiarity with Flight Search Company to control for user experience bias.

Next, we conducted manipulation check based on 8 questions to make sure that there was a difference in perception of the two scenarios among respondents. The detailed description, statistics and discussion of the manipulation check results are further presented in Chapter 5.3.

The next two pages of the survey covered 3 constructs of contextual information quality and 3 constructs of representational information quality. We chose to present the two dimensions on two separate pages to avoid overwhelming respondents with too many questions at once. The constructs within each dimension, however, were clearly separated from one another to avoid any confusion.

Finally, respondents filled in a demographic profile, including questions on gender, age, level of education and native language, which were further used in the study as control variables. After the demographic questions, respondents were debriefed and provided with researchers' contacts for feedback opportunity.

5.2. Sample Description

The survey was distributed via NHH and WU mailing lists, as well as social networks to student community. The survey ran for two weeks from May 4th, 2017 to May 18th, 2017, collecting 225 responses in total.

Due to incomplete responses, we had to remove 110 entries from the sample before conducting the analysis. The high drop rate of 48.9% may indicate potential respondent bias in the sample, so we further investigated the dropped surveys (see Table 3 below). Of 88 respondents that stopped at the scenario presentation page, 76 were faced with traditional search situation, i.e. the task that would take up to 15 minutes (see Appendix 3, Scenario 1). We therefore assume that the main reason behind such a high drop rate is the time investment that was required from the respondents that were randomly assigned to traditional search situation.

Next, we analysed the task completion time (amount of time spent on scenario page), removing 2 more responses that took below 4 seconds, which is technically too low to complete the task at hand. Finally, we analysed remaining 113 responses for patterns in construct evaluation (see Appendix 4, Q11-Q37). The standard deviation below 0.9 between the 27 scores was taken as an indicator of a pattern and, consequently, a careless response for another 2 respondents.

Response type	Detailed description	# of responses	Sample %	Cumulative %
Incomplete responses	Did not complete the task in the scenario	88	39.1%	39.1%
	Did not complete manipulation check	15	6.7%	45.8%
	Did not evaluate of IQ constructs	7	3.1%	48.9%
Careless responses	Too low completion time	2	0.9%	49.8%
	Pattern of filling in	2	0.9%	50.7%
Analysed responses	Evaluated only one IQ dimension of two	6	2.7%	53.3%
	Fully completed questionnaires	105	46.7%	100.0%
Total		225	100.0%	

Table 3. Summary of Dropped Response Reasons and Survey Completion Rate. Created by authors.

The 111 remaining responses were taken for further analysis in scope of this study. First, we gathered sample descriptive statistics using IBM SPSS Statistics v23 analytical software package (further in text, SPSS).

Due to random scenario assignment, 59 responses (53.2%) were based on micro-moments scenario and 52 responses (46.8%) related to traditional search situation. 58.5% of respondents were moderately to very familiar with Flight Search Company’s website, yet, another 21.6% were not familiar at all. Since the distribution of familiarity was approximately similar in both manipulated groups, we conclude that the total sample reasonably represented the population of both tech-savvy and avid travellers, as well as people new to online travel tools.

The demographic profile was completed by 105 respondents with the following statistics:

- Gender: 45.7% male, 53.3% female, 1% preferred not to answer;
- Age: range from 19 to 50 and average of 26.9 years.

The sample statistics go in line with international data on the Internet usage by gender and age groups (Statista, 2014, 2015), thus deeming this sample representative of the total population of Internet users. Due to distribution methods to mostly student community in Norway and Austria, the education levels mainly distributed between bachelor and master degrees, and 90.5% of the sample indicated native language as other than English.

5.3. Manipulation Check

The experimental design of this research implies high internal validity since the expected moderator (micro-moments situation) is directly manipulated for the respondents, so we are able to attribute the observed effects to the experimental variable, and not to other factors (Churchill and Iacobucci, 2005, p. 131).

5.3.1. Survey Pilot Test

We have included manipulation check in the survey, asking for respondents' perception of the situation they were exposed to. According to McTigue (2015), micro-moments happen rapidly in customer's spare time, such as commuting, waiting in a queue or simply being bored. In addition, as described previously by Google (2015, p. 9), micro-moments differ in terms of user intent both between themselves and from traditional information search. Finally, by definition, micro-moments are also short in time, while during traditional search user is willing to invest more time to make a fully informed decision. Therefore, the manipulation check covered two areas where micro-moments are different from traditional situations: perception of time and search intention (see Appendix 4, Q3-Q10).

Before distributing the survey to a larger population, we conducted a pilot test of original scenarios and manipulation check questions on 24 respondents. Even though the manipulation check returned statistically significant differences between two scenario groups in a relatively small sample, we still adjusted the scenarios based on respondents' detailed feedback. The second version of scenarios was recognised as more realistic setup by the participants of pilot study, as well as manipulation check statements became more straightforward and easier to understand. The scenarios, questionnaire and survey data included in this study present only the revised version of the survey.

5.3.2. Manipulation Check in the Final Survey

Based on the final data set, we conducted manipulation check for 111 respondents, using SPSS. Prior to that, three variables had to be recoded as they have been reversed on a scale from traditional to micro-moments situation perception (see Appendix 4, Q5-Q7).

To test the differences in the perception of experiment setting, we conducted one-way ANOVA test for the 8 statements. Table 4 reports the significant mean differences in the sample between manipulated groups on all 8 statements, which go in the expected direction, i.e. higher for micro-moments situation respondents.

Manipulation Check Statement		N	Mean	Std. Dev.	F	Sig.
I was conducting the search to fill the idle time	M[2]	59	3.797	1.323	33.127	0.000
	T	52	2.346	1.327		
I was feeling bored before conducting the search	M	59	3.729	1.350	29.212	0.000
	T	52	2.365	1.299		
I needed to choose the flight after the search (R)	M	59	3.746	1.359	24.576	0.000
	T	52	2.481	1.321		
I needed to decide on the flight dates (R)	M	59	3.339	1.527	15.603	0.000
	T	52	2.250	1.356		
I would be ready to complete the ticket purchase based on the information I found (R)	M	59	3.780	1.451	42.359	0.000
	T	52	2.173	1.098		
I did not have enough time to discover all information	M	59	3.593	1.366	45.176	0.000
	T	52	2.019	1.057		
I felt the time pressure while conducting the search	M	59	3.814	1.319	60.650	0.000
	T	52	2.019	1.075		
Usually, I would use more time to find my flight details and buy the ticket	M	59	4.661	0,734	25.259	0.000
	T	52	3.654	1.327		

Table 4. One-way ANOVA Test for Mean Comparison between Manipulated Groups on Individual Manipulation Check Statements. Created by authors.

We then performed exploratory factor analysis in SPSS to see whether the 8 statements load on two factors, perception of time and search intention, as we described above. The Kaiser-Meyer-Olkin (KMO) test for sampling adequacy returned a satisfactory value of 0.834, well above the minimum of 0.6 for factor analysis (Pallant, 2006, p. 174). Using the maximum likelihood extraction method with Oblimin rotation, the eigenvalues test (Pallant, 2006, p. 175) resulted in one-factor solution, scoring 4.636. Yet, two-factor solution scored 0.910, which signifies that it is also plausible. We therefore ran one more round of factor analysis, manually

[2] In this and further tables, M stands for micro-moments' scenario group and T stands for traditional search scenario group.

fixing the number of factors to 2. There, two items load above 0.7 (Chin, 1998, p. xiii) on "time" factor, and two on "purpose" factor (see shaded cells of Table 5).

Manipulation Check Statement	Time Factor	Purpose Factor
I was conducting the search to fill the idle time	0.145	0.626
I was feeling bored before conducting the search	0.409	0.418
I needed to choose the flight after the search (R)	-0.021	0.834
I needed to decide on the flight dates (R)	-0.093	0.889
I would be ready to complete the ticket purchase based on the information I found (R)	0.316	0.466
I did not have enough time to discover all information	0.720	0.097
I felt the time pressure while conducting the search	1.081	-0.131
Usually, I would use more time to find my flight details and buy the ticket	0.401	0.220
Extraction Method: Maximum Likelihood *Rotation Method: Oblimin with Kaiser Normalisation, converged in 5 iterations.*		

Table 5. Factor Loadings (Pattern Matrix) on Individual Manipulation Check Statements. Created by authors.

Next, we have combined mean values of mentioned statements to create two manipulation dimensions and performed one-way ANOVA test in SPSS to confirm the mean differences in the sample between manipulated groups again (see Table 6).

Manipulation Dimension		N	Mean	Std. Dev.	F	Sig.
Purpose	M	59	3.542	1.277	23,821	0,000
	T	52	2.365	1.257		
Time	M	59	3.703	1.222	63,046	0,000
	T	52	2.019	0.980		

Table 6. One-way ANOVA Test for Mean Comparison between Manipulated Groups on Manipulation Dimensions. Created by authors.

Note that that the two means are 3.70 and 2.02 on 1-5 scale for "time" factor, and 3.54 and 2.37 for "purpose" factor. This finding is important as it demonstrates that though the sample groups were manipulated successfully, in the end we compared low-to-medium values of the micro-moments perception rather than low-to-high values, which might be relevant to the estimated magnitude of difference in the perception of information quality dimensions.

5.4. Information Quality Constructs

First, we explored the correlation between statements within each construct one-by-one, as well as checked whether the statements within one construct load on one factor with confirmatory factor analysis.

Both methods demonstrated that all of the reversed items that we used according to Lee at al (2002, p. 143) did not work in the sample. After we have recoded them to go in the same direction as non-reversed items, they negatively correlated with the non-reversed items even though both were intended to measure the same construct (see Appendix 5, Tables 21-26).

Consequently, the recoded reversed items also did not load well on one factor with the non-reversed items (see Appendix 6, Tables 27-36). Based on these two methods we removed the reversed items from further analysis, as well as one additional item in *Completeness* construct (Appendix 4, Q18).

5.4.1. Exploratory Factor Analysis

We then established discriminant validity of the model by performing exploratory factor analysis on all selected items in SPSS. The Kaiser-Meyer-Olkin (KMO) test for sampling adequacy returned a satisfactory value of 0.766 (Pallant, 2006, p. 174). Using the maximum likelihood extraction method, the eigenvalues test (Pallant, 2006, p. 175) returned 4 factors instead of expected 6, though five-factor and six-factor solutions still scored relatively high: 0.911 and 0.814 respectively (see Table 7). Factor loadings in pattern matrix for both 4-factor and 6-factor solutions are reported in Appendix 7, Tables 37 and 38, respectively.

Factor	Initial Eigenvalues	% of Variance	Cumulative %
1	7.162	35.808	35.808
2	2.653	13.265	49.073
3	2.459	12.296	61.369
4	1.675	8.374	69.743
5	0.911	4.555	74.298
6	0.814	4.071	78.369

Table 7. Initial Eigenvalues for Exploratory Factor Analysis. Created by authors.

The main observation is that the *Ease of Understanding* loads on the same factor with *Interpretability*, as well as *Completeness* loads together with the *Amount of Data*. From the theoretical perspective, this could be explained by close relationships and interconnectedness of all dimensions of information quality, as described in Chapter 4. *Ease of Understanding* and *Interpretability* are both dimensions of representational information quality, while *Completeness* and the *Amount of Data* are both categorised as contextual information quality, which means that constructs within each pair are quite similar. Yet, the original information quality taxonomy provides clear overview of how each dimension is different from the others even if they are grouped in the same category (Wang & Strong, 1996; described in Chapter 3.3. in more detail).

There might be also the statistical reason behind lower eigenvalue test for a 6-factor solution: the sample size is relatively low for this kind of analysis, as well as for some constructs we had just 2 or 3 items left after removal of the reversed ones. Already from the factor loadings we also expect that the *Amount of Data* construct might cause further issues in data analysis, which are addressed in the next chapters.

We believe that 0.841 eigenvalue score for 6-factor solution is still rather close to 1, given that with 5th and 6th factor explaining more than 4% of the total variance each. Joint with the theoretical background of this study (see Chapters 3 and 4), we decided to proceed with 6-factor solution.

5.4.2. Convergent and Discriminant Validity

As described in the previous chapter, we selected the items that load strongly on one factor (close to or higher than 0.7) to ensure the convergent validity of constructs used in the analysis. To investigate the validity even further, we compute average variance extracted (AVE) and composite reliability (CR) for each construct.

Fornell and Larcker (1981, p. 46) state that AVE should be larger than 0.5 and CR should be larger than 0.7 to confirm that items measure just one construct and the convergent validity of the model is satisfied. Table 8 below presents factor loadings from MPlus statistical modelling software, obtained in exploratory factor analysis of each construct separately, as well as manually computed values of CR and AVE. In contrast to SPSS, MPlus methods allowed for factor loading calculation for the *Amount of Data* construct, which was based on just two items.

Construct	Factor Loadings						CR	AVE
	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6		
Relevancy	0.696	0.860	0.760	0.897	n/a	n/a	0.881	0.652
Completeness	0.725	excl.	0.790	excl.	0.804	0.682	0.838	0.565
Amount of Data	0.718	excl.	excl.	0.574	n/a	n/a	0.591	0.423
Interpretability	0.824	excl.	excl.	0.742	0.757	n/a	0.818	0.601
Ease of Understanding	0.808	excl.	0.821	0.865	n/a	n/a	0.871	0.692
Conciseness	0.947	0.878	0.939	0.875	n/a	n/a	0.951	0.829

n/a - no 5th or 6th item was included in the survey for respective construct
excl. - item was excluded from further study based on exploratory factor analysis

Table 8. Composite Reliability and Average Variance Extracted of Information Quality Constructs. Created by authors.

Then, we created a correlation matrix of constructs using Pearson correlation coefficient obtained from SPSS analysis, and compared it to the square root of AVE of each construct to establish the discriminant validity once again. The square root of AVE should be larger than the correlation (Gefen & Straub, 2005, p. 94), which is the case for all six constructs. Again, the *Amount of Data* construct is a borderline acceptable case due to its relatively low AVE and high correlation with *Completeness*.

	Relevancy	Complete ness	Amount of Data	Interpreta bility	Ease of Underst.	Concise Repres.	√AVE
Relevancy	1	-0.176	-0.109	-0.304**	-0.286**	-0.243*	0.807
Completeness	-0.176	1	0.603**	0.342**	0.317**	0.263**	0.752
Amount of Data	-0.109	0.603**	1	0.231*	0.276**	0.378**	0.650
Interpretability	-0.304**	0.342**	0.231*	1	0.648**	0.458**	0.775
Ease of Underst.	-0.286**	0.317**	0.276**	0.648**	1	0.566**	0.832
Concise Repres.	-0.243*	0.263**	0.378**	0.458**	0.566**	1	0.832

**. *Correlation is significant at the 0.01 level (2-tailed)*
*. *Correlation is significant at the 0.05 level (2-tailed)*

Table 9. Correlation Matrix of Information Quality Constructs. Created by authors.

5.5. Study Limitations

Despite high convergent and discriminant validity, this study has two important limitations. First, the total sample size is only 111 observations, which are further split into groups of 59 and 52 by the manipulation. While the sample size around 50 observations allows for some statistical inference, it hinders deeper analysis, such as inclusion of control variables since those reduce the sample size further.

The next limitation is evident from the statistics on the manipulation check. As discussed in Chapter 5.3.2, the mean values for both "time" and "purpose" factors are rather low for micro-moments group. We believe that despite successful manipulation, the experiment setup did not create a strong feeling of a micro-moment. The respondents definitely recognised the purpose stated in the scenario, as well as the time shortage, but they did not experience a micro-moment per se. Rather, respondents were *prompted to imagine* themselves in a micro-moment, which is a natural drawback of quasi-experiment. In scope of present study, this might have created a potential bias in the perception of information quality dimensions: as they did not feel the micro-moments as strongly as they would in the real world, their estimates might gravitate closer to those of traditional situation group.

We address these limitations throughout the analysis, as well as suggest ways to resolve them in Chapter 7.3., as we discuss potential paths of further research.

6. Analysis

6.1. Assumptions of Multivariate Analysis

In order to test the model, we computed single mean values for each construct based on the items selected in the factor analysis. We assume the independence of the responses due to distribution method of online survey that implied individual completion of the task and the questionnaire.

Another important assumption is normality of the data, for which we look on the third and fourth momentum of sample data distribution, i.e. skewness and kurtosis of both dependent variable and computed constructs. As seen from Table 10 below, both are equal or close to 0 within 95% confidence interval for all variables, which generally corresponds to the parameters of a normal distribution (Pallant, 2006, p. 54).

Note also that the mean values of independent variables are rather skewed down (just 4 points out of 10 for all except *Relevancy*), as well as the standard deviations are relatively high, which might be due to the low sample size that allows high user subjectivity to show in the data.

	N	Mean	Std. Dev.	Skewness, 95% CI		Kurtosis, 95% CI	
Satisfaction	111	3.541	1.051	-1.108	-0.209	-1.223	0.561
Relevancy	111	6.818	1.431	-1.189	-0.290	-0.209	1.575
Completeness	111	4.207	2.584	-0.677	0.222	-2.142	-0.358
Amount of Data	111	4.095	2.463	-0.642	0.257	-1.892	-0.108
Interpretability	105	3.946	3.072	-0.634	0.290	-2.494	-0.662
Ease of Understanding	105	4.184	3.222	-0.684	0.240	-2.515	-0.684
Concise Represent.	105	4.226	3.064	-0.850	0.074	-2.398	-0.567

Table 10. Descriptive Statistics of Variables Used in the Model. Created by authors.

It is also important to note that due to 6 partially incomplete responses (see Table 3 in Chapter 5.2.), further regressions were run on a sample of 105 observations: 50 for traditional scenario and 55 for micro-moments scenario.

6.2. Initial Model Test

First, to control for common method bias (CMB) we conducted Harman's single factor test by loading all variables in factor analysis and restricting the number of factors to one (Mat Roni, 2014, p. 33). The first component accounts for just 35% of total variance explained, meaning there is no substantial common method bias present in the data.

Originally, we planned applying structural equation modelling (SEM) approach using MPlus software. However, due to sample size limitation it was only possible to estimate the general model, not accounting for control variables or manipulation. During the initial analysis, MPlus reported error on the *Amount of Data* construct, which as discussed before, is not entirely sound in terms of both convergent and discriminant validity. We therefore opted out to use SPSS software to test the model separately for each manipulated group, and then compared the results by manual calculations, as is explained in further sections.

6.2.1. Main Model Specification

Due to the low convergent and discriminant validity, we considered eliminating the *Amount of Data* construct from the model test entirely, yet that would contradict the theoretical build-up from Chapters 3 and 4. Therefore, we decided to use a single-item construct (Appendix 4, Q21), as the most straightforward measure. To support the choice further, two models were tested. Both have *Satisfaction* as dependent variable and computed mean values of all constructs; the difference in the second model is a single item construct used for the *Amount of Data* variable:

$$(1)\ Satisfaction = \beta_0 + \beta_1 * \mu(Relevancy) + \beta_2 * \mu(Completeness) + \boldsymbol{\beta_3 * \mu(Amount\ of\ Data)} + \\ + \beta_4 * \mu(Interpretability) + \beta_5 * \mu(Ease\ of\ Understanding) + \beta_6 * \mu(Concise\ Representation)$$

$$(2)\ Satisfaction = \beta_0 + \beta_1 * \mu(Relevancy) + \beta_2 * \mu(Completeness) + \boldsymbol{\beta_3 * (Amount\ of\ Data\ Q21)} + \\ + \beta_4 * \mu(Interpretability) + \beta_5 * \mu(Ease\ of\ Understanding) + \beta_6 * \mu(Concise\ Representation)$$

Table 11 below shows that the model fit does not change essentially from the change in the *Amount of Data* variable.

Model	R	R^2	Adjusted R^2	Std. Err.
Mean construct (1)	0.521	0.271	0.226	0.945
Single construct (2)	0.512	0.262	0.217	0.951

Table 11. Model Fit Comparison for Models with Mean and Single Construct. Created by authors.

We estimate F-statistic to compare the model fit according to the simplified formula (Duke University, 2016, p. 3) of the ratio between residual sum of squares (RSS), as the number of observations, independent variables and, consequently, number of degrees of freedom is the same for both models:

$$F = \frac{RSS_1}{RSS_2} = \frac{87.512}{88.607} = 0.987$$

The corresponding p-value of this F statistic is 0.526. Though the difference between the model fit is not statistically significant even at 10% significance level, we proceed with the model (2) as a primary model. We consider single construct to have higher validity based on the exploratory factor analysis (see Chapter 5.4.1).

6.2.2. Model Specification with Control Variables

The tests for differences controlling for gender or familiarity returned no significant results due to high variances from the low sample size, since the 111 observations had to be split in further smaller groups based on manipulation variable and respective control variable. As demographic parameters were not the main focus of current study, the next chapter presents the outcomes for the basic model (2) only.

6.3. Final Model Test

Finally, we have tested the linear regression model on the total sample population, as well as each of the manipulated groups separately, using SPSS. As motivated previously in Chapter 6.2.2., we have used the model (2), i.e. the model with customer satisfaction as dependent variable, as well as a single construct for the *Amount of Data* and computed mean constructs for other independent variables.

We report both unstandardized and standardized estimates for the coefficients, as one provides basis for computing the differences between two sets of estimates, while the latter allows for logical interpretation.

In addition, we test all variables for multicollinearity. Both tolerance and variance inflation factor (VIF) are reported along with regression results in Tables 12, 13 and 14. According to Pallant (2006, p. 150), tolerance below 0.10 or VIF above 10 would raise concerns about multicollinearity. Yet, in all three regressions tolerance varies from 0.404 to 0.919, while VIF ranges from 1.088 to 2.476, indicating no issues with multicollinearity.

6.3.1. Test on the Total Sample Population

First, we ran general linear regression in SPSS on the total sample population to test the first set of hypotheses (see Chapter 4.5.1., H1a-H1f) and confirm that information quality dimensions in question are indeed antecedents of customer satisfaction. The sample size is 105 observations, and R^2-adjusted is 0.217. Table 12 presents complete regression output, with statistically significant coefficients shaded grey.

	Unstandardized β	Std. Err.	Standardized β	t	Sig.	Tol.	VIF
(Constant)	1.743	0.565		3.087	0.003		
Relevancy	0.249	0.069	0.336	3.639	0.000	0.885	1.130
Completeness	0.005	0.046	0.013	0.114	0.909	0.607	1.649
Amount of Data	0.104	0.037	0.305	2.811	0.006	0.641	1.561
Interpretability	-0.075	0.041	-0.216	-1.822	0.071	0.538	1.860
Ease of Understanding	0.056	0.042	0.168	1.343	0.182	0.481	2.077
Concise Representation	-0.073	0.038	-0.207	-1.912	0.059	0.640	1.562

Table 12. Linear Regression Output for Total Sample Population. Created by authors.

We find a positive standardized effect of 0.336 for *Relevancy*, significant at 1% significance level, which supports hypothesis H1a: relevancy has positive influence on the satisfaction with the use of mobile service.

The *Amount of Data* has effect of 0.104, significant at 1% significance level as well. We have hypothesised previously that the concept of cognitive overload may cause the relationship between amount of data and satisfaction to be nonlinear. However, in the data collected we did not notice strong signs of nonlinearity for the *Amount of Data* construct. We believe that it comes from the fact that in our experiment setup the data quantity did not reach the tipping point, so we might have observed only the half of actual function. We therefore conclude that hypothesis H1c is partially supported: amount of data has positive influence on the satisfaction with the use of mobile service; yet, we do not have a definitive inference about the point of cognitive overload.

Overall, we confirm hypotheses H1a and H1c in the total sample.

6.3.2. Test on the Traditional Group

Next, we analyse the group that was exposed to traditional search task. Splitting the sample population according to the scenario manipulation allows testing the first set of hypotheses (see Chapter 4.5.1., H1a-H1f) without potential influences of the micro-moments context. The sample size is limited to 50 observations, and R^2-adjusted is 0.286. Table 13 presents complete regression output, with statistically significant coefficients shaded grey.

	Unstandardized β	Std. Err.	Standardized β	t	Sig.	Tol.	VIF
(Constant)	1.851	0.840		2.203	0.033		
Relevancy	0.236	0.097	0.331	2.435	0.019	0.791	1.263
Completeness	-0.089	0.059	-0.234	-1.496	0.142	0.598	1.671
Amount of Data	0.155	0.045	0.523	3.451	0.001	0.634	1.577
Interpretability	-0.076	0.056	-0.248	-1.354	0.183	0.434	2.306
Ease of Understanding	0.138	0.053	0.471	2.595	0.013	0.443	2.256
Concise Representation	-0.110	0.047	-0.352	-2.346	0.024	0.649	1.540

Table 13. Linear Regression Output for Group Manipulated with Traditional Scenario. Created by authors.

Hypothesis H1a is further confirmed with a positive standardized effect of 0.331 for *Relevancy*, significant at 5% significance level. The effect of the *Amount of Data* is much stronger (0.523), significant at 1% significance level, supporting hypothesis H1c. In contrast to the results in the total sample, we observe a positive coefficient of 0.471 on *Ease of Understanding* construct, significant at 5% significance level, which supports hypothesis H1d: ease of understanding has positive influence on the satisfaction with the use of mobile service.

We further confirm hypotheses H1a and H1c, as well as gain new evidence to confirm hypothesis H1d.

6.3.3. Test on the Micro-Moments Group

Finally, we explore the results of the group that was manipulated to the micro-moments scenario. This analysis is important to generate data for further test of the second set of hypotheses (see Chapter 4.5.2., H2a-H2f), which is then presented in Chapters 6.3.4. and 6.3.5. The sample size is limited to 55 observations, and R^2-adjusted is 0.169. Table 14 presents complete regression output, with statistically significant coefficient shaded grey.

	Unstandardized β	Std. Err.	Standardized β	t	Sig.	Tol.	VIF
(Constant)	1.618	0.791		2.047	0.046		
Relevancy	0.272	0.098	0.357	2.758	0.008	0.919	1.088
Completeness	0.054	0.077	0.118	0.706	0.484	0.554	1.806
Amount of Data	0.091	0.064	0.235	1.428	0.160	0.568	1.761
Interpretability	-0.085	0.063	-0.218	-1.357	0.181	0.599	1.669
Ease of Understanding	-0.006	0.073	-0.015	-0.076	0.940	0.404	2.476
Concise Representation	-0.045	0.065	-0.117	-0.693	0.492	0.536	1.866

Table 14. Linear Regression Output for Group Manipulated with Micro-Moments Scenario. Created by authors.

We observe that most constructs have no statistically significant coefficients even at 10% significance level. *Relevancy*, however, has a positive effect of 0.357, which is slightly higher than the coefficient obtained from the sample based on traditional scenario (see Chapter 6.3.2.). The next section presents a statistical approach to compare the results between two sample groups.

6.3.4. Comparing Models Between Manipulated Groups

First, we compare the absolute values of R^2-adjusted of both models (see Table 15), since dependent variable was the same in both regressions, as well as they had identical number of parameters and the only difference was the sample size and manipulation.

Manipulated Group	R	R^2	Adjusted R^2	Std. Err.
Traditional Scenario (1)	0.611	0.373	0.286	0.801
Micro-moments Scenario (2)	0.511	0.261	0.169	1.080

Table 15. Model Fit Comparison between Manipulated Groups. Created by authors.

We then estimate F-statistic to compare the model fit according to the following formula (Duke University, 2016, p. 3), based on the ratio between residual sum of squares (RSS) and degrees of freedom (df) of each model:

$$F = \frac{(RSS_a - RSS_b)\ /\ (df_1 - df_2)}{RSS_b\ /\ df_2} = \frac{(55.945 - 27.587)/\ (48 - 43)}{27.587\ /\ 43} = 4.866$$

The corresponding p-value of such statistic is 0.001, meaning the difference is significant at 1% significance level. Thus, we conclude that the model fit is indeed much better for the sample group that was exposed to traditional situation, compared to that with micro-moments scenario.

One explanation to such dramatic difference is that the underlying theory of information quality, on which we built our model, was originally developed for traditional information systems (e.g. desktop-based websites) in traditional context. In that view, the model results in the micro-moments scenario group call for proposition that the antecedents of customer satisfaction might be entirely different in micro-moments contexts, deeming information quality dimensions irrelevant. Alternatively, there might be some other unobserved influence from the micro-moments context, controlling for which would raise the explanatory power of existing model.

6.3.5. Comparing Coefficients Between Manipulated Groups

Aside from explanatory power comparison, we have compared the coefficients derived in each of the manipulated groups. This required manual calculation of statistical tests, as we were unable to run structural equation modelling due to sample limitations. There are two ways to test for the difference between the coefficients of identical models obtained from different samples (t-statics and Z-statistics), computed by the following formulas (Clogg, Petkova & Haritou, 1995, p. 1276):

$$t = \frac{\beta_a - \beta_b}{\sigma_a + \sigma_b} \; ; \; Z = \frac{\beta_a - \beta_b}{\sqrt{\sigma_a^2 + \sigma_b^2}}$$

where β denotes unstandardized coefficient, σ - standard deviation of that coefficient and subscripts a and b distinguish between two samples, respectively. None of the differences turned out to be significant in both tests even with 10% significance level (see Table 16, cells shaded grey indicate coefficients that were found statistically significant in previous sections).

Construct	Traditional Group			Micro-moments Group			t	Z
	β_a	σ_a	Sig.	β_b	σ_b	Sig.		
Relevancy	0.236	0.097	0.019	0.272	0.098	0.008	-0.182	-0.257
Completeness	-0.089	0.059	0.142	0.054	0.077	0.484	-1.050	-1.473
Amount of Data	0.155	0.045	0.001	0.091	0.064	0.160	0.593	0.826
Interpretability	-0.076	0.056	0.183	-0.085	0.063	0.181	0.075	0.105
Ease of Understanding	0.138	0.053	0.013	-0.006	0.073	0.940	1.140	1.593
Concise Representation	-0.110	0.047	0.024	-0.045	0.065	0.492	-0.583	-0.814

Table 16. Coefficient Comparison between Manipulated Groups. Created by authors.

Since there is no statistically significant difference between two sets coefficients of coefficients, we reject the second set of hypotheses (Chapter 4.5.2., H2a-H2f) entirely. The effects of information quality dimensions on customer satisfaction in micro-moments are not stronger than those in traditional search situations.

Previously, we have discussed both marketing and psychological perspectives on the perception of information quality, and how and why it might change in the micro-moments situation (see Chapter 4). We therefore attribute lack of supportive findings to the discrepancy in model fit between the two sample groups, reported above. Further discussion builds on this finding, looking deeper in psychological and behavioural theories for possible explanation.

7. Conclusion

7.1. Main Findings

In the previous chapter we have presented the results of this study. We have found support to hypotheses H1a, H1c and H1d, and confirmed that some dimensions of the perceived information quality are the antecedents of customer satisfaction with the use of a mobile service.

A striking finding was that *Interpretability* has a negative effect on satisfaction in the total sample population, significant at 10%. Likewise, *Concise Representation* was found to have a negative effect on satisfaction in the group manipulated for the traditional scenario, significant at 5%. Both findings contradict the empirical evidence from prior research (e.g. Bliemel & Hassanein, 2007; Ghasemaghaei & Hassanein, 2015), and thus present an interesting direction for further research.

Naturally, the sample size limitations and quasi-experimental study design, discussed in Chapter 5.5., might be the reason behind the results obtained in the model analysis, or the lack of those. However, in Chapters 6.3.4. and 6.3.5. we argue that the information quality theory was built for the traditional information systems, such as regular websites, as well as traditional contexts, such as customers purposefully looking for information on their desktop computers at home or in the office.

7.2. Discussion

Recent innovations have changed both information systems and the context they are used in. Nowadays, mobile phones enable consumers with ubiquitous connectivity at all times, and the consumer behaviour has adjusted to it as well (Google, 2015, p. 18-20), leading to the emergence of the micro-moments concept. Watson et al (2002, p. 332) foresaw that the development of ubiquitous commerce might challenge the existing marketing theories, thus it is possible that the antecedents of customer satisfaction have changed along with the changes in consumer behaviour.

Could it be possible then that information quality is entirely irrelevant as the antecedent of customer satisfaction in micro-moments? There is a large underlying body of recent research (e.g. Evanschitzky et al, 2004; Eom et al, 2012; Gao et al, 2012; Ghasemaghaei & Hassanein, 2015) that finds information quality important and relevant in various modern contexts. Moreover, as early as in 2002 Watson et al (p. 339) recognised that information is becoming the core of marketing, and thus is an important factor to consider.

What might be changing, however, is the customers' perceptions of the information quality in the micro-moments setting. As this perception is highly individual and subjective (Koivumäki, Ristola & Kesti, 2008, p. 376), it might have influenced the results of our model and, thus, calls for a more elaborate discussion.

7.2.1. Theoretical Development

We would like to return to the contextual theory building, the approach we discussed in detail in Chapter 4. Wang and Strong (1996, p. 7) have already stressed that the information quality should be considered within the context of consumers' current tasks. Yet, the contextual theory building became a modern area of research among the information quality studies only recently (e.g. Ghasemaghaei & Hassanein, 2015; Gao et al, 2012), stating that the relationship between the information quality and customer satisfaction highly depends on the context in which it is analysed.

In our study we have assumed that the micro-moments themselves are the context having a moderating influence on the relationship between the information quality and customer satisfaction. We have previously adopted the definition of the information quality as the information suitability for the use of information consumers, i.e. quality information is information which has been manipulated in a way that answers users' questions and expands their existing knowledge (EURIM, 2011, p.4). Yet, prior studies (e.g. Koivumäki, Ristola & Kesti, 2008) highlight that the evaluation of the information quality is subject to users' perceptions rather than objective indicators. Google (2015, p. 9) also demonstrates that consumer attitudes vary primarily depending on the individual intent. We, therefore, want to explore the premise that "context" in the micro-moments setting becomes important on the individual, subjective level and thus is specific to every single customer.

There are both pros and cons of such approach. No single theory would be able to accommodate nearly infinite number of individual contexts and characteristics; thus the generalizability of conclusions would potentially suffer. On the other hand, it would make possible to explain the inconsistencies stemming from these contexts and improve the applicability of conclusions (Johns, 2006, p. 389).

We proceed with examining each of the dimensions in the proposed research model (see Chapter 4.4.), outlining the individual characteristics of users that might be relevant.

7.2.1.1. Relevancy

Google (2015) states that consumers browse the Internet to find support for their decision-making process. Thus, information provided by the online information systems should be relevant for the choice or decision a consumer is about to make. Since consumers use mobile services for varied reasons, the relevancy of a particular service is likely to highly alter between users. Furthermore, the reasons also vary between the traditional moments nd the micro-moments for every consumer: between the situation when leisurely browsing the web at home and the moment when they are out, on the go or need information fast.

Previous studies (Brug, Steenhuis, van Assema, Glanz & De Vries, 1999; Kreuter, Skinner, Steger-May, Holt, Bucholtz, Clark, & Haire-Joshu, 2004) show that tailored information has a greater effect on users rather than generic. There are various ways, in which companies can tailor information they are providing so that it is relevant to a consumer. Kreuter and Wray (2003, p. 231) state that information users tend to view messages as more relevant if these reflect their life experience, current life circumstances or cultural markers revealing cultural or societal norms of the users' current location.

7.2.1.2. Completeness

Research shows that users' depth of knowledge affects their decision-making performance through the perceived information completeness (Ahituv, Igbaria & Sella, 1998). Highly knowledgeable users evaluate complete data sets as high quality information, while for less knowledgeable users even an incomplete data set will qualify as highly qualitative.

The effect of the information completeness on the decision-making performance has been previously studied by researchers specialising in the decision-making theory. For one, Ahituv et al (1998) studied Israeli Air Force soldiers and found that complete information improves top-strategic commanders' level of performance, but diminishes the performance of mid-level field commanders.

7.2.1.3. Interpretability

Marketing managers are responsible for the information presented through their company's mobile services, websites and other information systems. Naturally, they expect that the information published would be interpreted by the users in the way the company intended, yet, it is not necessarily always the case.

Within the field of psychology, the term "interpretation" usually refers to an activity taking place between two communicators, the sender and the receiver, via symbols that lack inherent universally accepted meaning (Hancher, 1970). Through the symbols the sender communicates their intended message. Through an active interpretation process affected by one's cultural and political context the receiver forms a meaning for the symbols received from the sender.

Companies should be aware that the meaning users retrieve from the information published by the company might alter from the company's intended meaning. False or alternative meanings may lead to weakened user interpretation and, thus, less than ideal user response, questions left unanswered and user's knowledge not improving.

7.2.1.4. Ease of Understanding

Within the field of psychology, numerous researchers over the past decades have studied the human understanding, but there are still many aspects of this topic not explored fully. Yet, it has been established that the human information processing requires the use of the limited human cognitive processing capabilities (Broadbent, 2013).

According to past studies, it seems as humans not just lower, but stop their information processing altogether once their cognitive processing power is exhausted (Plass, Moreno & Brünken, 2010, p. 29). Based on this notion, companies should avoid cognitive overload when supplying information online.

Human cognitive processing power is not a given constant but rather varies from one person to another (Jaeggi, Buschkuehl, Etienne, Ozdoba, Perrig & Nirkko, 2007, p. 87). In order to avoid the state of cognitive overload, managers should seek to understand the cognitive capabilities of their target audience. In order for information to be understood, tailoring information load to target audience cognitive capabilities is the key.

7.2.1.5. Amount of Data and Concise Representation

Since the human cognitive processing capabilities are limited, a large amount of information slows users' information processing down. Since the information processing capabilities vary among individuals, the scale of slowing down significantly varies between people as well. Yet, the conciseness of information can help to alleviate some of the limitations, thus, we analyse these two dimensions together.

A concise text is short and to the point, communicating more in fewer words (Morkes & Nielsen, 1997). We hypothesise that both the amount of data and the information conciseness are relating to the text quantity, the human cognitive processing and the cognitive overload.

When users are facing time restrictions, the cognitive overload may be preventable by the text conciseness. Dyson and Haselgrove (2001) studied users' reading speeds, line lengths and their effect on reading effectiveness. Their results show that the reading speed varies among users.

Based on the aforementioned, the amount of useful information users are able to gather from the information system depends on users’ cognitive processing capabilities, reading speed and possible time restrictions. The cognitive overload may leave users’ questions partly unanswered, and thus generate negative user responses and decreased information quality.

Based on the prior discussion, it seems beneficial for companies to study their target group in order to determine their cognitive capabilities and the time available in order to tailor their online sites.

7.2.1.6. Extended Research Model

Research in psychology and other fields found that consumers vary in terms of their individual characteristics, such as cognitive abilities, demographic profiles, knowledge, cultural and educational backgrounds (e.g. Taylor, 1975; D’Andrade, 1981; Sigmund, 1994). Focus on the subjective perception of the information quality is becoming increasingly relevant. Google's Senior VP of Ads & Commerce Sridhar Ramaswamy (2017) highlighted the prevalent trend is towards the age of assistance. He states that mass messages will fail in the future, and marketing managers shall focus on tailored communication.

The proposed extended model (see Figure 7) highlights the subjectivity in the perception of the information quality, which affects how consumers process and rank information based on their *individual characteristics*. The perception of the information quality, in turn, affects customer satisfaction, as was partially confirmed by this study. Further on, we keep the *individual context* as a moderating factor: it is not the micro-moments situation per se that moderates the relationship, but rather individual intent, knowledge level, location and other factors that are unique to each consumer in each micro-moment.

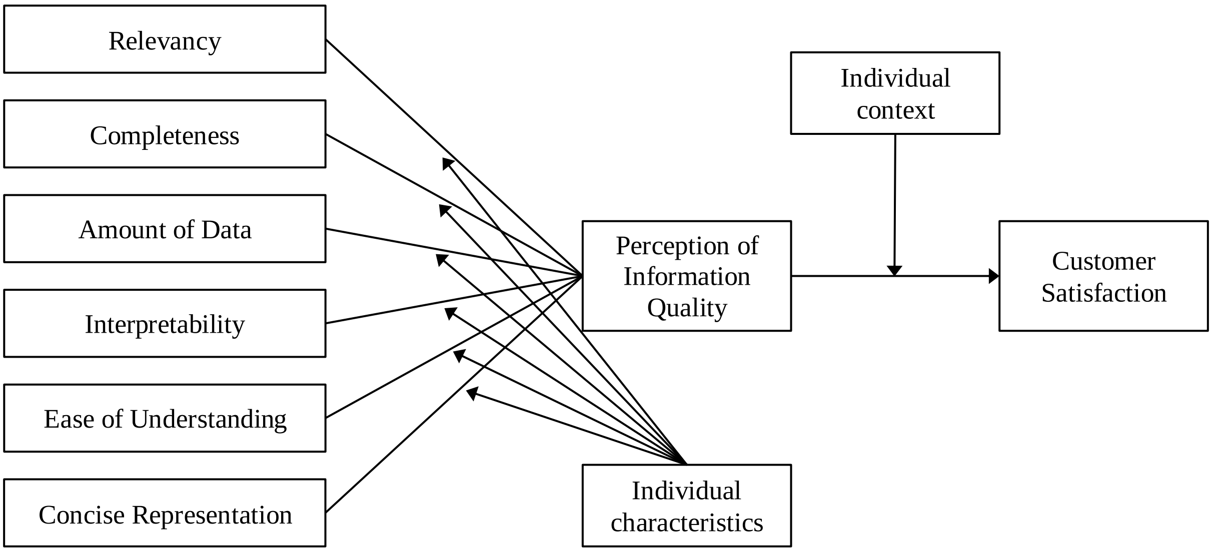

Figure 7. Extended Research Model. Created by authors.

It also illustrates how multidisciplinary is the information quality theory, as it links to numerous other areas of research, e.g. psychology, marketing, information technologies, decision-making, behavioural sciences etc. To fully understand the relationship between the information quality and customer satisfaction, researchers should study it from all of these perspectives.

7.2.2. Managerial Implications

In Chapters 6.3.4 and 6.3.5 we did not find evidence supporting the hypothesis that the effects of information quality dimensions on customer satisfaction are stronger in micro-moments situations. Moreover, the lack of statistically significant findings in Chapter 6.3.3. leads to a conclusion that other factors might be relevant for stimulating customer satisfaction in micro-moments.

In line with the previous discussion in this chapter, the review of the most recent empirical evidence shows a strong trend for personalisation of marketing messages (e.g. Ramaswamy, 2017; Reynolds, 2016). The more targeted the marketing efforts are, the more relevant is the brand story for the customer (Reynolds, 2016).

Mobile phones help gather insights about consumers' behaviour and backgrounds (Google, 2015, p. 11), which may be used to adapt marketing to each customer's needs. As previously stated, customers or users are unique in their individual characteristics such as cognitive capabilities, demographic factors, behavioural and cultural details. In addition, each of them is exposed to information in a unique combination of time, location and intent. Having the data on thousands of users allows creating distinct customer clusters or groups that could be targeted with specific strategies or messages.

Almost every company that deals with mobile services nowadays has access to the consumer data, but not all managers make use of it or are able to employ big data analytics. Still, there are tools and insights provided by the largest data collectors, such as Facebook or Google (Lawson, 2016) that can aid marketing managers in understanding their customers better and personalising their communication.

Finally, in line with Watson et al (2002), we found that the information quality dimensions are indeed significant antecedents of customer satisfaction (see Chapter 6.3.1. and 6.3.2.) and, consequently, the information systems success in general context. It, therefore, means that marketing managers should pay attention to the information quality provided by the company's online media and services. Meanwhile, we hope that the concept of micro-moments will be researched deeper and will serve as a basis for further recommendations for marketing strategies.

7.3. Further Research

We have identified two distinct paths for further exploration of the micro-moments context in the information system success theory. One is to resolve sample and study design limitations of the present study, as well as to test the new extended research model (see Chapter 7.2.1.). Additionally, it is possible to investigate the ideas that were left out of scope of this work, but might shed some light on the micro-moments context.

7.3.1. Testing Extended Research Model

Recognising the issue with the sample size, we would suggest replicating the study on a bigger audience, as it may potentially result in lower variance in the perceived information quality, produce more stable estimates and allow to draw statistically more reliable conclusions. Yet, increasing the sample size would not resolve other limitations of the current study, as well as will not provide support for the concept of individual contexts, or subjectivity that we have discussed in Chapter 7.2.

In addition, a detailed exploration of items used to measure each construct is suggested. As we demonstrated in Chapter 5.4., the reversed items negatively correlated with the regular ones and we had to discard them from further analysis. Reasons behind this negative correlation should be examined in more detail, and alternative measures should be used, so that each of the final constructs has at least four items to build on.

We also think that further research would benefit from using a more realistic experiment setting, so that respondents are not prompted into a micro-moments situation, but realistically experience it. Ideally, we propose a study in partnering with a mobile service provider so that the survey is distributed to real users during their actual micro-moments. Similar approach was already used in the studies on mobile banking that we examined in Appendix 1 (e.g. Chung & Kwon, 2009; Lee & Chung, 2009). However, researchers should be aware that customers in micro-moments would probably lack time and incentive to fill in the survey due to the nature of their information search.

Using a real-life setting for the study would also allow to automatically gather multiple observations on each user, including their demographic profile, interests and frequency of visits via HTTP cookies that are enabled and collected by most websites. The awareness of particular actions, performed by the user online, as well as device, time and location data would also allow to draw conclusions on the information search purpose and intention.

The researchers would obtain multiple data points for each respondent, which would allow to control for many subjective factors and raise the explanatory power of the new proposed model. A potential drawback, however, is that a large dataset might be not feasible for the standard means of statistical analysis, such as regressions or structural equation modelling, and would call for use of more advanced analytical techniques, e.g. big data tools.

7.3.2. Antecedents Other than Information Quality

The exploratory research would investigate the concepts that were left out of the scope of this study. It is possible to go back to the original IS success model (DeLone & McLean, 2003) and explore the system quality or service quality, as they might be stronger determinants of customer satisfaction within the micro-moments context than the information quality. Nelson, Todd and Wixom (2005, p. 208) state that the system quality and the information quality are strongly interconnected and their interaction has an influence on customer satisfaction. Therefore, it would be beneficial to look at both parameters simultaneously. We would expect an increase in explanatory power (i.e. R^2-adjusted) of such model compared to what was obtained in the present study.

Next, we would like to point out that we have investigated only one of four types of micro-moments (see Chapter 2.2.1.), the “I want to know” moment. As we explained in Chapter 5.1.3., other types of micro-moments were more difficult to replicate in a quasi-experiment. Using a real-life setting in partnership with a mobile service provider would allow to control for user location, prior user experience as well as for user engagement with the mobile service (e.g. actions performed on the website or in the app). This data would help to understand the purpose of customer's visit and distinguish between their "I want to go", "I want to do" and "I want to buy" moments. It should be noted, of course, that further division of micro-moments context into 4 categories would require a proportional increase in the sample size.

Finally, we would like to propose a new study approach that does not involve quantitative methods and, thus, does not require a large sample. In their study of micro-moments in travel industry, Google (2016b, p. 9) partnered with Luth Research to build case studies that focused on individual customers and their online journey across devices and services towards the purchase. While this approach does not allow generalisation to the wider population, it provides an example of how subjective factors are affecting the interaction between the customer and the information service. It stresses the importance of personalisation and shows uniqueness of each customer discussed in Chapter 7.2.1. In the academic field, a case study is a recognised qualitative method, which works well in complex and information-rich environments. Alternatively, it could be extended to a focus group approach.

This study explored the concept of micro-moments, the moments of high intent and engagement that happen rapidly in customer's spare time, and how they influence the mobile services' success, measured as customer satisfaction. Using the contextual theory building, we have related the established theories of the information system success and the information quality with the human processing capabilities in the context of micro-moments.

The empirical results from an online quasi-experiment demonstrated that some dimensions of the information quality are indeed the antecedents of customer satisfaction with the use of a mobile service. Yet, the comparison between micro-moments and traditional search situation led to a conclusion that the information quality theory was built for traditional information systems, such as regular websites, and traditional contexts. Based on the results of this study, we have developed a set of theoretical and managerial implications. Finally, we proposed a number of both conceptual and methodological routes to study micro-moments further.

References

Ahituv, N., Igbaria, M., & Sella, A. V. (1998). The Effects of Time Pressure and Completeness of Information on Decision Making. *Journal of Management Information Systems, 15*(2), 153-172.

Aidi, X. (2009). *Cognitive Overload and Its Countermeasures from the Angle of Information Processing*. Third International Symposium on IITA, Vol. 1, 391-394.

Alvarez, G. A., & Cavanagh, P. (2004). The Capacity of Visual Short-term Memory is Set both by Visual Information Load and by Number of Objects. *Psychological science, 15*(2), 106-111.

Amin, M., Rezaei, S., & Abolghasemi, M. (2014). User Satisfaction with Mobile Websites: the Impact of Perceived Usefulness (PU), Perceived Ease of Use (PEOU) and Trust. *Nankai Business Review International, 5*(3), 258-274.

Anderson, E. W., Fornell, C., & Lehmann, D. R. (1994). Customer Satisfaction, Market Share, and Profitability: Findings from Sweden. *Journal of Marketing, 58*(3), 53-66.

Anderson, E. W., & Sullivan, M. W. (1993). The Antecedents and Consequences of Customer Satisfaction for Firms. *Marketing science, 12*(2), 125-143.

Ayadi, O., Cheikhrouhou, N., & Masmoudi, F. (2013). A Decision Support System Assessing the Trust Level in Supply Chains based on Information Sharing Dimensions. *Computers & Industrial Engineering, 66*(2), 242-257.

Balasubramanian, S., Peterson, R. A., & Jarvenpaa, S. L. (2002). Exploring the Implications of M-commerce for Markets and Marketing. *Journal of the Academy of Marketing Science, 30*(4), 348.

Bamberger, P. (2008). Beyond Contextualization: Using Context Theories to Narrow the Mirco-Macro Gap in Management Research. *Academy of Management Journal, 51*(5), 839-846.

Bassi, B. (2015). 6 Common Website Security Vulnerabilities. Retrieved on 22.03.2017. from http://www.commonplaces.com/blog/6-common-website-security-vulnerabilities

Becker, M. W., & Pashler, H. (2002). Volatile Visual Representations: Failing to Detect Changes in Recently Processed Information. *Psychonomic Bulletin & Review, 9*(4), 744-750.

Bliemel, M., & Hassanein, K. (2007). Consumer Satisfaction with Online Health Information Retrieval: A Model and Empirical study. *E-service Journal, 5*(2), 53-84.

Bourne, J. (2016). ABI Research: Companies need to move beyond EMM, while SMS revenues will decline. Retrieved on 06.06.2017. from http://www.appstechnews.com/news/2016/jul/26/abi-research-companies-need-move-beyond-emm-while-sms-revenues-will-decline

Broadbent, D. E. (2013). *Perception and Communication*: Elsevier.

Brug, J., Steenhuis, I., van Assema, P., Glanz, K., & De Vries, H. (1999). Computer-tailored Nutrition Education: Differences Between Two Interventions. *Health Education Research, 14*(2), 249-256.

Chaffey, D. (2013). Mobile Marketing Statistics Compilation. Retrieved on 15.08.2016. from http://www.smartinsights.com/mobile-marketing/mobile-marketing-analytics/mobile-marketing-statistics

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly, 36*(4), 1165-1188.

Chen, L. Y. (2013). Antecedents of Customer Satisfaction and Purchase Intention with Mobile Shopping System Use. *International Journal of Services and Operations Management, 15*(3), 259-274.

Chin, W. W. (1998). Commentary: Issues and Opinion on Structural Equation Modeling. *MIS Quarterly, 22*(1), vii-xvi.

Chiu, C. M., Chiu, C. S., & Chang, H. C. (2007). Examining the Integrated Influence of Fairness and Quality on Learners' Satisfaction and Web-based Learning Continuance Intention. *Information Systems Journal, 17*(3), 271-287.

Chung, N., & Kwon, S. J. (2009). Effect of Trust Level on Mobile Banking Satisfaction: A Multi-Group Analysis of Information System Success Instruments. *Behaviour & Information Technology, 28*(6), 549-562.

Churchill, G. A., & Iacobucci, D. (2005). *Marketing Research: Methodological Foundations*: Thomson/South-Western.

Churchill, G. A., Jr., & Surprenant, C. (1982). An Investigation into the Determinants of Customer Satisfaction. *Journal of Marketing Research, 19*(4), 491-504.

Clogg, C. C., Petkova, E., & Haritou, A. (1995). Statistical Methods for Comparing Regression Coefficients between Models. *American Journal of Sociology, 100*(5), 1261-1293.

comScore. (2014). *The U.S. Mobile App Report*. Retrieved on 18.08.2016. from http://www.comscore.com/Insights/Presentations-and-Whitepapers/2014/The-US-Mobile-App-Report

Cowan, N. (2001). The Magical Number 4 in Short-term Memory: A Reconsideration of Mental Storage Capacity. *Behavioral and Brain Sciences, 24*(1), 87-114.

D'Andrade, R. G. (1981). The Cultural Part of Cognition. *Cognitive Science, 5*(3), 179-195.

David, K. T., Nicosia, F. M., & Wilton, P. C. (1990). Consumer Satisfaction as a Process. *Psychology and Marketing, 7*(3), 177-193.

DeLone, W. H., & McLean, E. R. The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *19*(4), 9-30.

Duke University. (2016). Using the F-test to Compare Two Models. Retrieved on 19.05.2017. from https://sakai.duke.edu

Dyson, M. C., & Haselgrove, M. (2001). The Influence of Reading Speed and Line Length on the Effectiveness of Reading from Screen. *International Journal of Human-Computer Studies, 54*(4), 585-612.

Eom, S., Ashill, N. J., Arbaugh, J. B., & Stapleton, J. L. (2012). The Role of Information Technology in E-learning Systems Success. *Human Systems Management, 31*(3), 147-163.

EURIM. (2011). *Improving the Evidence Base.* The Quality of Information Status Report and Recommendations of the EURIM Sub-group on the Quality of Information. Retrieved on 07.06.2017. from http://www.eurim.org.uk

Evanschitzky, H., Iyer, G. R., Hesse, J., & Ahlert, D. (2004). E-satisfaction: A Re-examination. *Journal of Retailing, 80*(3), 239-247.

Fischetti, M. (2001). In the Fast Lane. *Scientific American, 285*(6), 92-93.

Flanagin, A. J., & Metzger, M. J. (2000). Perceptions of Internet Information Credibility. *Journalism & Mass Communication Quarterly, 77*(3), 515-540.

Fornell, C. (1992). A National Customer Satisfaction Barometer: The Swedish Experience. *Journal of Marketing, 56*(1), 6-21.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research, 18*(1), 39-50.

Forrester Consulting. (2015). *Moments That Matter*. Retrieved on 06.03.2016. from https://storage.googleapis.com/think/docs/forrester-moments-that-matter-research-study.pdf

Fuchs, C., & Diamantopoulos, A. (2009). Using Single-item Measures for Construct Measurement in Management Research: Conceptual Issues and Application Guidelines. *Die Betriebswirtschaft, 69*(2), 195-210.

Gao, J., Zhang, C., Wang, K., & Ba, S. (2012). Understanding Online Purchase Decision Making: The Effects of Unconscious Thought, Information Quality, and Information Quantity. *Decision Support Systems, 53*(4), 772-781.

Gefen, D., & Straub, D. (2005). A Practical Guide to Factorial Validity using PLS-Graph: Tutorial and Annotated Example. *Communications of the Association for Information Systems, 16*(1), 91-109.

Ghasemaghaei, M., & Hassanein, K. (2015). Online Information Quality and Consumer Satisfaction: The Moderating Roles of Contextual Factors – A meta-analysis. *Information & Management, 52*(8), 965-981.

Google. (2015). *Micro-Moments: Your Guide to Winning the Shift to Mobile*. Retrieved on 27.02.2016. from https://think.storage.googleapis.com/images/micromoments-guide-to-winning-shift-to-mobile-download.pdf

Google. (2016a). *4 New Moments Every Marketer Should Know.* Retrieved on 19.08.2016. from https://think.storage.googleapis.com/docs/4-new-moments-every-marketer-should-know.pdf

Google. (2016b). *How Micro-Moments Are Reshaping the Travel Customer Journey.* Retrieved on 24.05.2017. from https://www.thinkwithgoogle.com/marketing-resources/micro-moments/micro-moments-travel-customer-journey

Google, & Nielsen. (2013). *Mobile Path to Purchase*. Retrieved on 19.08.2016. from http://ssl.gstatic.com/think/docs/mobile-path-to-purchase-5-key-findings_research-studies.pdf

Halawi, L. A., McCarthy, R. V., & Aronson, J. E. (2007). An Empirical Investigation of Knowledge Management Systems' Success. *Journal of Computer Information Systems, 48*(2), 121-135.

Hancher, M. (1970). The Science of Interpretation, and the Art of Interpretation. *MLN, 85*(6), 791-802.

Hathaway, S. N. (1992). *Effects of Conciseness on Comprehension of Textual Information Presented Linearly by Computer Screen.* (9231550 Ph.D.), Indiana University, Ann Arbor.

Heppner, P. P., Wampold, B. E., & Kivlighan, D. M. (2007). *Research Design in Counseling*: Cengage Learning.

Isham, M. (2013). 5 Common Causes of Slow Website Performance. Retrieved on 10.03.2017. from https://zoompf.com/blog/2013/04/top-5-causes

Jaeggi, S. M., Buschkuehl, M., Etienne, A., Ozdoba, C., Perrig, W. J., & Nirkko, A. C. (2007). On How High Performers Keep Cool Brains in Situations of Cognitive Overload. *Cognitive, Affective, & Behavioral Neuroscience, 7*(2), 75-89.

Johns, G. (2006). The Essential Impact of Context on Organizational Behavior. *Academy of Management Review, 31*(2), 386-408.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision Under Risk. *Econometrica: Journal of the Econometric Society, 47*(2), 263-292.

Kim, J., Jung, L., Han, K., & Lee, M. (2002). Businesses as Buildings: Metrics for the Architectural Quality of Internet Businesses. *Information Systems Research, 13*(3), 239-254.

Koivumäki, T., Ristola, A., & Kesti, M. (2008). The Effects of Information Quality of Mobile Information Services on User Satisfaction and Service Acceptance–Empirical Evidence from Finland. *Behaviour & Information Technology, 27*(5), 375-385.

Kool, W., McGuire, J. T., Rosen, Z. B., & Botvinick, M. M. (2010). Decision Making and the Avoidance of Cognitive Demand. *Journal of Experimental Psychology General, 139*(4), 665-682.

Kreuter, M. W., & Wray, R. J. (2003). Tailored and Targeted Health Communication: Strategies for Enhancing Information Relevance. *American Journal of Health Behavior, 27*(1), 227-232.

Kulkarni, U. R., Ravindran, S., & Freeze, R. (2006). A Knowledge Management Success Model: Theoretical Development and Empirical Validation. *Journal of Management Information Systems, 23*(3), 309-347.

Lawson, M. (2016). *5 Ways to Find the Micro-Moments Your Brand Can Win.* Retrieved on 27.05.2017. from https://www.thinkwithgoogle.com/marketing-resources/micro-moments/identify-micro-moments-brand-consumer-insights

Lecinski, J. (2011). *ZMOT: Winning the Zero Moment of Truth*.

Lee, K. C., & Chung, N. (2009). Understanding Factors Affecting Trust in and Satisfaction with Mobile Banking in Korea: A Modified DeLone and McLean's Model Perspective. *Interacting with Computers, 21*(5–6), 385-392.

Lee, Y. W., Strong, D. M., Kahn, B. K., & Wang, R. Y. (2002). AIMQ: A Methodology for Information Quality Assessment. *Information & Management, 40*(2), 133-146.

Legault, M.-J. (2015). Marketing in Micro-moments. Retrieved on 29.02.2016. from http://www.origindesign.ca/marketing-in-micro-moments

Lim, H., Widdows, R., & Hooker, N. H. (2009). Web Content Analysis of E-grocery Retailers: A Longitudinal Study. *International Journal of Retail & Distribution Management, 37*(10), 839-851.

lo Storto, C. (2013). Evaluating Ecommerce Websites Cognitive Efficiency: An Integrative Framework Based on Data Envelopment Analysis. *Applied Ergonomics, 44*(6), 1004-1014.

Loeb, S., & Panagos, E. (2011). *Information Filtering and Personalization: Context, Serendipity and Group Profile Effects.* Paper presented at the Consumer Communications and Networking Conference (CCNC).

Marois, R., & Ivanoff, J. (2005). Capacity Limits of Information Processing in the Brain. *Trends in Cognitive Sciences, 9*(6), 296-305.

Mat Roni, S. (2014). Introduction to SPSS. School of Business, Edith Cowan University, Australia. Retrieved on 13.06.2017. from www.researchgate.net/publication/262151892_Introduction_to_SPSS

McNamara, D. S., Kintsch, E., Songer, N. B., & Kintsch, W. (1996). Are Good Texts Always Better? Interactions of Text Coherence, Background Knowledge, and Levels of Understanding in Learning from Text. *Cognition and Instruction, 14*(1), 1-43.

McTigue, J. (2015). How to Harness Micro-Moments in Your Marketing Strategy. Retrieved on 28.02.2016. from https://www.kunocreative.com/blog/harnessing-micro-moments-in-your-marketing-strategy

Miller, H. (1996). The Multiple Dimensions of Information Quality. *Information Systems Management*, *13*(2), 79-82.

Morkes, J., & Nielsen, J. (1997). Concise, Scannable, and Objective: How to Write for the Web. *Useit.com*.

Myerson, J., Hale, S., Chen, J., & Lawrence, B. (1997). General Lexical Slowing and the Semantic Priming Effect: The Roles of Age and Ability. *Acta Psychologica*, *96*(1–2), 83-101.

Nantel, J., & Glaser, E. (2008). The Impact of Language and Culture on Perceived Website Usability. *Journal of Engineering and Technology Management*, *25*(1), 112-122.

Nelson, R. R., Todd, P. A., & Wixom, B. H. (2005). Antecedents of Information and System Quality: An Empirical Examination within the Context of Data Warehousing. *Journal of Management Information Systems, 21*(4), 199-235.

Okazaki, S., & Barwise, P. (2011). Has the Time Finally Come for the Medium of the Future? Research on Mobile Advertising. *Journal of Advertising Research*, *51*(March).

Okazaki, S., Li, H., & Hirose, M. (2009). Consumer Privacy Concerns and Preference for Degree of Regulatory Control: A Study of Mobile Advertising in Japan. *Journal of Advertising, 38*(4), 63-77.

Okazaki, S., & Mendez, F. (2013a). Exploring Convenience in Mobile Commerce: Moderating Effects of Gender. *Computers in Human Behavior, 29*(3), 1234-1242.

Okazaki, S., & Mendez, F. (2013b). Perceived Ubiquity in Mobile Services. *Journal of Interactive Marketing, 27*(2), 98-111.

Oliver, R. L. (1977). Effect of Expectation and Disconfirmation on Post-exposure Product Evaluations: An Alternative Interpretation. *Journal of Applied Psychology, 62*(4), 480-486.

Oliver, R. L. (1980). A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. *Journal of Marketing Research*, 460-469.

Pallant, J. (2006). *SPSS Survival Maunual v.12*: McGraw-Hill Education.

Palmer, J. W. (2002). Web Site Usability, Design, and Performance Metrics. *Information Systems Research, 13*(2), 151-167.

Parasuraman, A., & Zinkhan, G. M. (2002). Marketing to and Serving Customers through the Internet: An Overview and Research Agenda. *Journal of the Academy of Marketing Science, 30*(4), 286-295.

Petter, S., DeLone, W., & McLean, E. R. (2013). Information Systems Success: The Quest for the Independent Variables. *Journal of Management Information Systems, 29*(4), 7-61.

Plass, J. L., Moreno, R., & Brünken, R. (2010). *Cognitive Load Theory*: Cambridge University Press.

Plautz, J. (2016). The Most-searched Travel Destinations in 2016. *Travel and Leisure.* Retrieved on 05.04.2017. from http://www.travelandleisure.com/trip-ideas/most-searched-destinations-2016

Ramaswamy, S. (2017). *Micro-Moments Are Multiplying - Are You Ready for the Future of Marketing?* Retrieved on 04.06.2017. from https://www.thinkwithgoogle.com/marketing-resources/micro-moments/future-of-marketing-machine-learning-micro-moments

Rensink, R. A. (2002). Change Detection. *Annual Review of Psychology, 53*(1), 245-277.

Reynolds, E. (2016). *Fighting Consumer Indifference by Winning Micro-Moments.* Retrieved on 01.06.2017. from https://www.thinkwithgoogle.com/marketing-resources/micro-moments/fighting-consumer-indifference-winning-micro-moments

Sabherwal, R., Jeyaraj, A., & Chowa, C. (2006). Information System Success: Individual and Organizational Determinants. *Management Science, 52*(12), 1849-1864.

Santosa, P. I. (2010). Cost and Benefit of Information Search Using Two Different Strategies. *Telecommunication, Computing, Electronics and Control, 8*(3), 195-206.

Statista. (2014). Internet Use by Age Group Worldwide. Retrieved on 30.05.2017. from https://www.statista.com/statistics/272365/age-distribution-of-internet-users-worldwide

Statista. (2015). Internet Usage Rate Worldwide by Gender and Region. Retrieved on 30.05.2017. from https://www.statista.com/statistics/491387/gender-distribution-of-internet-users-region

Sweller, J. (1994). Cognitive Load Theory, Learning Difficulty, and Instructional Design. *Learning and Instruction, 4*(4), 295-312.

Szymanski, D. M., & Hise, R. T. (2000). E-satisfaction: An Initial Examination. *Journal of Retailing, 76*(3), 309-322.

Taylor, R. N. (1975). Age and Experience as Determinants of Managerial Information Processing and Decision Making Performance. *The Academy of Management Journal, 18*(1), 74-81.

Trawick, I. F., & Swan, J. E. (1982). *Complaint Behavior by Industrial Buyers: Buyer Roles and Organizational Factors*.

Tucker-Drob, E. M., Johnson, K. E., & Jones, R. N. (2009). The Cognitive Reserve Hypothesis: A Longitudinal Examination of Age-associated Declines in Reasoning and Processing Speed. *Developmental Psychology, 45*(2), 431.

Vertes, V., Wilson, G. T., & Wolpe, J. (1990). Worry Changes Decision Making: The Effect of Negative Thoughts on Cognitive Processing.

Wang, R. Y., Lee, Y. W., Pipino, L. L., & Strong, D. M. (1998). Manage Your Information as a Product. *Sloan Management Review, 39*(4), 95-105.

Wang, R. Y., & Strong, D. M. (1996). Beyond Accuracy: What Data Quality Means to Data Consumers. *Journal of Management Information Systems, 12*(4), 5-33.

Watson, R. T., Pitt, L. F., Berthon, P., & Zinkhan, G. M. (2002). U-commerce: Expanding the Universe of Marketing. *Journal of the Academy of Marketing Science, 30*(4), 333-347.

Westbrook, R. A., & Oliver, R. L. (1991). The Dimensionality of Consumption Emotion Patterns and Consumer Satisfaction. *Journal of Consumer Research, 18*(1), 84-91.

Wixom, B. H., & Todd, P. A. (2005). A Theoretical Integration of User Satisfaction and Technology Acceptance. *Information Systems Research, 16*(1), 85-102.

Zhu, H., Madnick, S. E., Lee, Y. W., & Wang, R. Y. (2014). Data and Information Quality Research: Its Evolution and Future.

Appendix 1. Systematic Literature Review

The initial literature review was conducted based on Vienna University of Economics and Business (Wirtschaftsuniversität Wien, WU) extended library catalogue. As WU is the largest university focusing on business and economics in Europe, its library has an extensive access to publications and databases.

We have used title search for academic articles using terms “mobile” and “satisfaction” to identify whether antecedents of customer satisfaction were studied in mobile setting. This search returned 594 publications in English, of which 282 were peer-reviewed.

Additionally, we looked for articles published only after 2007 to eliminate publications that certainly did not cover the "post-iPhone" marketing world and focused on older technologies. This narrowed our selection to 246 articles, after which we removed duplicates, resulting in a set of 200 publications.

We then analysed these publications with regards of the topic, as WU library catalogue covers not only economics, business and management publications, but also several databases on the intersection of management and other disciplines. While “satisfaction” search term meant the marketing concept of “customer satisfaction” in most cases, the “mobile” meaning varied. See Table 17 for the summary results of this analysis.

Publications	Discipline	Meaning of "mobile" in the publication context
25	Medicine	- able to move or be moved physically - mobile device (phone or tablet) - service, based on use of mobile device
6	Education	- mobile device (phone or tablet) - able to move geographically - service, based on use of mobile device
17	Information Technology, Engineering	- mobile device (phone or tablet) - wireless networks (radio, GSM)
5	Finance, Human Resource Management	- service, based on use of mobile device - able to move geographically
147	Marketing, Branding, Consumer Behaviour	- mobile device (phone or tablet) - wireless networks (radio, GSM) - service, based on use of mobile device - mobile application

Table 17. Summary of Stage 1 of Literature Review. Created by authors.

The 147 articles that were identified to belong to the field of marketing or related disciplines were manually inspected in more detail to identify, whether the study is related to customer satisfaction in mobile setting or the focus of the study is different. See Table 18 for the summary results of this analysis.

Publications	Focus of the publication
67	Customer satisfaction is studied in the scope of **telecommunications** industry, i.e. **mobile network providers** and their interaction with customers is analysed.
26	Customer satisfaction is studied in the scope of production, marketing and sales of **mobile phones** as **physical devices** with certain features.
17	Customer satisfaction is mentioned as factor influencing customer loyalty. Publications cover **customer loyalty** concept, customer retention, repurchase.
11	Emergence of **mobile applications** and analysis of consumer behaviour patterns in applications' use; mobile app is considered as the product in this context.
5	**Trust** is analysed either **in parallel to customer satisfaction** as predictor of usage intention, or **as an antecedent of satisfaction** itself. Two studies investigate **the moderating effect of trust** in IQ influence on customer satisfaction. All research is framed by the context of mobile banking.
3	Studies of **antecedents of customer satisfaction in mobile setting**, e.g. mobile websites or apps.
18	Miscellaneous publications on pricing, branding, adoption, intention to use etc, each of the contexts appearing in the selection 1 or 2 times only.

Table 18. Summary of Stage 2 of Literature Review. Created by authors.

We further looked at 5 studies that are directly relevant to the theme of our research: three that study antecedents of customer satisfaction in mobile setting, as well as two related to trust in mobile banking, where trust is considered a moderator in relationship between information system quality and customer satisfaction. Table 19 presents a short summary of methods and findings of these five studies.

Based on this overview, we discovered the information quality concept and its influence on the customer satisfaction. Going in line with the practical understanding of micro-moments (e.g. Google, 2015) and the role that information plays in modern marketing (e.g. Watson et al, 2002, p. 332-333), we took information quality concept as a starting point for further theoretical development. The concepts used as the basis for present study are presented in Chapter 3, and are later used for contextual theory building in Chapter 4, based on Petter, DeLone and McLean (2013). Further on, the five most relevant studies, summarised in Table 19, were used as reference points throughout the current study.

Year	Authors	Journal	Title	Method	Results & Further Comments
2009	Chung & Kwon	Behaviour & Information Technology	Effect of trust level on mobile banking satisfaction: A multi-group analysis of information system success instruments.	Partial Least Squares (PLS) for Confirmatory Factor Analysis (CFA) based on an online survey	System Quality, Information Quality are viewed as antecedents to satisfaction, while trust has a moderating effect in each relationship. Information Presentation does not have a statistically significant effect on satisfaction. The generalizability of this study is limited due to its focus on mobile banking, since trust might be less significant for satisfaction with non-financial transactions and services.
2009	Lee & Chung	Interacting with Computers	Understanding factors affecting trust in and satisfaction with mobile banking in Korea: A modified DeLone and McLean's model perspective	Partial Least Squares (PLS) for Confirmatory Factor Analysis (CFA) based on an online survey	System Quality, Information Quality and Interface Design Quality are found to influence both trust and satisfaction directly, as well as trust is found to influence satisfaction. The study is conducted in exactly the same context as Chung & Kwon (2009), though the tested model is slightly different. These mixed results thus require further investigation.
2014	Amin, Rezaei & Abolghasemi	Nankai Business Review International	User satisfaction with mobile websites: the impact of perceived usefulness (PU), perceived ease of use (PEUO) and trust	Structural Equation Modelling (SEM), Confirmatory Factor Analysis (CFA) based on an online survey	Perceived usefulness (PU), perceived ease of use (PEUO) and trust are found to influence mobile user satisfaction. In addition, positive relationship between PEUO and PU is found, as well as one between PU and trust.
2008	Kolvumäki, Ristola & Kesti	Behaviour & Information Technology	The effects of information quality of mobile information services on user satisfaction and service acceptance-empirical evidence from Finland	Structural Equation Modelling (SEM), Confirmatory Factor Analysis (CFA) based on two field trials	Content Quality, Connection Quality, Interaction and Contextual Quality are all positively related to user satisfaction. User satisfaction is positively related to intention to use the service. The effect of content quality is much stronger for the users with hedonic goals compared to utilitarian ones.
2013	Chen	International Journal of Services and Operations Management	Antecedents of customer satisfaction and purchase intention with mobile shopping system use	Partial Least Squares (PLS) for Confirmatory Factor Analysis (CFA) based on an online survey	System Quality, Information Quality and Service Quality positively affect both perceived usefulness and customer satisfaction, which in turn increase purchase intention. In addition, perceived usefulness positively affects satisfaction.

Table 19. Summary of Stage 3 of Literature Review. Created by authors.

Appendix 2. Overview of IQ Dimensions in Research Model

IQ Dimension	Research Model	Motivation and Sources
Intrinsic IQ	Excluded	Perception of Internet information credibility based on Flanagin and Metzger (2000)
Accessibility	Excluded	Technical reasons behind most accessibility issues that are out of the responsibilities of marketing managers, based on Isham (2013) and Bassi (2015)
Contextual IQ		
Relevancy	Included	Importance of relevant information to the customer based on Chen, Chiang and Storey (2012), as well as Google (2015) "be useful" strategy
Completeness	Included	Limitations of human visual short-term memory (VSTM) based on Marois and Ivanoff (2005), as well as Google (2015) "be quick" strategy
Amount of Data	Included	Data volume limitations of human brain based on Kool et al (2010), as well as Google (2015) "be quick" strategy
Value Added	Excluded	Review of information quality dimensions by Lee et al (2002)
Timeliness	Excluded	Based on Google (2015) differentiation between consumer intents, as well as the definition by Wang and Strong (1996)
Representational IQ		
Interpretability	Included	Speed of processing in native versus foreign language based on Nantel and Glaser (2008), as well as Google (2015) "be quick" strategy
Ease of Understanding	Included	Coherence and knowledge study by McNamara et al (1996), as well as Google (2015) "be quick" strategy
Concise Representation	Included	Correlation between conciseness and reading time (Hathaway, 1992), as well as Google (2015) "be quick" strategy
Consistent Representation	Excluded	Definition by Wang and Strong (1996)

Table 20. Overview of Information Quality Dimensions in Research Model. Created by authors.

Appendix 3. Survey Script

Introduction

Hello! We are Fanni Tuomisto & Marina Snegirjova, MSc students from the Norwegian School of Economics. This survey is designed as a part of our master thesis on certain aspects of mobile marketing and consumer behaviour.

The survey consists of two parts: a simple task involving some online research and a questionnaire. The study may take approximately 7 to 15 minutes to complete, so thank you for taking the time to complete it!

IMPORTANT! You need a mobile phone with Internet access to complete the task, so please make sure to have your phone at hand and that your WiFi is properly functioning.

All responses will be kept confidential. Once the responses have been analysed, all answers will be permanently deleted. It is completely voluntary to participate in this study.

Scenario 1. Control Group: Traditional Search

(1) Please read the instructions until the end before beginning the task. Please open the Internet browser on your mobile phone and go to the www.FlightSearch.net website.

You will have fifteen (15) minutes to complete the task. If you feel that you are done with the task earlier, feel free to proceed further by clicking ">>" button. If not, the survey will take you to the next page to answer several questions related to our study after the 15 minutes run out.

Now, if you are ready to begin (have your mobile & stable Internet connection on it), please click the ">>" button on the bottom-right corner of this page.

(2) Imagine you are planning a trip from London, United Kingdom, to New York City, United States. The dates are not set precisely, but you are willing to travel in July 2017. You decide to conduct a proper search to find the dates when it would be cheapest and most convenient for you to fly, so you can finalise the trip.

Please search for the information on the following flight on www.FlightSearch.net:

- London, United Kingdom to New York City, United States
- Return flight, travelling for a week
- Travel in July 2017, but feel free to pick any dates

Pay attention to the details of the flight that might concern you as a traveller, such as travel time, connecting flights, ticket price or times of departure and arrival.

Scenario 2. Experiment Group: Micro-Moments Simulation

(1) Please read the instructions until the end before beginning the task. Please open the Internet browser on your mobile phone and go to the www.FlightSearch.net website.

You will have three (3) minutes to complete the task. If you feel that you are done with the task earlier, feel free to proceed further by clicking ">>" button. If not, the survey will take you to the next page to answer several questions related to our study after the 3 minutes run out.

Now, if you are ready to begin (have your mobile & stable Internet connection on it), please click the ">>" button on the bottom-right corner of this page.

(2) Imagine you are planning a trip from London, United Kingdom, to New York City, United States. The dates are not set precisely, but you are willing to travel in July 2017. You haven't decided on a trip 100%, but you are now sitting in a queue, you are bored and have some idle time at hand, so you want to check out the flight options and get the price estimate.

Please search for the information on the following flight on www.FlightSearch.net:

- London, United Kingdom to New York City, United States
- Return flight, travelling for a week
- Travel in July 2017, but feel free to pick any dates

Pay attention to the details of the flight that might concern you as a traveller, such as travel time, connecting flights, ticket price or times of departure and arrival.

Debrief

We thank you for your time spent taking this survey. Your response has been recorded.

MSc students of Norwegian School of Economics Marina Snegirjova and Fanni Tuomisto are entirely responsible for the content of this questionnaire. The survey is conducted purely for academic purposes as a part of the master thesis. Flight Search Company Ltd, the legal owner of www.FlightSearch.net domain, has no relation to the survey.

In case you did not have a good experience filling out the survey, please let us know! We will be grateful for your feedback. See our contacts below:

marina.snegirjova@student.nhh.no

fanni.tuomisto@student.nhh.no

Best regards, Marina & Fanni

Appendix 4. Questionnaire

Page 1

Q1. Overall, how do you feel about your flight search experience?

Extremely dissatisfied (1)	Somewhat dissatisfied (2)	Neither satisfied nor dissatisfied (3)	Somewhat satisfied (4)	Extremely satisfied (5)

Q2. How familiar are you with the www.FlightSearch.net website?

Not familiar at all (1)	Slightly familiar (2)	Moderately familiar (3)	Very familiar (4)	Extremely familiar (5)

Page 2

Please indicate to what extent do you agree with the following statements, relating to the imaginary situation described in your task.

	Strongly disagree (1)	(2)	(3)	(4)	Strongly agree (5)
Q3. I was conducting the search to fill the idle time					
Q4. I was feeling bored before conducting the search					
Q5. I needed to choose the flight after the search					
Q6. I needed to decide on the flight dates					
Q7. I would be ready to complete the ticket purchase based on the information I found					

Please indicate to what extent do you agree with the following statements, relating to the imaginary situation described in your task.

	Strongly disagree (1)	(2)	(3)	(4)	Strongly agree (5)
Q8. I did not have enough time to discover all information					
Q9. I felt the time pressure while conducting the search					
Q10. Usually, I would use more time to find my flight details and buy the ticket					

Page 3

Please indicate to what extent the following statements reflect your experience with information you obtained from www.FlightSearch.net website while performing the task, 0 being "completely disagree" and 10 being "completely agree"[3].

	Completely disagree (0)	(1) – (9)	Completely agree (10)
Q11. This information was useful to my task.			
Q12. This information was relevant to my task.			
Q13. This information was appropriate for my task.			
Q14. This information was applicable to my task.			

	Completely disagree (0)	(1) – (9)	Completely agree (10)
Q15. This information included all necessary values.			
Q16. This information was incomplete.			
Q17. This information was complete.			
Q18. This information was sufficiently complete for my needs.			
Q19. This information covered the needs of my task.			
Q20. This information had sufficient breadth and depth for my task.			

	Completely disagree (0)	(1) – (9)	Completely agree (10)
Q21. This information was of sufficient volume for my needs.			
Q22. The amount of information did not match my needs.			
Q23. The amount of information was not sufficient for my needs.			
Q24. The amount of information was neither too much nor too little.			

[3] Questions Q11-Q37 were presented in a similar grid-like structure as Q3-Q10 with “radio button” selection options. For visual presentation purposes, the grid structure is condensed in Appendix 4: answer options (1) to (9) are not presented.

Page 4

Please indicate to what extent the following statements reflect your experience with information you obtained from www.FlightSearch.net website while performing the task, 0 being "completely disagree" and 10 being "completely agree".

	Completely disagree (0)	(1) – (9)	Completely agree (10)
Q25. It was easy to interpret what this information means.			
Q26. This information was difficult to interpret.			
Q27. It was difficult to interpret the coded information.			
Q28. This information was easily interpretable.			
Q29. The measurement units for this information were clear.			

	Completely disagree (0)	(1) – (9)	Completely agree (10)
Q30. This information was easy to understand.			
Q31. The meaning of this information was difficult to understand.			
Q32. This information was easy to comprehend.			
Q33. The meaning of this information was easy to understand.			

	Completely disagree (0)	(1) – (9)	Completely agree (10)
Q34. This information was formatted compactly.			
Q35. This information was presented concisely.			
Q36. This information was presented in a compact form.			
Q37. The representation of this information was compact and concise.			

Page 5

Q38. Please indicate your gender

- Male (1)
- Female (2)
- Prefer not to answer (3)

Q39. Please indicate your age (as number of full years)

Q40. Please indicate the highest level of education attained

- High school graduate (1)
- Some university credits, no degree (2)
- Bachelor's degree (3)
- Master's degree (4)
- Doctorate degree (5)

Q41. Please indicate your native language

- English (1)
- Other than English (2)

Appendix 5. Correlations of Individual Constructs

**. Correlation is significant at the 0.01 level (2-tailed)
*. Correlation is significant at the 0.05 level (2-tailed)

Relevancy	Item 1	Item 2	Item 3	Item 3
Item 1	1	0.578**	0.668**	0.571**
Item 2	0.578**	1	0.603**	0.799**
Item 3	0.668**	0.603**	1	0.679**
Item 4	0.571**	0.799**	0.679**	1

Table 21. Correlations of Items within Relevancy Construct. Created by authors.

Completeness	Item 1	Item 2 R	Item 3	Item 4	Item 5	Item 6
Item 1	1	-0.194*	0.651**	-0.012	0.596**	0.391**
Item 2 R	-0.194*	1	-0.143	0.533**	-0.264**	-0.090
Item 3	0.651**	-0.143	1	0.017	0.604**	0.481**
Item 4	-0.012	0.533**	0.017	1	-0.019	0.086
Item 5	0.596**	-0.264**	0.604**	-0.019	1	0.621**
Item 6	0.391**	-0.090	0.481**	0.086	0.621**	1

Table 22. Correlations of Items within Completeness Construct. Created by authors.

Amount of Data	Item 1	Item 2 R	Item 3 R	Item 4
Item 1	1	-0.157	-0.060	0.412**
Item 2 R	-0.157	1	0.844**	-0.160
Item 3 R	-0.060	0.844**	1	-0.157
Item 4	0.412**	-0.160	-0.157	1

Table 23. Correlations of Items within Amount of Data Construct. Created by authors.

Interpretability	Item 1	Item 2 R	Item 3 R	Item 4	Item 5
Item 1	1	-0.571**	-0.506**	0.619**	0.600**
Item 2 R	-0.571**	1	0.670**	-0.396**	-0.317**
Item 3 R	-0.506**	0.670**	1	-0.191	-0.384**
Item 4	0.619**	-0.396**	-0.191	1	0.593**
Item 5	0.600**	-0.317**	-0.384**	0.593**	1

Table 24. Correlations of Items within Interpretability Construct. Created by authors.

Ease of Understanding	Item 1	Item 2 R	Item 3	Item 4
Item 1	1	-0.401**	0.656**	0.687**
Item 2 R	-0.401**	1	-0.304**	-0.395**
Item 3	0.656**	-0.304**	1	0.728**
Item 4	0.687**	-0.395**	0.728**	1

Table 25. Correlations of Items within Ease of Understanding Construct. Created by authors.

Concise Representation	Item 1	Item 2	Item 3	Item 4
Item 1	1	0.799**	0.912**	0.815**
Item 2	0.799**	1	0.813**	0.854**
Item 3	0.912**	0.813**	1	0.795**
Item 4	0.815**	0.854**	0.795**	1

Table 26. Correlations of Items within Concise Representation Construct. Created by authors.

Appendix 6. Factor Loadings of Individual Constructs

Panel A: Eigenvalues test

	Eigenvalues	% of Var.	Cumulative %
1	2.952	73.798	73.798
2	0.528	13.195	86.993
3	0.335	8.387	95.380
4	0.185	4.620	100.000

Panel B: Factor Matrix

	Factor 1
Relevancy 1	0.684
Relevancy 2	0.861
Relevancy 3	0.758
Relevancy 4	0.903

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.765
Extraction Method: Maximum Likelihood, converged in 5 iterations.

Table 27. Initial Factor Loadings for Relevancy Construct. Created by authors.

Panel A: Eigenvalues test

	Eigenvalues	% of Var.	Cumulative %
1	2.753	45.881	45.881
2	1.509	25.154	71.035
3	0.652	10.859	81.894
4	0.446	7.435	89.328
5	0.342	5.699	95.027
6	0.298	4.973	100.000

Panel B: Pattern Matrix

	Factor 1	Factor 2
Completeness 1	-0.033	0.732
Completeness 2 R	0.940	-0.142
Completeness 3	0.030	0.774
Completeness 4	0.578	0.076
Completeness 5	-0.083	0.824
Completeness 6	0.063	0.668

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.712
Extraction Method: Maximum Likelihood, converged in 3 iterations.

Table 28. Initial Factor Loadings for Completeness Construct. Created by authors.

Panel A: Eigenvalues test

	Eigenvalues	% of Var.	Cumulative %
1	2.679	66.972	66.972
2	0.656	16.393	83.365
3	0.359	8.978	92.343
4	0.306	7.657	100.000

Panel B: Factor Matrix

	Factor 1
Completeness 1	0.742
Completeness 3	0.778
Completeness 5	0.823
Completeness 6	0.654

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.758
Extraction Method: Maximum Likelihood, converged in 4 iterations.

Table 29. Factor Loadings for Completeness Construct without Reversed Items. Created by authors.

Panel A: Eigenvalues test

	Eigenvalues	% of Var.	Cumulative %
1	1.973	49.321	49.321
2	1.287	32.184	81.505
3	0.591	14.766	96.271
4	0.149	3.729	100.000

Panel B: Factor Matrix

	Factor 1
Amount of Data 1	-0.157
Amount of Data 2 R	0.999
Amount of Data 3 R	0.844
Amount of Data 4	-0.160

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.501
Extraction Method: Maximum Likelihood, converged in 12 iterations.

Table 30. Initial Factor Loadings for Amount of Data Construct. Created by authors.

Panel A: Eigenvalues test

	Eigenvalues	% of Var.	Cumulative %
1	1.412	70.610	70.610
2	0.588	29.390	100.000

Panel B: Factor Matrix

Factor Matrix was not produced even with high number of iterations.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.500
Extraction Method: Maximum Likelihood, did not converge.

Table 31. Factor Loadings for Amount of Data Construct without Reversed Items. Created by authors.

Panel A: Eigenvalues test

	Eigenvalues	% of Var.	Cumulative %
1	2.952	59.045	59.045
2	1.006	20.111	79.156
3	0.505	10.106	89.262
4	0.313	6.252	95.513
5	0.224	4.487	100.000

Panel B: Factor Matrix

	Factor 1	Factor 2
Interpretability 1	-0.507	0.640
Interpretability 2 R	0.671	-0.294
Interpretability 3 R	0.999	0.002
Interpretability 4	-0.193	0.837
Interpretability 5	-0.386	0.603

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.692
Extraction Method: Maximum Likelihood, converged in 10 iterations.

Table 32. Initial Factor Loadings for Interpretability Construct. Created by authors.

Panel A: Eigenvalues test

	Eigenvalues	% of Var.	Cumulative %
1	2.208	73.585	73.585
2	0.412	13.722	87.307
3	0.381	12.693	100.000

Panel B: Factor Matrix

	Factor 1
Interpretability 1	0.948
Interpretability 4	0.871
Interpretability 5	0.946

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.719
Extraction Method: Maximum Likelihood, converged in 3 iterations.

Table 33. Factor Loadings for Interpretability Construct without Reversed Items. Created by authors.

Panel A: Eigenvalues test

	Eigenvalues	% of Var.	Cumulative %
1	2.628	65.703	65.703
2	0.765	19.127	84.830
3	0.343	8.579	93.408
4	0.264	6.592	100.000

Panel B: Factor Matrix

	Factor 1
Ease of Understanding 1	0.794
Ease of Understanding 2 R	-0.439
Ease of Understanding 3	0.822
Ease of Understanding 4	0.878

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.770
Extraction Method: Maximum Likelihood, converged in 4 iterations.

Table 34. Initial Factor Loadings for Ease of Understanding Construct. Created by authors.

Panel A: Eigenvalues test

	Eigenvalues	% of Var.	Cumulative %
1	2.381	79.353	79.353
2	0.351	11.706	91.059
3	0.268	8.941	100.000

Panel B: Factor Matrix

	Factor 1
Ease of Understanding 1	0.787
Ease of Understanding 3	0.834
Ease of Understanding 4	0.873

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.735
Extraction Method: Maximum Likelihood, converged in 4 iterations.

Table 35. Factor Loadings for Ease of Understanding Construct without Reversed Items. Created by authors.

Panel A: Eigenvalues test

	Eigenvalues	% of Var.	Cumulative %
1	3.494	87.355	87.355
2	0.271	6.778	94.133
3	0.151	3.774	97.907
4	0.084	2.093	100.000

Panel B: Factor Matrix

	Factor 1
Concise Representation 1	0.948
Concise Representation 2	0.871
Concise Representation 3	0.946
Concise Representation 4	0.870

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.812
Extraction Method: Maximum Likelihood, converged in 5 iterations.

Table 36. Initial Factor Loadings for Concise Representation Construct. Created by authors.

Appendix 7. Factor Loadings of All Constructs

Factor:	1	2	3	4
Relevancy 1	0.008	0.611	-0.115	-0.158
Relevancy 2	0.017	0.879	0.013	-0.009
Relevancy 3	-0.046	0.732	-0.008	0.019
Relevancy 4	-0.065	0.967	0.076	0.085
Completeness 1	0.036	0.083	0.654	0.151
Completeness 3	-0.004	-0.071	0.798	-0.033
Completeness 5	-0.223	-0.128	0.792	0.122
Completeness 6	0.013	0.025	0.766	-0.075
Amount of Data 1	0.063	0.024	0.609	0.017
Amount of Data 4	0.242	0.024	0.408	-0.036
Interpretability 1	0.045	-0.011	0.043	0.696
Interpretability 4	-0.044	-0.107	0.022	0.614
Interpretability 5	-0.049	0.019	0.079	0.691
Ease of Understanding 1	0.052	0.018	-0.048	0.803
Ease of Understanding 3	0.184	0.051	-0.016	0.689
Ease of Understanding 4	0.039	0.002	-0.047	0.835
Concise Representation 1	0.895	-0.018	0.036	0.075
Concise Representation 2	0.777	-0.091	-0.001	0.136
Concise Representation 3	0.939	-0.018	0.077	-0.031
Concise Representation 4	0.817	-0.044	-0.044	0.105
Extraction Method: Maximum Likelihood, converged in 5 iterations.				

Table 37. Factor Loadings (Pattern Matrix) on All Items of Information Quality Constructs in 4-factor Solution. Created by authors.

Factor:	1	2	3	4	5	6
Relevancy 1	0.028	-0.023	0.590	-0.105	-0.252	0.029
Relevancy 2	-0.078	0.035	0.894	0.009	0.075	0.021
Relevancy 3	-0.081	-0.005	0.736	-0.014	0.073	0.019
Relevancy 4	0.102	-0.069	0.955	0.051	-0.015	-0.074
Completeness 1	0.161	0.073	0.070	0.732	-0.011	0.204
Completeness 3	-0.046	0.035	-0.076	0.796	-0.021	-0.035
Completeness 5	0.016	-0.172	-0.119	0.782	0.159	0.048
Completeness 6	-0.066	0.021	0.042	0.702	0.058	-0.095
Amount of Data 1	0.066	0.037	-0.002	0.525	-0.091	-0.467
Amount of Data 4	0.025	0.230	0.019	0.355	-0.051	-0.159
Interpretability 1	0.209	0.128	-0.007	0.074	0.548	-0.022
Interpretability 4	-0.025	0.054	-0.043	0.034	0.850	0.091
Interpretability 5	0.339	-0.025	0.026	0.044	0.522	-0.146
Ease of Understanding 1	0.515	0.110	-0.046	0.007	0.218	-0.105
Ease of Understanding 3	0.583	0.213	-0.009	0.038	0.094	0.048
Ease of Understanding 4	1,017	-0.046	-0.074	-0.017	-0.019	0.016
Concise Representation 1	0.133	0.905	-0.018	0.069	-0.040	0.168
Concise Representation 2	0.017	0.794	-0.081	-0.095	0.156	-0.287
Concise Representation 3	0.006	0.944	-0.003	0.092	-0.011	0.134
Concise Representation 4	0.009	0.840	-0.039	-0.087	0.088	-0.133
Extraction Method: Maximum Likelihood, converged in 7 iterations.						

Table 38. Factor Loadings (Pattern Matrix) on All Items of Information Quality Constructs in 6-factor Solution. Created by authors.