Fabio Alves Pena
Therese Hide

Retail Innovations: The Role of Familiarity and Cultural Values

Master's thesis in International Business and Marketing (Siviløkonom)
Supervisor: Mark Pasquine
July 2020

Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Department of International Business

NTNU
Norwegian University of
Science and Technology

Acknowledgments

This master thesis marks the completion of our Master`s degree in International Business and Marketing (Siviløkonom) at the Norwegian University of Science and Technology, Ålesund.

Firstly, we would like to express our deepest appreciation to our supervisor Mark Pasquine for his contributions, time and efforts throughout the entire writing process. We are thankful for all the encouragement, feedback and valuable insights.

We would also like to extend our sincere gratitude and appreciation to Richard Glavee-Geo and Erik Nesset for their dedication, enthusiasm and continued support. Their input was most helpful and have assisted un is making significant improvements.

Lastly, we would like to thank our families and friends for all the support and motivation through this entire academic journey and especially during the writing process of this thesis. We are forever thankful for your unconditional support.

Abstract

Artificial Intelligence (AI) capabilities are empowering businesses by enhancing operational efficiency, productivity and improving customer experiences. Recent innovations in retailing resulting from AI applications are adding convenience by eliminating friction and making the customer journey seamless. Innovations in retailing caused by AI applications are transforming the way traditional grocery shopping is performed. This research adopted a cross-cultural context to examine technology acceptance through the lenses of an unfamiliar concept. Our study contributes to the body of knowledge of technology acceptance by proposing an extension of the unified theory of acceptance and use of technology (UTAUT2) by Venkatesh et al. (2012), combining the moderating effect of cultural dimensions by Hofstede at the individual level and the addition of familiarity and trust.

This study adopted a quantitative method approach and the analysis of data was performed by structural equation modeling (SEM) using SmartPLS. To explain the moderating effect of cultural dimensions on the acceptance of an unfamiliar technology – two specific dimensions were selected to moderated familiarity and trust towards behavioral intention. Long-term orientation had a significant moderating effect on the relationship between trust and behavior intention. Additionally, low levels of familiarity exerted an indirect effect inhibiting behavior intention in the remaining hypotheses.

Contents

List of figures:

List of tables

1 Introduction

It has been widely acknowledged that retailers around the world are embracing Artificial Intelligence (AI). Artificial intelligence – the collection of capabilities and behavior by learning systems that are perceived by humans as intelligence (Jacobs *et al.*, 2018). According to Jacobs, et al. (2018), more than a quarter of the top 250 global retailer are integrating AI into their organizations. "It is estimated that global annual spending on AI by retailers will top $7.3 billion by 2022." (Jacobs *et al.*, 2018, p. 2). The driver for such significant strategic investment is the value gained by unleashing AI across functions. AI capabilities allow retailers to improve the customer experience while enhancing operational efficiency and productivity (Jacobs *et al.*, 2018). Typical AI capabilities have enabled businesses to solve complex analytics and estimate accurate predictions, by doing so, taught businesses what it takes to yield benefits from AI. The accelerating deployment of AI in retail has transformed traditional routines and revolutionize industries. However, deploying innovative solutions for traditional "daily routines" (i.e., grocery shopping) may require adaptation and cognitive efforts from a consumer perspective. Such technological innovations may be perceived as unfamiliar procedures by consumers, and levels of familiarity have considerable influences in technology acceptance (Gefen, 2000). Familiarity is an understanding, often based on previous interactions, experiences, and learning of what, why, where, and when others do what they do (Gefen, 2000). Limited understanding of technological principles prevents experienced-based attitudes and behavioral intentions (Feindt and Poortvliet, 2020). Thus, the lack of familiarity implies limited knowledge or understanding.

In addition, familiarity or lack thereof may be perceived differently by individuals from different cultural backgrounds. Gefen et al., (2000) argued that familiarity is culture and experience dependent. Thus, this study investigates technology acceptance through the lenses of an unfamiliar technology while considering the cultural values of individuals from two different countries. Given the impact of cultural influences on business practices worldwide, the present thesis considers the culture dimensions by Hofstede at the individual level. Hofstede's himself acknowledged that "the individual level of human programming is truly unique and no two people are programmed exactly alike." (Hofstede, 2001, p. 2). The application of Hofstede's cultural dimensions has been widely adopted by numerous studies (Hofstede, 2010). Nevertheless, it has been applied mostly at the country level. The present thesis acknowledges the existence of cultural value variances among individuals regardless of the predominant cultural values of their country of origin – and aims to achieve such variance within specific cultural dimensions while investigating the acceptance of an unfamiliar technology.

1.1 Purpose of the study and research question

This thesis focuses on the moderating effect of Masculinity (MAS) and Long-term Orientation (LTO) on technology acceptance. First, our intention was to obtain variation among these two cultural dimensions to explore the moderating impact of both MAS and LTO on technology acceptance. The criterion for country selection was based on the ability to attain this variation and the means to achieve such variation were the culture dimension of MAS and LTO given that the countries selected for this study share opposite views in these two dimensions. Our belief is that by examining the variation in cultural values among MAS and LTO individuals the chances of obtaining clearly distinct results concerning behavior intentions based on cultural values will be greater. Second, this study investigates technology acceptance from the perspective of an unfamiliar technology. Low level of familiarity may be an inhibiting factor towards technology acceptance. Therefore, it is important to consider strong stimuli to overcome low levels of familiarity and, thus entice the acceptance of an unfamiliar technology. The cultural values pertaining to individuals of MAS (assertive, work goal-oriented) and LTO (risk-taking, future reward oriented) cultures are to our belief, such strong values. Therefore, in addition to allowing us to attain cultural value variation these two dimensions also possess strong inherent factors that may contribute to the acceptance of an unfamiliar technology. This study will be the first empirical research performing a cross-cultural analysis at the individual level concerning the influences of cultural dimensions on the acceptance of an unfamiliar technology in two European countries. Hence, the following research questions for the present thesis is proposed.

1. ***How do cultural dimensions influence the acceptance of an unfamiliar technology?***

This thesis is organized in 6 chapters and the structure goes as follows: chapter one is the introductory chapter presenting the purpose of the study and research question. Chapter two introduces the literature review which forms the theoretical framework of this thesis. Chapter three presents the research model and hypotheses development. Chapter four introduces the methodologies and overall strategies utilized to achieve the objectives of the present study. Chapter five provides the analysis and results, and lastly, chapter six presents the discussion, implications, limitations and conclusion remarks of this research.

2 Literature Review

This chapter aims to perform a thorough review of existing knowledge on the following subjects: technology acceptance model progression, familiarity, trust and dimensions of national culture. By doing so, this chapter will provide sufficient information regarding the theoretical framework of this study and establish the legitimacy of this thesis. The first portion provides a complete review of the technology acceptance models, including the adaptations made over time, which led these models to expand their reach and areas of concentration. Followed by the role of familiarity and trust in technology acceptance, and lastly, a review of Hofstede's national cultural dimensions including its contribution to technology acceptance.

2.1 Technology Acceptance – the progression of technology models

Understanding the rationale of why users reject or accept any new technology has become one of the most valuable areas in the information technology field today (Momani and Jamous, 2017). Several theoretical models have been developed in an attempt to explain technology acceptance and use, namely: The theoretical model chosen for this thesis is based on several predominant models and theories of individual acceptance: Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), Combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), Social Cognitive Theory (SCT). The common denominator of all these models is that they try to understand how users accept and use technology. Many variables affect user's choices about how and when they will use a new technology introduced to them (Fishbein and Ajzen, 1975). Due to a limited number of pages, only a few of these will be mentioned in the literature review, namely: TRA, TPB, TAM1, TAM2, TAM3, and UTAUT. The objective of presenting the technology models is to build a road map to the theoretical model used in this thesis; UTAUT2.

2.1.1 Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA) analyzes the determinants of conscious behavior from social psychology, and it is one of the most important and influential theories in human behavior (Ajzen, 2002). Since its origin, the theory has been broadly applied across multiple behaviors, contexts, and populations. The theory focuses on theoretical constructs regarding individual motivational factors as determinants of the probability of performing particular behaviors. The underlying assumption of TRA is that intention is the best predictor of behavior. Where attitudes toward, and social normative perceptions regarding the behavior determine intention (Glanz, Rimer and Viswanath, 2015). A Meta-analysis of TRA showed that it had been used to predict a broad range of behaviors. Besides, strong overall evidence for the predictive utility of the model was found (Sheppard, Hartwick and Warshaw, 1988). The theory consists of theoretical constructs concerned with individual motivational factors as determinants of the likelihood or intention of performing a specific task (behavioral intention). Behavioral Intention (BI) is determined by the person's attitude (A) and the Subjective Norms (SN) toward the behavior (Fishbein and Ajzen, 1975). The core constructs of TRA is 1) Attitude Toward Behavior: “an individual`s positive or negative feelings (evaluative effect) about performing the target behavior” (Fishbein and Ajzen, 1975, p. 216). And 2) Subjective Norm: “the person`s perception that most people`s people who are important to him think he should or should not perform the behavior in question ” (Fishbein and Ajzen, 1975, p. 302). TRA is not designed for a specific behavior or technology, making it a general model that can be used in many fields.

TRA has manifested validity in the Information Systems (IS) as it has been proven to be suitable in many fields, and it is broadly used in both academia and business today (Samaradiwakara and Chandra, 2014). Nonetheless, the model has some limitations. First, there is a significant risk of confusion between attitudes and norms as attitudes frequently can be reviewed as norms and the other way around. Secondly, the assumption that an individual will be free to act without limitation when someone forms an intention to act. Limited ability, time, environmental or organizational limits, and subliminal habits are all constraints in practice that will limit the freedom to act. Theory of Planned Behavior was developed to resolve the limitations of TRA. This theory will be further discussed below

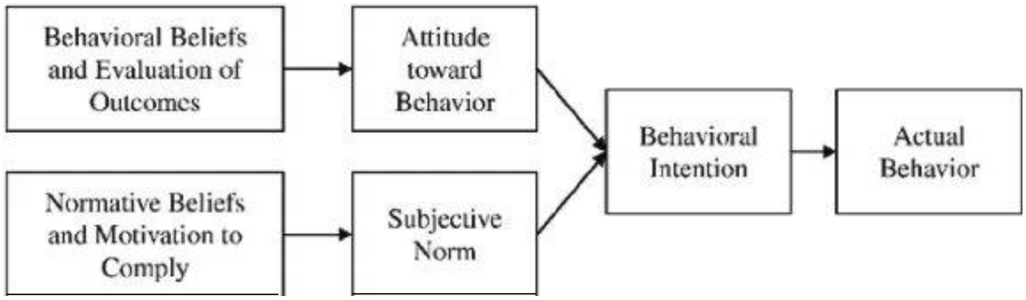


Figure 2-1: Theory of Reasoned Action (Fishbein and Ajzen, 1975)

2.1.2 Theory of Planned Behavior (TPB)

Theory of Planned Behavior (TPB) is an extension of TRA where perceived behavioral control was added as a new construct to determine intention and behavior. This new construct was added to account for the claims saying the behavior is not completely voluntary, and in an attempt to resolve the limitations of TRA (Hazen *et al.*, 2014). The TPB suggests that volitional human behavior is a function of the intention to execute the behavior and perceived behavioral control (PBC). The theory can be used to predict if a person has a positive attitude towards an act or behavior. The best predictors for forming a behavioral intention that will lead that individual to demonstrate that particular behavior or act is if favorable social norms surround the individual and he/she has a high level of PBC (Ajzen, 2005).

A central factor in TPB is the individual's intention to perform a given task (Venkatesh *et al.*, 2003a). As in TRA, intentions are explained as the motivational factors influencing behavior (Ajzen, 2005). TPB consists of three constructs.

Attitude towards the act or behavior – an individual's belief if a certain behavior or act makes a positive or a negative contribution to his/her life.

Subjective Norm – the individual's social network, cultural norms, group beliefs, and others.

Perceived Behavioral Control – an individual's belief of how easy or hard it is to demonstrate a particular behavior or act in a particular way (Ajzen, 2005).

Ajzen (1991) proposes that behavioral intentions drive individual behaviors. Further, he describes behavioral intentions as a function of the decision maker's attitude toward the behavior, the denotation subjective norms of the decision-maker, and the decision-makers perceived control of the behavior (see figure 2). Ajzen (1991) reviewed different studies using different views of the TPB and found that TPB successfully predicted intention and behavior in a vast number of settings (Ajzen, 1991). Many studies have successfully used TPB to understand individual acceptance and usage of a variety of technologies (Dezdar, 2017; Harrison, Mykytyn and Riemenschneider, 1997). Several studies have also presented that the TPB can predict behavior (Ajzen *et al.*, 2011; Chu and Chen, 2016; Park, Jung and Lee, 2011). TPB is said to have formed the psychological theorizing. The theory has taught us that intention and PBC are largely constant predictors of behavior (McEachan *et al.*, 2011), furthermore that interventions followed by extensive changes in intention are probable also to change behavior (Webb and Sheeran, 2006).

Nevertheless, the theory of TPB has also been criticized. One of the criticisms is about the balance between parsimony and validity, where the question is if a theory of all volitional behavior based on solely four explanatory concepts is elaborated sufficiently. One example is the criticism for only concentrating on rational reasoning, ignoring unconscious influences on behavior (Sheeran, Gollwitzer and Bargh, 2013), and the role of emotions beyond expected affective outcomes (Conner *et al.*, 2012). Additionally, the stagnant explanatory disposition of the TPB does not benefit the understanding of the effects of behavior on cognitions and forthcoming behavior (McEachan *et al.*, 2011). The central point of the criticism towards TPB is about its limited predictive validity. It is undoubtedly shown from the reviews that most of the variability in observed behavior is not considered by the measures of the TPB. Specifically, the difficulty of individuals who build an intention and later fail to act (“inclined abstainers”), has been identified as a limitation of the TPB and remains unevaluated by the theory (Orbell and Sheeran, 1998).

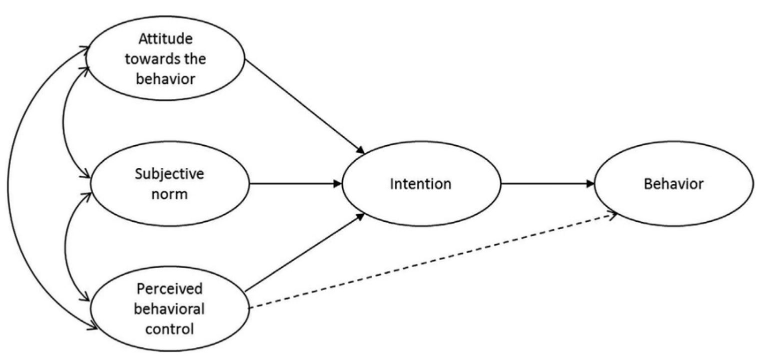


Figure 2-2: Theory of Planned Behavior (Ajzen, 1991)

2.1.3 Technology Acceptance Model (TAM-1)

The technology acceptance model (TAM) was initially formulated by Davis (1985) and is one of the most widely tested models. TAM is an adaptation of TRA, originally tailored for predicting information technology usage and acceptance in organizations (Davis, 1985). It is one of the most influential models of technology acceptance – it is widely reported, and its references and application descriptions are present in numerous journals and publications concerning technological acceptance in several different fields. Despite being developed for predicting acceptance and usage at the workplace, TAM has, over the years, been used in many different contexts. As a result, TAM has become adequately accepted as a robust and powerful model for predicting user experience (Rondan-Cataluña, Arenas-Gaitán and Ramírez-Correa, 2015).

TAM's purpose is to provide an explanation for technology acceptance based on psychological constructs influencing the behavior, adoption, and interaction of users with new technological processes. The model's core construct is composed of the following main variables: Perceived Usefulness (PU) and Perceived Ease of use (PEOU), which determines an individual's behavioral intention to use a system. Davis (1989) defined PU as the user`s "subjective probability that using a specific application system will increase his or her job performance within an organizational context" (Davis, Bagozzi and Warshaw, 1989, p. 985). It is the measure by which the use of technological interfaces provides benefit to the users and could also be related to the perceived level of improvement caused by a technological implementation. Contrary to PU, PEOU is defined by Davis (1989) as "the degree to which the user expects the target system to be free of efforts" (Davis, Bagozzi and Warshaw, 1989, p. 985). In other words, it measures to which degree an individual considers the interaction with technological interfaces user-friendly. According to Davis (1989), belief is a determinant factor contributing to an individual's attitude towards acceptance. Therefore, PE and PU are two psychological constructs directly linked to the attitude of users toward technology acceptance. If there is a positive relationship between PE and PU, users are more likely to develop a positive behavioral intention (BI) toward the actual usage of a new technology. The opposite will occur if PE and PU have a negative link toward attitude as it will likely inhibit users from accepting (Davis, Bagozzi and Warshaw, 1989).

TAM can and has been applied to explain or predict individual behaviors across a wide range of end-user computing technologies and user groups, as it specifies general determinants of individual technology acceptance (Davis, Bagozzi and Warshaw, 1989). At the same time, TAM positively distinguished from TRA and TPB in parsimonious capability (Samaradiwakara and Chandra, 2014). TAM contributes to a fast and reasonable way of collecting general information about an individual's perception of technology, making TAM easier to use than TPB.

As already mentioned, TAM has become adequately established as a strong and powerful model for predicting user's acceptance of technology. However, few studies have included all of its original construct when attempting to validate the full TAM model (Venkatesh, 2000). Moreover, a Meta-analysis of TAM found that different methodological and measurement factors characterize many of the previous TAM studies. As a result, there are, to some extent, confusing and inconsistent findings that differ greatly regarding statistical significance, direction, and magnitude (Yousafzai, Foxall and Pallister, 2007). Furthermore, Yousafzai et al., (2007) states that the varied findings both weaken the accuracy of TAM, but also impede IT practitioners and academics attempts to better comprehend user`s technology acceptance behavior. Nevertheless, TAM has shown to be widely applicable to many different technological innovations. Another question about the TAM model is if it is applicable in all countries. McCoy et al., (2007) suggest the need of caution in applying TAM in at least 20 countries; as his findings show that the model does not hold for particular cultural orientations; low Uncertainty Avoidance, high Masculinity, high Power Distance, and Collectivism as these dimensions imply to revoke the effects of PU and PEOU (McCoy, Galletta and King, 2007).

2.1.4 Technology Acceptance Model (TAM-2)

According to Venkatesh and Davis (2000), several empirical studies have verified that TAM explains a considerable proportion of the variance (about 40%) in usage intention and behavior. Further, they state that TAM has a favorable differentiation with other models such as TRA and TPB (Venkatesh and Davis, 2000). One decade went from the original TAM model to be established to the TAM2 being established. Over these years, TAM had already become well-established as a powerful and robust model for predicting user acceptance. Over the years, PU proved to be a strong determinant of usage intentions, across the many empirical tests. Perceived Usefulness (PU) has shown, across many empirical tests of TAM, to be a persistent strong determinant of usage intention. TAM`s other direct determinant of intention, Perceived Ease of

Use (PEOU), has exhibited a less consistent effect on intention across studies (Venkatesh and Davis, 2000). According to Venkatesh and Davis, some research has been done to model the determinants of PEOU, while the determinants of PU had been relatively overlooked. Given that PU was a highly important driver of usage intention, Venkatesh and Davis (2000) wanted to understand the determinants of this construct and how their impacts transform over time with increasing experience using the system (Venkatesh and Davis, 2000). An improved understanding of the determinants of PU would allow Venkatesh and Davis (2000) to design organizational interventions that would raise user acceptance and usage of new systems (Venkatesh and Davis, 2000). The goal of developing TAM2 was, therefore to incorporate additional fundamental determinants of TAM`s PU and usage intention constructs, in addition to recognizing the effects of these determinants change with growing user experience throughout using the specific system (Venkatesh and Davis, 2000).

The TAM 2 model was based on the original TAM model and developed in a longitudinal field study. Additional theoretical constructs connected social influence processes (subjective norms, voluntariness, and image), and cognitive instrumental processes (job relevance, output quality, result demonstrability, and PEOU). The social processes help to determine whether an individual will adopt or reject a new system. The result of Venkatesh and Davis (2000)'s study showed that both social influence processes and cognitive instrumental processes significantly influenced user acceptance. The social influence processes and cognitive instrumental processes will be further explained below.

Social Influence processes

Subjective norm (SN) – adopted from TRA and defined as a "person`s perception that most people who are important to him think he should or should not perform the behavior in question" (Fishbein and Ajzen, 1975, p. 302). In TRA and TPB, SN is a direct determinant of behavioral intention. SN, as a direct determinant on BI, has shown mixed results from different studies. After grouping respondents into mandatory and voluntary usage context, SN had a significant effect on intention in mandatory settings; however, not in voluntary settings. TAM2, therefore, theorized that SN would have an effect on intention and perceived usefulness in mandatory usage context (Venkatesh and Davis, 2000).

Voluntariness – Used as a moderating variable to distinguish between mandatory and voluntary usage settings, and can be defined as "the extent to which potential adopters perceive the adoption decision to be non-mandatory" (Venkatesh and Davis, 2000, p. 188).

Image – To maintain a favorable image, individuals often reply to social normative influences to set up or maintain a positive image within a reference group (Venkatesh and Davis, 2000). Venkatesh and Davis (2000) adopted the definition of Image from Moore and Benbasat (1991) and defined Image as "The degree to which use of an innovation perceived to enhance one`s status in one`s social system" (Moore and Benbasat, 1991, p. 195).

Experience – With increased system experience, SN to intentions may subside over time. The interesting element to Experience is if the effects of social influences processes shift with growing experience using a target system (Venkatesh and Davis, 2000).

Cognitive instrumental processes

Job relevance – "An individual's perception regarding the degree to which the target system is applicable to his or her job. In other words, job relevance is a function of the importance within one's job of the set of tasks the system is capable of supporting." (Venkatesh and Davis, 2000, p. 191).

Output quality – can be defined as people's consideration of how well a system performs specific tasks: how capable a system is to perform the task and the degree to which the specific task matches their job goals (job relevance). This is what Venkatesh and David (2000) called perception of output quality (Venkatesh and Davis, 2000).

Result Demonstrability – Venkatesh and Davis used Moore and Benbasat (1991)'s definition of Result Demonstrability (RD) and defined it as the "tangibility of the results of using the innovation" (Moore and Benbasat, 1991, p. 203). In other words, it indicates that an individual's attitude about the system`s usefulness will be more positive if the difference between usage and positive results can be observed without difficulty.

Venkatesh and Davis (2000), argue that TAM2 suggests that all cognitive instrumental processes positively influence perceived usefulness, and eventually, an individual's intention to use an information system (Venkatesh and Davis, 2000). The result of Venkatesh and Davis (2000) research found that TAM2 was strongly supported across their samples. The model contributes to a detailed account of the important forces underlying judgments of PU (60% of the variance explained). Furthermore, by showing that SN utilizes a significant direct impact on usage intention over and above PU, in addition to PEOU for mandatory use, TAM2 extends TAM (Venkatesh and Davis, 2000). To sum it up, TAM2 is based on the extension of the antecedents of PU. As previously mentioned, PU has proven to be a consistently strong determinant of BI across the many empirical tests of TAM. Using TAM as a foundation, TAM2 combines additional theoretical constructs connecting social influence processes and cognitive instrumental processes. Where the incorporation of SN affects both BI directly and through PU (see Figure 3: Technology Acceptance Models).

2.1.5 Technology Acceptance Model (TAM-3)

Venkatesh and Davis (2008) developed TAM3, having the same goal as for TAM2 - to complete the model by combining the antecedents of the original TAM (Venkatesh and Bala, 2008). As TAM2 added the antecedents of PU, TAM3 was expanded by the antecedents of PEOU. Previous research on the TAM models had focused on how and why employees decide on the adoption and use of information technologies (ITs) in the workplace (Venkatesh and Bala, 2008). Developing TAM3 Venkatesh and Bala (2008) discussed the importance of adoption and use of ITs from an organizational point of view – specifically, they wanted to find out how managers make informed decisions about interventions that can lead to greater acceptance and effective utilization of IT from an organizational point of view. At the time, there was little research dealing with the role of interventions to benefit managers in making decisions about IT implementation. Venkatesh and Bala (2008) developed a model of the determinants of PEOU by building on the anchoring (computer, self-efficacy, computer anxiety, computer playfulness, and perceptions of external control) and adjustment framing (perceived enjoyment and objective usability) of human decision making (Venkatesh and Bala, 2008).

Determinants of perceived ease of use:

Computer Self-Efficacy – "The degree to which an individual believes that he or she has the ability to perform a specific task/job using the computer" (Venkatesh and Bala, 2008, p. 279).

Perception of External Control – "The degree to which an individual believes that organizational and technical resources exist to support the use of the system" (Venkatesh and Bala, 2008, p. 279).

Computer Anxiety – The degree of "an individual's apprehension, or even fear, when he/she is faced with the possibility of using computers" (Venkatesh and Davis, 2000, p. 349).

Computer Playfulness – "the degree of cognitive spontaneity in microcomputer interactions." (Webster and Martocchio, 1992, p. 204).
Perceived Enjoyment – The extent to which "the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use" (Venkatesh and Davis, 2000, p. 351).
Objective Usability – A "comparison of systems based on the actual level (rather than perceptions) of effort required for completing specific tasks" (Venkatesh and Davis, 2000, pp. 350-351).

The findings of Venkatesh and Bala (2008) supported managerial decision making by offering a framework to determine what interventions to put into use during both pre and postimplementation stages and for what kind of systems (Venkatesh and Davis, 2000).

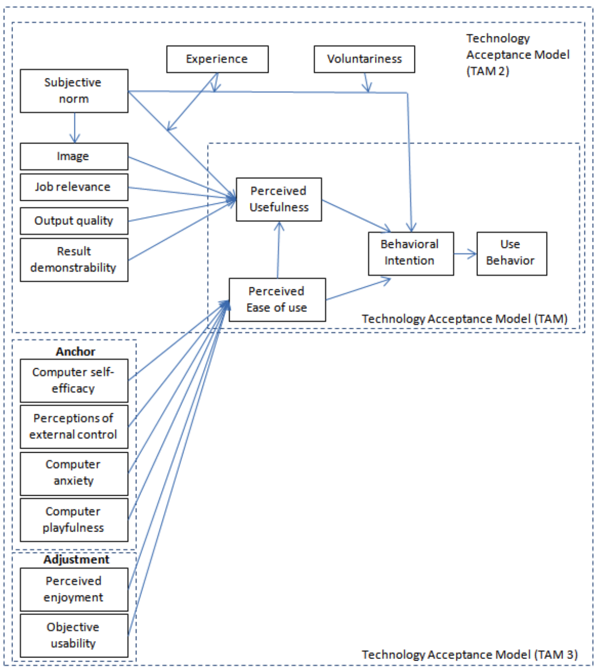


Figure 2-3: Technology Acceptance Model (TAM 1-2&3) (Venkatesh and Bala, 2008)

2.1.6 Unified Theory of Acceptance and Use of Technology (UTAUT)

In 2003 Venkatesh et al. (2003) consolidated the disintegrated theory and researched individual acceptance of information technology into a unified theoretical model. The unified model was based upon criticism of TAM's predictive capacity (Venkatesh *et al.*, 2003b).
The UTAUT model was developed by reviewing and unifying eight respected models in the user acceptance literature trying to explain IS usage behavior. Theory of Reasoned Action (TRA)

(Fishbein and Ajzen, 1975), Technology acceptance Model (TAM1-2) (Davis, 1989), TPB (Ajzen, 1991), Social Cognitive Theory (SCT) (Compeau and Higgins, 1995), combined TAM and TPB (C-TAM-TPB) (Taylor and Todd, 1995), Model of PC Utilization (MPCU) (Thompson, Higgins and Howell, 1991), Innovation Diffusion Theory (IDT) (Rogers, 1995), and Motivational Model (MM) (Davis, Bagozzi and Warshaw, 1992). These models explain the individual acceptance of information technology and presented the fundamental conceptual framework that formed the foundation of Venkatesh`s research in 2003 (Venkatesh *et al.*, 2003b).

The Unified theory of acceptance and use of technology model (UTAUT) consists of four determinants: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). These constructs portray a significant role as direct determinants of Behavior Intention (BI) and Usage Behavior (UB). Gender, age, experience, and voluntariness of use are moderators. The purpose of UTAUT is the prediction of BI to use a technology, primarily in organizational contexts (Venkatesh *et al.*, 2003b). As mentioned previously, UTAUT integrated eight eminent models on individual adoption mechanisms and hypothesized that three fundamental constructs (PE, EE, and SI) determine Behavioral Intention. Following, BI and FC influence UB. The four moderating effects (different combinations of gender, age, experience, and voluntariness of use) included in the model determines the influence of the fundamental constructs on BI together with UB (Venkatesh *et al.*, 2003b). In the longitudinal study performed by Venkatesh *et al (2003)*, they found that about 70 percent of the variance in behavioral intention to use a technology and about 50 percent of the technology use was explained by UTAUT (Venkatesh *et al.*, 2003b). The relationship and interaction between the predictors in the model, and the moderator’s effects, are shown in the figure below. The constructs of UTAUT will be further explained below.

***Behavioral Intention (BI)*:** can be defined as the individual willingness or likelihood that consumers will use a technology system in the context of technology adoption (Venkatesh, Thong and Xu, 2012a). BI is based on attitude toward behavior, subjective norm, and perceived behavioral control, which shows that various antecedents may affect an individual’s behavioral intention. Use behavior (UB) is also included in the original UTAUT2 model. However, since this study is researching the behavior intention for a retail innovation technology that has not yet been launched in the European market, it does not make sense to include UB here. Several other studies have also only measured BI (Oliveira *et al.*, 2016; Slade *et al.*, 2015), and it has been proven from past studies that BI is a strong predictor of actual use (Schepers and Wetzels, 2007).

Performance Expectancy (PE): can be defined as – to which degree the use of a technology gives advantages to conducting work-related activities. The construct PE was derived from usefulness perceptions (TAM) (Davis, 1989), extrinsic motivation, Motivation Model (Davis, Bagozzi and Warshaw, 1992), Job-fit, Model of PC Utilization (Thompson, Higgins and Howell, 1991), relative advantage, Innovation Diffusion Theory (Moore and Benbasat, 1991) and outcome expectations, Social Cognition Theory (Compeau and Higgins, 1995). Improvement in job performance, and increased productivity and efficiency in a person's work are examples of technology advantage in the workplace. PE is the one construct in the UTAUT model that has shown the strongest empirical predictor of behavior (Venkatesh, Thong and Xu, 2012a). In general, customers appear to be more motivated to accept a new technology if they recognize a technology to be more beneficial and useful in their everyday life (Alalwan, Dwivedi and Williams, 2016; Davis, Bagozzi and Warshaw, 1989). Several studies have shown that PE has a significant influence on the adoption of different technologies as for example mobile internet (Venkatesh, Thong and Xu, 2012a), biometric technologies (Lancelot Miltgen, Popovič and Oliveira, 2013), and Mobile payments (Abrahão, Moriguchi and Andrade, 2016). Other studies have found PE to significantly influence Perceived Value (PV) (Shaw and Sergueeva, 2019).

Effort Expectancy (EE): Was first formulated in the UTAUT model, and is defined as "the degree of ease associated with the use of the system" (Venkatesh *et al.*, 2003a, p. 350), in other words, to which degree the technology or system is perceived as easy or difficult to understand and use. This construct is consisting of three constructs from already existing models: perceived ease of use TAM & TAM2 (Davis, 1989), complexity MPCU (Thompson, Higgins and Howell, 1991), and ease of use IDT (Moore and Benbasat, 1991), which all have been proved to have a significant influence on behavioral intention in previous studies; (Oliveira *et al.*, 2016) for the adoption of mobile payments, and (Alalwan, Dwivedi and Rana, 2017) for adapting Mobile banking. The impact of EE on behavioral usage was significant in a meta-analysis (Faaeq *et al.*, 2013), while (Shaw and Sergueeva, 2019) found EE not to be significant on Intention to use.

Social Influence (SI): is the degree to which an individual perceives what friends, family, and colleagues expect or believe that one should use the new system. Whether people who are important to you think you should use a certain technology (Venkatesh, Thong and Xu, 2012a). This construct is a direct determinant of behavioral intention and is described as a subjective norm in TRA, TAM2, TPB/DTP, and C-TAM-TPB. In MPCU and IDT, the construct is described as social factors and image (Venkatesh *et al.*, 2003a). Social Influence portrays an intricate role in technology acceptance and affects behavior through mechanisms such as compliance and internalization. Internationalization leads to a change in inner perception and makes the individual more accepting of responding to technology that potentially increases social status. Compliance is about changing one's intentions because of social pressure (Venkatesh, Thong and Xu, 2012a). Other studies have found SI to be significant on usage (Blaise, Halloran and Muchnick, 2018) and on intention (Xu, 2014; Tak and Panwar, 2017).

Facilitating conditions (FC): refers to the consumer's perception and beliefs that there are available technological resources and support for using a system. FC comprehends three different constructs from previous models: perceived behavioral control TPB/DTPB, C-TAM-TPB, facilitating conditions MPCU, and compatibility IDT. The constructs from previous models are implemented to include aspects of the technological and/or organizational environment designed to erase barriers to use a certain system (Venkatesh *et al.*, 2003a). Specifically, this includes whether or not the consumer has the necessary technical knowledge and resources to use the system and has access to get help from others if needed (e.g., customer support) in the event of difficulties using the system. In any organization where they use mandatory systems, there is a help desk for the employees. In a consumer context, numerous support channels are available, depending on the problem to be solved. When smartphones are the tool for technological interaction, there would be one helpdesk to support problems with the actual phone, another helpdesk to support problems related to the phone application, and an additional help desk for network issues. However, as the technology has been expanded over the years, consumers will expect their smartphone application to work correctly (Mohamamd Alamgir *et al.*, 2017).

There is, however, some varied evidence for these predictors' significance for behavioral intention. Findings from a Meta-study from 2013, found that the relationship between FC and BI, and FC and UB, are weak (Taiwo and Downe, 2013). Other studies have proven FC to significantly influence BI and actual usage (Tak and Panwar, 2017) (mobile shopping applications), and (Gharaibeh and Mohd Arshad, 2018) (Intention to use mobile banking).

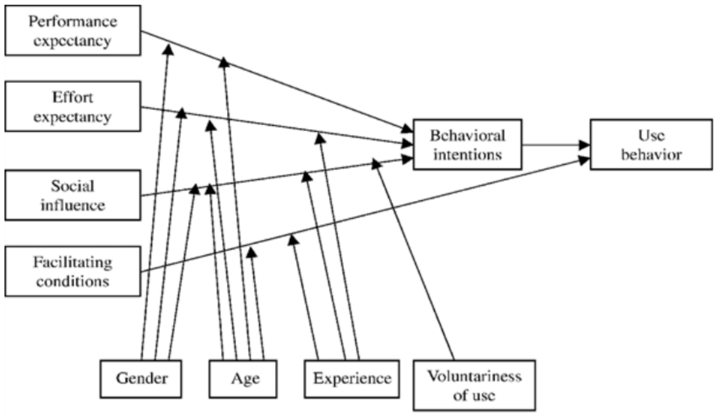


Figure 2-4: The Unified Theory of Acceptance and Use of Technology-1 (UTAUT) (Venkatesh et al.*, 2003b)*

2.2 Cognitive Outcomes & Technology acceptance the role of familiarity and trust

A research on the dimensions of consumer expertise has proposed familiarity as one of the major components of consumer knowledge. Upon reviewing primary empirical results from the psychological literature, they were able to add a significant contribution to the consumer knowledge research field – and thus, define familiarity as following "the number of product related experiences that have been accumulated by the consumer" (Alba and Hutchinson, 1987, p. 411). Familiarity with a task or situation leads to the development of approaches to problem-solving, which may not be optimal or perfectly rational; however, it contributes to simplifying the decision-making process (Kinard, Capella and Kinard, 2009). Familiarity is often based on prior exposure, experiences, and interactions with products and services – the more acquainted consumers become to a product or service, the less likely they are to be affected by external factors such as embarrassment, social presence, or incidental situations. From a consumer point of view, this might indicate that a positive relationship between familiarity and technology acceptance should reduce the effect of external factors, thus mitigating the risk of consumers avoiding interaction with new technology. According to (Luhmann, 2017), familiarity is a precondition for trust – and a study investigating the role of familiarity and trust in e-commerce engagement identified trust as a prerequisite of social behavior, which influences decision making. Besides, their data showed that familiarity builds trust – and that acceptance of e-commerce (interaction) can, therefore, be influenced by people's familiarity with online shopping and their trust in the overall purchase process (Gefen, 2000).

Technological advancements, however, have changed the way consumers do traditional shopping. An American advertising agency has reported that currently, e-commerce represents 10% of retail sales. In 2019, e-commerce was responsible for around 3.5 trillion dollars in sales and was expected to reach 4.9 trillion by 2021 in the USA alone (Hatch, 2020). Online shopping has added convenience and enhanced customer experience by allowing shoppers to purchase from virtually anywhere and the added benefit of freeing them from waiting in line. However, despite undeniably convenient, not everything is purchased online – and most people still do in-store shopping, i.e., groceries. Technological innovations in the retail field are becoming increasingly automated to replicate the convenience and frictionless online shopping experience. Self-service technologies such as self-scanning and self-checkout are examples of retail innovations, promoting a seamless customer journey. A study on consumer acceptance of self-service technology has examined the importance of ability and willingness to accept self-service technologies. They have reasoned that the Theory of Planned Behavior (TPB) has provided support for the relationship between these two constructs and, therefore, hypothesized that ability positively affects consumer willingness to accept technology. Their research has highlighted that previous studies on consumer acceptance of self-service technologies have focused mainly on willingness while overlooking the potential effects of ability on consumer willingness to accept. Their proposed model has examined antecedent constructs` impacting ability and the influence of ability on willingness towards acceptance of technology. Lastly, in their concluding remarks, they have highlighted a positive effect of ability on willingness to accept technology (Wang, 2017).

In a way, these antecedents describe characteristics addressed by Bhattacherjee's model of trust, which focused on the consequences of trust for e-commerce. The model consists of three components: Familiarity, Trust, and Willingness (Garfinkel and Cranor, 2005). As defined previously, familiarity is knowledge gained through previous interactions and experiences, and trust is assumed to be made up of beliefs in ability. This assumption is primarily based on the proposed model of trust by (Mayer, Davis and Schoorman, 1995), which has significantly contributed to organizational studies. Bhattacherjee stated that familiarity could lead to trust, which in turn leads to willingness. Also, familiarity can lead to willingness directly, even without the sense of trust – and this can be attributed to purchase habits or convenience (Garfinkel and Cranor, 2005). Scholars have expressed a great deal of interest in familiarity – and statistically, its relevance towards technology acceptance has been acknowledged; however, currently, there are no empirical studies concerning the acceptance of an unfamiliar technology in the contexts that our study is examining. Our belief is that level of familiarity might have something to say regarding the acceptance of technology. Given that this is a cross-cultural context, the study levels of national culture can also play a key role in technology acceptance.

2.3 Cultural dimensions – an introduction to inherent behavior

While working for IBM Corporation, Hofstede developed the original four cultural dimensions. He investigated a sizable database of employee value scores gathered within IBM between 1967 and 1973, accounting for 70 countries from which he used data of 50 countries from 3 regions (Hofstede, 2010). In the 1970s' Hofstede applied a similar questionnaire on a population of non-IBM managers. The results were undeniably comparable to those obtained in IBM – and this was Hofstede's first sign that the national culture differences found inside IBM existed elsewhere (Hofstede, Hofstede and Minkov, 2010a). Even though several decades have passed since Hofstede's development the cultural dimensions his work is used worldwide in both academic and professional management settings (Hofstede, 2010). Most studies considering culture values still rely on Hofstede's work – even researchers who disagree with his dimensions. This indicates that his work still contributes to research (McCoy, Galletta and King, 2005).

The literature concerning cultural effects in IS research is mostly grounded on the national or organizational level. One of the standard procedures is to use nationality as a representative for culture, contrasting similar samples of participants from two or more countries, and applying any distinctions to the presumed cultural differences between the respective countries. There are a few reasons why this approach could be problematic. Firstly, researchers generally depend on historical findings concerning the cultural characteristics of specific countries or regions, originating from Hofstede's initial findings. McCoy, Galletta and King (2005) reviewed the most popular conceptualization of national culture and indicated that shifts may have occurred in the last 30 years, making Hofstede's country scores no longer representative of the perspectives of all individuals from a particular country (McCoy, Galletta and King, 2005). The importance of measuring individual's cultural values within any research is argued by the findings of McCoy, Galetta and King (2005). Though individuals from the same country may score differently on a given cultural dimension, most researchers still refer to the average country index. An individual approach is presumably more advantageous when identifying cultural characteristics as antecedents to outcomes in cultural-based models. The reason for this may be that heterogeneous samples from each country are likely to reduce the levels of explained variance in the culture-based models (McCoy, Galletta and King, 2005). The findings of McCoy, Galletta and King (2005) argued for the relevance of directly measuring individual cultural values within technology acceptance studies and other studies using cultural values. Secondly, individuals will vary on cultural dimensions within the same country. The acceptance of a technology by end-users is an individual-level phenomenon, while national culture is a macro-level phenomenon. Using the national measurement score to predict or measure individual behavior is not possible as there is no instrument to generalize cultural characteristics of individuals within the same country. This is especially important when measuring actual behavior in the adoption and acceptance of technology (McCoy, Galletta and King, 2005; Udo, Bagchi and Kirs, 2012; Yoon, 2009). According to McCoy, Galetta and King (2005), studies using individual-level research models such as TAM and UTAUT2 should use individual-level culture measures and not country-level measures (McCoy, Galletta and King, 2005). An example of individual-level culture measure is the individualized measure of national culture (based on the work of Hofstede 1980 and others) by Dorfman and Howell (1988). Srite and Karahanna (2006) followed the same path as Dorfman and Howell (1988) in their studies of the general acceptance of computing technology. The scales were used to measure cultural values at the individual level and efficiently managed to integrate the scales with a model derived from TAM (Srite and Karahanna, 2006). The scales used in their study were based on the work of both Hofstede (1980) and Dorfman and Howel (1988) (Srite and Karahanna, 2006; Dorfman and Howell, 1988). According to Hofstede et al. (2001), it is impossible to find two individuals that are programmed the same, not even identical twins. Individual personalities give a broad spectrum of alternative behaviors within the same collective culture (Hofstede, 2001). With that in mind, our strategy is to adopt the approach of Srite and Karahanna (2006); Dorfman and Howell (1988), and investigate cultural differences at the individual level. The moderating effects of culture within the conceptual model of this research will then be allowed to be meaningfully explored. Focusing on the individual level does not take credits away from country-level analysis, these are just arguments to support our choice of research approach. Our focus lies at the individual level however, this is a cross-cultural study analysis at the country level will also be reported in the discussion section.

2.3.1 Power Distance (PD)

In some cultures, people are more likely to accept higher degrees of unequally distributed power. Most commonly, power is ranked according to relative status and categorized by hierarchy, which is nothing more than a word used to distinguish authority levels within an organization. Although hierarchy is present both small and large poles of PD, the distinction has to do with how people in small and large PD cultures perceive power use. According to (Hofstede, Hofstede and Minkov, 2010a), PD scores merely inform dependency relationship levels within a society. In small-power-distance cultures, subordinates are less dependent on their bosses – that is, presence of an interdependence among boss and subordinate or a preference for a consultative style of decision-making rather than an autocratic or paternalistic decision-making style. In small PD cultures, the emotional distance between boss and subordinate is relatively small, allowing subordinates to easily approach their bosses, consult, contradict, and have direct participation in decision-making. On the contrary, in large-power-distance cultures, hierarchy acts as a barrier, and subordinates' dependence on bosses is considerably high. In such cultures, subordinates are either prone to an autocratic, paternalistic relationship or averse to it. Psychology defines as counter-dependence – that is, dependence, but a negative dependence – where subordinates do not necessarily agree with the emotional distance created by such a hierarchy. In large PD countries, subordinates are less likely to contradict their bosses, and have no participation in decision-making. Power distance can be defined as "the extent to which the less powerful members of institutions and organizations within a country expect and accept that power is distributed unequally. Institutions are basic elements of society, such as the family, the school, and the community; organizations are the places where people work" (Hofstede, Hofstede and Minkov, 2010a, p. 61)

2.3.2 PD levels affecting technology acceptance & consumption

Power Distance measures to which degree individuals expect and tolerate differences in power between different people (Hofstede and Eckhardt, 2002). Inequality is present in every society; the difference is that some societies are more unequal than others. According to Pearlson et al. (2020), individuals with large PD values are less prone to innovation and tend to have lower levels of trust in technology. Individuals that are less concerned with levels of power disparities (small PD values) are more likely to adopt technological innovations, especially if it helps promote equality (Pearlson, Saunders and Galleta, 2019). A cross-cultural study examining the impact of power distance acceptance and disparity of power expectancy on consumer preferences for status brands has contributed to the global status consumption literature. The researchers have concluded that consumers with large PD levels tend to have stronger preferences for status brand consumption than those with small PD levels (Kim and Zhang, 2014). Their research hypothesized that the consumption of status brands might be an alternative to improve one's social standing in large PD countries. As an attempt to enhance their self-worth, consumers from large PD societies associate brands to social status. This is a typical behavior of large PD consumers – and this has been addressed by (Ruvio, 2013, p. 207) in their study of compensatory consumption theory defined as the following: "the desire for acquisition or use of products to respond to a psychological need or deficit." The contributions of this research have opened opportunities to investigate the impact of PD further in other categories.

A study considering the adoption of mobile banking in Brazil has applied Hofstede's cultural dimensions as moderators on UTAUT2. Their objective was to examine the effect of cultural dimensions in the adoption of banking services. Their findings concluded a weak significance of the dimensions toward use behavior (UB). Out of five cultural dimensions, three were not significant, and two dimensions, namely – collectivism and short-term orientation, presented a weak significance toward use behavior of mobile banking services. Lastly, the authors concluded that the influence of BI on UB of mobile banking services considering the effect of culture dimensions as moderators is not applicable (Goularte and Zilber, 2019). This had been supported previously by Baptista et al., (2015), who has conducted a similar study combining the UTAUT2 with Hofstede's cultural dimensions as moderators to further explain behavior intention of mobile banking usage in Mozambique. Their research model validated a significant influence of four national cultural dimensions toward BI over UB, namely: Collectivism, Uncertainty Avoidance, Short-term orientation, and Power Distance (Baptista and Oliveira, 2015). Despite researching different contexts, both studies examined the same concept and applied the moderating effects of cultural dimensions to the same model (UTAUT2). However, their findings were slightly different. It could be partially attributed to differences in inherent culture (individuals) influencing technology acceptance, given that cultural levels may differ in between countries, and within the individuals of a country. One of the suggested remarks by Goularte et al. (2019), is to apply the cultural dimensions on an independent variable and analyze the effects caused on BI. Our research extends the UTAUT2 to examine the moderating effects of MAS and LTO on two independent variables, leading to a dependent variable. This, coupled with the differences in concept, contexts, and an analysis at the individual level, are unique aspects of this study.

2.3.3 Individualism vs. Collectivism (IDV)

According to Hofstede IDV is the degree to which individuals are integrated into groups and to the extent the individual interests triumph over the group´s interest (Hofstede and Eckhardt, 2002). It is common knowledge that traditionally, clusters of individualism may be found in Anglo countries, Germanic Europe, and Nordic Europe whereas, clusters of collectivism are often found in Latin America, Southern Asia, and Arab Countries. Individualistic cultures prioritize self-interest over the needs of a group, and given that in these societies, people are generally more independent. Naturally, social behavior is guided by personal preferences and dependency, which is often presumed unnecessary and even shameful (Beyo Global, 2019).

High IDV score is proportionally inverse to collectivism values - meaning that individualism and collectivism can be considered opposite poles (Hofstede, Hofstede and Minkov, 2010a). In collectivist societies, individuals' immediate concerns are to look after each other with a rather strong expectancy of reciprocity. Here, self-centrism gives room to social values, cohesive in-groups, and collaboration amongst individuals. In these societies, it is common to see individuals making an extra effort for the greater good of the group, and cooperation is not only encouraged but seen as an essential way to achieve common objectives (Hofstede, 2011). In collectivist societies, individuals value "We" over 'I" as in preferably, the interest of the whole comes before the interest of one's self (Hofstede, 2010). According to (Hofstede, Hofstede and Minkov, 2010a, p. 92) Individualism vs. Collectivism can be defined as: "Individualism pertains to societies in which the ties between individuals are loose: everyone is expected to look after him-or herself and his or her immediate family. Collectivism as its opposite pertains to societies in which people from birth onward are integrated into strong, cohesive in-group, which throughout people's lifetime continue to protect them in exchange for unquestioning loyalty." As collectivist cultures value their in-group members' opinion, several authors have hypothesized that the relationship between SN (Social Influence) and BI would be stronger in collectivistic societies (Srite and Karahanna, 2006; Zakour, 2004; Li *et al.*, 2009). Individuals within a collectivistic culture are more likely to be concerned with themselves, while individuals of collectivist values are more concerned about preserving group cohesiveness. People from collectivist culture will show more willingness toward other people's opinion regarding technology. Baptista and Oliveira (2015) found that IDV had a significant moderating effect on BI and UB, where the relationship was stronger among people with collectivist values (Baptista and Oliveira, 2015).

2.3.4 Disparities in large and small IDV societies (retail)

Individualism versus Collectivism is a dimension characterized by the degree to which people are integrated into groups. Individualistic cultures have loose ties between individuals, whereas collectivist societies are inherently more integrated into tight groups. Several studies have linked the national cultural dimensions of Individualism vs. Collectivism and PD because, according to the findings of Hofstede, typically, countries scoring high on PD tend to be on the low side of the IDV dimension (collectivists) an indication that these dimensions are negatively correlated. The same applies to small (low) PD countries, which are more likely to be individualistic societies (Hofstede, Hofstede and Minkov, 2010a). The exception to this rule are Latin European countries such as France and Belgium, which presents a combination of medium PD with strong levels of individualism – and the reverse pattern found in Austria and Israel, presenting a combination of small PD with medium levels of collectivism (Hofstede, Hofstede and Minkov, 2010a). Given that most large PD countries are collectivist societies and vice versa, tracing a parallel between these two dimensions should encounter similar patterns of consumer behavior.

According to (Beyo Global, 2019), individualistic societies are more price rather than quality sensitive, which means that these consumers are not overly loyal to a brand. They are known for shopping fast and cheap both online and in-store – focused on the latest trends these consumers also return items more frequently, especially when purchasing from a brand they have not purchased before. In individualistic societies, consumers make more impulsive purchases, and as a result, they tend to shop more frequently. On the other hand, collectivist societies are more quality-oriented – these consumers would be willing to pay more for a higher quality product, which technically should last longer. Collectivists tend to be more loyal to brands, and most of their purchases are made in-store. People in these societies prefer to try before purchasing, making return items less frequent. Online purchases are not very common, and the frequency at which they shop is lower than in individualistic culture societies do.

A study examining the role of cultural dimensions in accepting retail innovations have included IDV as a moderating factor to predict technology acceptance of self-scan checkout technology.

The researchers emphasized the importance of understanding the impact of national culture dimensions in today`s globalized economy as international retail firms attempt to introduce innovative concepts into different countries (Mulaomerovic and Trappey, 2013). Understanding the variables that may compromise successful market entry is crucial. Therefore, considering national culture influences firms can adjust technology strategies accordingly (Mulaomerovic and Trappey, 2013). The results of this study have suggested the investigation of innovations in retail technology. Besides, they have suggested a cross-cultural comparison and the addition of factors (constructs) that could potentially influence technology acceptance. In individualistic societies, people are generally more independent and social behavior is based on the individual's preference and attitude instead of the group (Beyo Global, 2019). In individualistic societies, a task prevails over relationships while in collectivistic societies relationships prevail over a task (Hofstede, 2011). Bringing it to the context of this study, the unfamiliar concept used to test technology acceptance in this research is powered by an autonomous process that eliminates the need for personal interaction throughout the customer journey. This is in fact, one of the value propositions of this concept – and given the characteristics of Individualistic societies, technology acceptance should be greater in individualistic cultures.

2.3.5 Masculinity vs. Femininity

This dimension represents the degree to which traditional gender roles are diversified. Masculine values are characterized by assertiveness, toughness, and focus on material success. Feminine values can be characterized by modesty, quality of life, and tenderness (Hofstede, Hofstede and Minkov, 2010b). Among all the dimensions identified by Hofstede, this was the only one in which men and women scored consistently differently. None of the other dimensions have shown a systematic discrepancy in answers between genders as this dimension has (Hofstede, Hofstede and Minkov, 2010a). The masculinity side of this dimension has men attaching considerable importance to assertiveness, achievement, material reward earnings, and recognition. On the opposite side lies femininity placing a greater importance on relationships, quality of life, caring for others, modesty, and cooperation (Hofstede, 2010).

Hofstede stated, "the masculinity scores represent relative, not absolute, positions of countries – unlike with individualism, masculinity is unrelated to a country's degree of economic development: we find rich and poor masculine and rich and poor feminine countries." (Hofstede,

Hofstede and Minkov, 2010a, p. 140). Masculinity vs. femininity is a societal rather than an individual characteristic as it refers to the distribution of beliefs amongst genders. According to (Hofstede, 2011), assertiveness is considered a masculine value, whereas modesty and caring are considered feminine. Women in feminine societies possess similar values as the men do, i.e., modest, caring values. However, women in masculine societies are, to an extent, more assertive and competitive, but not as much as the men are. According to (Hofstede, Hofstede and Minkov, 2010a, p. 140) Masculinity vs. Femininity can be defined as following “A society is called masculine when emotional gender roles are clearly distinct: men are supposed to be assertive, tough and focused on material success, whereas women are supposed to be more modest, tender, and concerned with the quality of life. A society is called feminine when emotional gender roles overlap: both men and women are supposed to be modest, tender, and concerned with quality of life.” As this dimension has been hypothesized, it will be further discussed and explored in chapter three: Research model and hypotheses development.

2.3.6 Uncertainty Avoidance (UA)

Uncertainty Avoidance (UA) is the degree to which uncertainty and ambiguities are condoned by individuals (Hofstede, Hofstede and Minkov, 2010a). James G. March, known for his contributions toward organizational decision making and behavioral theory, recognized uncertainty while studying behavioral sciences in American organizations (Hofstede, Hofstede and Minkov, 2010a). In similar ways, uncertainty avoidance is present in societies. Hofstede stated: “uncertainty avoidance is not the same as risk avoidance; it deals with a society’s tolerance for ambiguity.” (Hofstede, 2011, p. 10). Ambiguous situations often lead to unmanageable anxiety levels, and every society has developed mechanisms to mitigate anxiety. The following coping mechanisms to prevent ambiguity and temper anxiety belong to the domains of law, religion, and technology. Take behavioral uncertainty to illustrate the effectiveness of laws and rules within a society. Given that people’s psychological makeup is distinct, the behavior is to an extent unpredictable; laws and rules are the most common societal mechanisms used to alleviate uncertainty caused by other people’s action; Religion, on the other hand, is one of the most efficient ways of controlling masses maintaining order as it deals with the unnatural forces that are meant to be accepted since they cannot be fully comprehended; technology, from its simplest to the most advanced and complex forms have reduced uncertainty caused by nature (Hofstede, Hofstede and Minkov, 2010a).

UA represents the extent to which ambiguity and dubious situations are accepted within a society, and it is present at different levels in every culture. It indicates how members of a society feel threatened or comfortable in unstructured situations (Hofstede, 2010). Weak UA cultures tend to accept the uncertainty inherent in life without hesitation. Citizens in these societies are more tolerant, have less anxiety and lower stress – often seen as competent by authorities, and generally more comfortable with ambiguity. On the opposite side, strong UA cultures tend to interpret the uncertainty inherent in life as a threat. People in these societies are generally emotionally affected by ambiguity and therefore have higher anxiety and stress levels (Hofstede, 2011). Uncertainty Avoidance has been defined as "the extent to which the members of a culture feel threatened by ambiguous situations or unknown situations. This feeling is, among other manifestations, expressed through nervous stress and in need for predictability: a need for written and unwritten rules" (Hofstede, Hofstede and Minkov, 2010a, p. 191).

2.3.7 UA influences on technology acceptance & innovation resistance

Uncertainty avoidance and its influence on technology acceptance is a somewhat controversial subject. UA deals with a society's level of comfort or discomfort when dealing with unstructured situations. In other words, it indicates society's tolerance for ambiguity ranging from weak to strong. There is a common misconception concerning the interpretation of this dimension's opposite poles, mainly when applied to technology acceptance models. Some of the literature reviewed suggested that weak UA cultures were more likely to adopt technology (Baptista and Oliveira, 2015; Tarhini *et al.*, 2017) due to societies' higher tolerance levels and a less controlling environment, which could increase the speed of IT infrastructure adoption (Png, Tan and Khai-Ling, 2001). Although researches have a reasonable argument for the ease of technology acceptance in weak UA cultures, Hofstede justification for technology acceptance in strong UA cultures has a stronger scientific foundation as he stated the following, strong UA cultures are more likely to embrace technological solutions as a way to reduce uncertainty since technology is more predictable than human solutions (Peter and Bryan, 2008). The likelihood of technology failure is much smaller than human failure. Another common misconception associated with the UA dimension is that most readers and researches have interpreted UA as "risk avoidance – for example, in business decisions." (Hofstede, 2001, p. 148). UA expresses the degree of ambiguity and anxiety acceptance within society members as opposed to degrees of risk. Uncertainty is dealing with the unknown. The extent to which a given society has lower or higher tolerance toward uncertainty defines them as weak or strong UA societies, whereas the risk is associated with the probability that a particular outcome may or may not occur. Strong UA societies are less comfortable with ambiguity as they seek for clarity and are averse to vagueness. These societies favor rules and well-structured environments, whereas weak UA societies tend to dislike rules written or unwritten; they have a higher tolerance for dubious situations and lower levels of anxiety (Hofstede, 2011).

2.3.8 Long-term Orientation vs. Short-term Normative Orientation (LTO)

Some individuals within a society appreciate more immediate gratification rather than long term fulfillment. These individuals tend to spend with ease as they attach greater importance and gratification to the present than future events. These are short-term oriented individuals, and for these people, traditions are essential. The counterpart, long-term oriented individuals – are willing to delay short-term gratification as their focus is future. These people tend to save up, value persistence and adapt to different circumstances with less resistance or difficulties (Hofstede, 2001). Every society has to maintain some links with its own past while dealing with the challenges of the present and the future. Societies prioritize these two existential goals differently. (Hofstede, 2010). The low side of this dimension tend to honor traditions and norms, and they usually are more skeptical or suspicious regarding changes. The opposite end – those scoring high on this dimension, have a rather pragmatic approach: they are prone to modern efforts to prepare for future events. This dimension has been defined as: “long-term orientation stands for the fostering virtues oriented toward future rewards – in particular, perseverance and thrift. Its opposite pole, short-term orientation, stands for the fostering of virtues related to the past and present – in particular, respect for tradition, presentation of “face,” and fulfilling social obligations.”(Hofstede, Hofstede and Minkov, 2010a, p. 239). This dimension’s characteristics give away an indication of where a firm would encounter less resistance when implementing new technological concepts. When considering technology acceptance, it is important to understand differences in behavior and belief are likely to cause an impact on technology acceptance. LTO is the second dimension hypothesized in this research, and it will be further explained in chapter three: Research model and hypotheses development.

3 Research Model & Hypotheses Development

The first part of this chapter describes the research model chosen for this study. The second part will present arguments for the development of the hypotheses based on previous literature. Starting with a discussion concerning the application of national culture dimensions at the individual level, followed by a review of the extended constructs of the research model; familiarity and trust. Lastly, a review of MAS and LTO individually along with arguments supporting their stated hypotheses will be presented.

For an extended time, several researchers have tried to explain user adoption of technology. Consequently, a significant number of theories have been developed to predict the determinants of information technology acceptance. Venkatesh et al., (2012) found that there was a need for a systematic investigation and theorizing of the pertinent factors that would apply to a consumer technology use context: an extended unified theory (Venkatesh et al., 2012). The objective for Venkatesh when developing UTAUT2 was therefore to give special attention to the consumer use context by establishing vital additional constructs and relationships to be unified in the model, modified to a consumer use context (Venkatesh et al., 2012). Based on the following gaps in the original model, it was expanded to the UTAUT2 model: Firstly, the original UTAUT model highlights the importance of utilitarian value (extrinsic motivation), the extended model (UTAUT2) pursued to achieve new elements that captured intrinsic motivation. PE (the construct linked to utility) is the strongest predictor of BI, while hedonic motivation (HM) is an essential predictor in considerable research about consumer behavior in the consumer technology use context. Secondly, from the viewpoint of effort expectancy in an organizational context, employees weigh time and effort in assembling views about the overall effort related to the acceptance and use of technologies. As consumers must bear the monetary costs related to the purchase of devices and services, unlike workplace technology, price is also an essential factor in a consumer technology use context. Lastly, UTAUT and associated models depend on intentionality as a key underlying theoretical mechanism that drives behavior. The importance of the incorporation of new theoretical mechanisms has been argued by many. Habit has shown to be a critical factor predicting technology use, compared to initial acceptance in a use context (Venkatesh et al., 2012). By that, UTAUT was extended to study acceptance and use of technology in a consumer context, and Venkatesh et al., (2012) integrated hedonic motivation, price value, and habit to form the UTAUT2 model (Venkatesh et al., 2012). The UTAUT2 model produced a considerable enhancement in the variance explained in behavioral intention (56 to 74 percent) and technology use (40 to 52 percent), compared to the UTAUT model (Venkatesh et al., 2012). The additional constructs for UTAUT2 will be explained below, the constructs that was developed for the original UTAUT was explained above and will therefore not be discussed here.

Hedonic motivation (HM): is defined as "the fun or pleasure derived from using a technology" (Venkatesh, Thong and Xu, 2012a), and it has been recognized to portray an essential part in determining technology acceptance and use. Hedonic motivation (conceptualized as perceived enjoyment) has been found to affect technology acceptance and use directly in IS research. Further, hedonic motivation is also an important determinant of technology acceptance and use in the consumer context (Venkatesh, Thong and Xu, 2012a).

According to Massimo Magni (2010) research, hedonic factors influence an individual's intention to explore a technology, where the effects differ across various stages of technology adoption (Magni, Susan Taylor and Venkatesh, 2010). Additionally, a consumer's behavioral intention to pursue a technology is positively influenced if it creates pleasure, enjoyment, and fun while using it (Lee, 2009). Hedonic motivation has been proved to have a significant influence on BI to adopt technologies in previous studies (Baptista and Oliveira, 2015; Tak and Panwar, 2017).

Price Value vs. Perceived Value (PV): Price value refers to the consumer's trade-off between financial benefits and costs of using a technology. Price is positive when the benefits of using a technology are greater than the costs linked to the technology, which again will have a positive impact on intentions to use (Venkatesh et al., 2012). As mentioned before, unlike technology systems used in the workplace, it is the individual itself who takes the costs in a consumer context. Therefore, in consumer behavior research and marketing, price is often included as a predictor (Sweeney and Soutar, 2001). Costs related to the technology in this thesis, may be mobile internet costs, device cost, service cost, and transaction fees. However, technology`s services reffered to in this thesis do not carry any direct costs or fees to the consumer. Costs for mobile internet, devices, service - and transaction fees are costs that will accrue if the technology is used or not. Also, a study on mobile banking showed that price value did not have a significant effect on intention to use (Baptista and Oliveira, 2015). The technology in this research does not have a direct monetary cost, and Price Value is therefore not relevant. For that reason, Price Value will be replaced with Perceived Value. Perceived value will be further explained below.

Perceived Value (PV): if the adoption of an IT artifact has no direct monetary costs associated with it, perceived value is hard to measure. Instead of using price value to explain the acceptance of a technology with no direct monetary cost, perceived value will be included in the extended UTAUT2 model for this research.

Even though perceived value has proven to be a challenging concept to define and measure (Woodruff, 1997); (Zeithaml, 1988), several researchers have tried to define the concept. William B. Dodds (1991), defined perceived value as the tradeoff between benefits and sacrifices, underlining that if the price is too high, there is no net perceived value (Dodds, Monroe and Grewal, 1991). Valarie Zeithaml defines value as a comparison between what consumers get and what they give, implying that value is a comparison of benefits and sacrifices, and summarized perceived value as the tradeoff between "what I get for what I give" (Zeithaml, 1988). Zeithaml also proposed that perceived value can be referred to as a "consumer's overall assessment of the utility of a product (or service) based on perceptions of what is received and what is given" (Zeithaml, 1988). A research done by McDougall and Levesque (2000) found that perceived value was one of the most important drivers of customer satisfaction, and define perceived value as "the consumers overall assessment of what is received relative to what is given" (McDougall and Levesque, 2000).

Venkatesh et al., (2012) defined Price Value as "the cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them" (Venkatesh, Thong and Xu, 2012a), where the research was about mobile internet that has a monetary price for the consumer. Nevertheless, there are contexts where the monetary price is not suitable. In the context of the technology used in this thesis, price is not relevant because virtually everyone owns a smartphone, which network coverage is a cost incurred to the consumer regardless of whether he/she shops at the store or not. Most consumers also pay a fixed amount of monthly usage; if they do not exceed their monthly usage, there will not be any additional costs. To sum it up, a smartphone has several applications and uses; According to SSB 2019, 73% of Norwegians between 9-79 years spend time on social media daily, and 95% of the same group owns a smartphone. It has also been identified that the most frequently used features or tools are; email, financial services, searching for information, and selling/purchasing products/services (SSB, 2019). Daily, multiple apps are used to fulfill different needs. A consumer's perceived value is the customer's expected benefit minus the customers perceived cost; Users are often asked to share personal information to experience the convenience of speed and time. Sharing information involves the tradeoff between utility or benefit and the perceived cost, which again could lead to unauthorized access. In the case of an unfamiliar technology, the cost is giving up information involves the risk of personal information exposure. The benefit will be the convenience the technology gives to the consumer. In this research, Perceived Value is defined in a manner borrowed from Valarie Zeithaml: a potential overall perception of the technology innovation in retail, customers are based on its benefits and sacrifices that affect adoption.

Shaw and Sergueeva (2019) conducted a research among Canadian consumers about the non-monetary benefits of mobile commerce where they found that performance expectancy and privacy concerns both significantly influence perceived value (Shaw and Sergueeva, 2019). Kim (2013) conducted a study on mobile user engagement in 2013, as the growth of mobile technology is accelerated by its accessibility and easiness to use (smartphones and tablets) (Kim, Kim and Wachter, 2013). Features like user friendliness and intuitive features drive user value and satisfaction. In their study they found that consumers are motivated to use smartphones because of the utilitarian value (completing a task), hedonic motivation (entertaining), and the social dimension (connecting with others) (Kim, Kim and Wachter, 2013). None of these studies mentioned monetary value. A Meta-analysis explaining the role of PV in UTAUT2, found that only 32 out of 70 studies excluded PV from their research model as the technology were free of cost to the customers (Tamilmani *et al.*, 2018).

Habit (HB): is defined in different ways; Limayem (2007), defines habit as the extent to which people tend to perform behaviors automatically because of learning (Limayem, Hirt and Cheung, 2007) while Sung Kim associates habit with automaticity (Kim, Malhotra and Narasimhan, 2005). According to Sung Kim and Naresh Malhotra (2005), habit is defined as prior behavior, and as the extent to which individuals consider their behavior to be automatic (Kim, Malhotra and Narasimhan, 2005). An essential assumption for the development of a habit is that the behavior in question is repetitively performed, the more frequently the behavior is performed. The more likely is it that the cognitive process will be automatic. For our study, it will mean that consumers get more knowledge after the initial introduction of the new technology, and later start using it more frequently - which will again lead to automatic behavior. Limayem (2007) illustrated that habit has a direct positive effect on the use of a technology and a moderate effect on the intention to use - the consumer`s consciousness to use the technology is less important when the habit is stronger (Limayem, Hirt and Cheung, 2007).

In this thesis, The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) has been chosen as a theoretical foundation (Venkatesh et al., 2012). There are many reasons for choosing UTAUT2 contrary to any of the other technology acceptance models that have been reviewed in this thesis. The first and foremost factor for choosing UTAUT2 is that it is a model developed and modified to a consumer use context. In contrast, the other models were primarily used to predict BI in an organizational context. Secondly, the UTAUT model showed a significant improvement over any of the eight previous models (and their extensions) investigated by Venkatesh et al., (2003) which was capable to account for 70 percent of the variance in usage intention and about 50 percent of the variance in technology use. Also, UTAUT2 is advantageous over the other adoption models as it was designed for researching technology adoption (Venkatesh et al., 2003a). Lastly, research done on a comparison on the different versions of popular technology acceptance models (Rondan-Cataluña et al., 2015) found that the UTAUT2 model achieved a better explanatory power than the rest of the technology acceptance models (TAM's). Because of the reasons listed above, the UTAUT2 model has been chosen as a theoretical foundation to investigate the influence of cultural dimensions, trust, and familiarity on technology adoption for this thesis.

The UTAUT2 model has been extended with two additional constructs: familiarity and trust. The relevance of these constructs towards the objective of the present thesis are going to be discussed further in this chapter under hypotheses development.

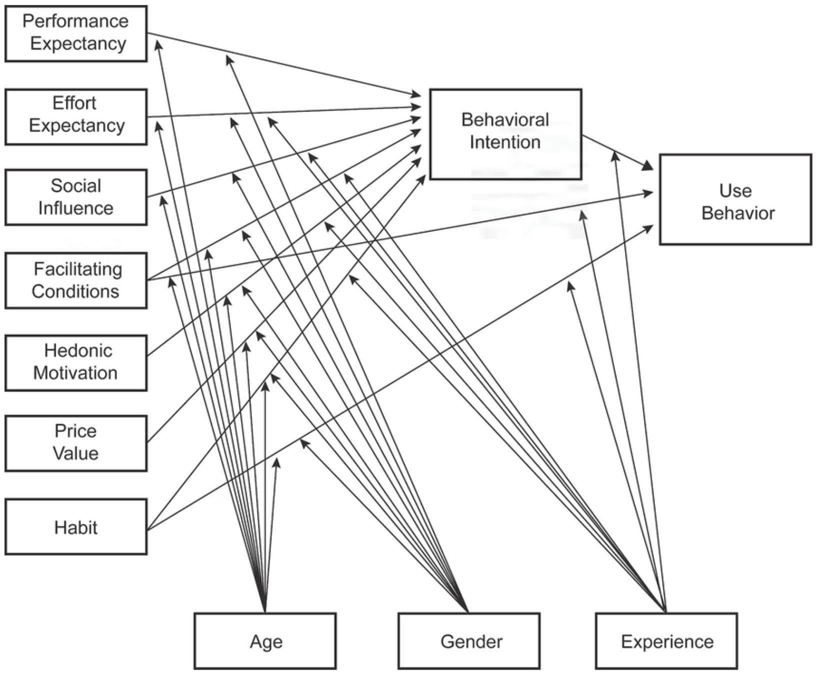


Figure 3-1: The Unified Theory of Acceptance and Use of Technology 2 (Venkatesh, Thong and Xu, 2012b)

3.1 Hypotheses Development

"A hypothesis is a logically conjectured relationship between two or more variables (measures) expressed in the form of testable statements." (Forza, 2002, p. 160). Hypotheses are used to test differences between two groups, or several groups, and it can be set either in the propositional or the if-then statement forms. "If terms such as "positive," "negative," "more than," "less than," and "like" are used in stating the relationship between two variables comparing groups – these hypotheses are directional" (Forza, 2002, p. 160). Hypotheses without a clear direction are denominated non-directional, and these are formulated when the relationship between variables has not been explored before or when denoting conflicting findings (Forza, 2002). This thesis has indicated a direction to all its hypotheses.

Numerous studies have investigated the influences of cultural values on technology acceptance at the country level. Although culture levels represent a country index, Hofstede's work has previously been applied to the individual level (Yoo, Donthu and Lenartowicz, 2011). However, there is a gap in the literature considering technology acceptance and the cultural dimensions at the individual level. The diverse cultures of individual users are fundamental for discussions and studies on technology usage and acceptance (Altman Klein, 2004); (Hillier, 2003). Hence, much effort has been dedicated to the impacts of cultural values on technology usage (Mark and Elena, 2006); (Kim *et al.*, 2018). A supporting argument is that countries are made up of diverse cultural backgrounds and heterogeneity of individuals despite a tendency to generalize values and behaviors into a “common denominator” or index (Farley and Lehmann, 1994). This is to say that a country’s index works as an average score, which might not be an exact representation at the individual level since cultural values can vary from one individual to another even within a society. Selecting two or more countries for data collection is an efficient method for cross-cultural comparison; however, when considering analysis at the individual level, it is also an effective strategy for increasing the variety of cultural differences within the dataset. Studies have presented user experience differences regarding the successful adoption of modern technologies while considering cultural values and technology acceptance levels as determinant factors in user’s introduction and responses to new technological concepts (Yoo, Donthu and Lenartowicz, 2011). Nevertheless, studies considering the impact of cultural influences on technology acceptance at the individual level are still seldom explored. This study attempts to examine technology acceptance by exploring this gap in the literature.

The present study focuses on the impacts of MAS and LTO on technology acceptance for three main reasons. 1) Our intention is to obtain variation among these two dimensions to explore the impact of both MAS and LTO on technology acceptance. An effective way to obtain such variation is by choosing countries that share opposite views on masculinity and long-term orientation. By achieving such variation, the chances of obtaining clearly distinct results concerning individuals’ intentions based on cultural values will be greater. 2) because the impacts of the other dimensions such as PD, UA and, IDV have been largely discussed by previous studies (Baptista and Oliveira, 2015; Gao *et al.*, 2018; Goularte and Zilber, 2019). 3) This thesis is investigating technology acceptance from the lenses of an unfamiliar technology. Low levels of familiarity may be an inhibiting factor towards technology acceptance. Therefore, it is important to consider strong stimuli to overcome low levels of familiarity and, thus, entice the acceptance of an unfamiliar technology. The cultural values of MAS (assertive, work goal-oriented) and LTO (risk-taking, future reward oriented) are to our belief, such strong values. Therefore, in addition to allowing us to attain cultural value variation these two dimensions also possess strong factors that can contribute to the acceptance of an unfamiliar technology.

Familiarity – limited understanding of the technological principles and value proposition that an unfamiliar technology has to offer prevent consumers from having an experienced-based attitude towards a new product or service. Lack of previous interaction leaves consumers with no option but to rely on cognitive interventions such as visual perceptions, which can be interpreted based on similar experiences, heuristic clues, and association. According to Idemudia et al. (2014) visual perception involves familiarity, cognitive, and mental processes (Idemudia and Raisinghani, 2014). In this context, an innovation in retail is used to test the acceptance of technology (unfamiliar) given the moderating effect of national cultural dimensions (MAS&LTO) on both familiarity and trust to BI. "Familiarity relates to the frequency of exposure to a certain stimulus. Higher is the frequency of this exposure; lesser is the perceived risk as familiarity increases with each exposure." (Chhabra, 2012, p. 29). Walczuch (2001) emphasized that it is important to distinguish experience from familiarity – "experience is the active interaction with a process, while familiarity is the mere exposure to a person, a store or an event." (Walczuch and Seelen, 2001, p. 6). Gefen (2000), examined familiarity in the context of e-commerce – and stated that familiarity reduces uncertainty by generating knowledge structure on individuals, which minimizes complexities through an understanding of how to interact with the given context involved (Gefen, 2000). (Psailla *et al.*, 2007) stated that familiarity facilitates decision making by reducing the necessary cognitive efforts. According to Luhmann (2017), familiarity makes it possible to entertain relatively reliable expectations – and "familiarity denotes neither favorable nor unfavorable expectations, but the conditions under which both are rendered possible" (Luhmann, 2017, p. 22). An aspect of complexity involved in this context is the amount of data one must give away. People might be reluctant to share their personal data and purchase patterns. Familiarity – knowledge about the given context and understanding its relevance should ease this complexity. According to Gefen (2000), "people's familiarity with the concept of secure internet communications could enable them to entertain specific beliefs concerning the security measures they expect from vendors." (Gefen, 2000, p. 728). The same rationale can be applied to this context. People's familiarity with innovations in retail (automated services, frictionless shopping, automatic digital payment methods) can alleviate complexities allowing consumers to build trust to the point where there is a positive attitude to the trade-off between giving away personal data in exchange for having access to the technology. This, in turn, indicates that increased levels of familiarity tend to facilitate technology acceptance.

However, currently, the technology referred to in this study is, unfamiliar to the present contexts. As mentioned by Gefen (2000), people's familiarity with a concept can enable them to entertain specific beliefs concerning security (Gefen, 2000), indicating that the lack of familiarity could raise skepticism regarding trust. Therefore, another construct playing an important role in technology acceptance in our proposed model is trust. Trust is an essential factor in situations that tend to have a certain level of perceived risks. According to Li et al., (2008), trust can be an essential predictor of technology usage and a fundamental construct for understanding user perception of technology as users must overcome perceptions of risk and uncertainty before interacting with innovative concepts. It is especially relevant to initial trust formation in an IS context (Li, Hess and Valacich, 2008). According to Alalwan et al. (2017), in previous literature, trust has been much accepted as a central factor determining customer's perception and intention to adopt technology (Alalwan, Dwivedi and Rana, 2017). Roger Mayer (1995), defines trust as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer, Davis and Schoorman, 1995, p. 712).

Altogether, familiarity and trust levels are going to be perceived differently by people from different cultural backgrounds. Culture has been defined as "The collective programming of the mind that distinguishes the members of one group or category of people from others"(Hofstede, Hofstede and Minkov, 2010a, p. 344). According to Keri Pearlson et al. (2019), one of the most popular researches in national cultural differences is Hofstede. Most studies considering national culture's effect on IS have used Hofstede's dimensions of national culture (Pearlson, Saunders and Galleta, 2019). Masculinity vs. Femininity is one of the six dimensions identified by Hofstede – and Femininity versus its opposite Masculinity concerns the distribution of values among genders. Hofstede et al. (2011) have identified differences in behavior among women and men's values within societies. These differences are considered by him opposite poles. The modest and caring pole has been defined as feminine while the assertive and competitive masculine pole (Hofstede, 2011). Modest and caring characteristics are far more similar across these two societies than assertive and competitive characteristics are. This is to say that values identified as feminine values differ less among societies than men's. Men in feminine societies carry similar caring and modest values as women do; however, women in a masculine society are more assertive and competitive, but not as much as men are (Hofstede, 2011). Hofstede has defined the following dimension as "A society is called masculine when emotional gender roles are clearly distinct: men are supposed to be assertive, tough, and focused on material success, whereas women are supposed to be more modest, tender, and concerned with the quality of life. A society is called feminine when emotional gender roles overlap: both men and women are supposed to be modest, tender, and concerned with quality of life." (Hofstede, Hofstede and Minkov, 2010a, p. 140). As it has been mentioned previously the masculine side of this dimension have men attaching considerable importance to assertiveness, achievement, material reward earnings and recognition while on the opposite side lies femininity placing a greater importance to relationships, quality of life, caring for others, modesty and cooperation (Hofstede, 2010). Feminine societies are quality of life goals oriented, whereas masculine societies are work goal-oriented. According to Srite & Karahanna (2006), work goals include an emphasis on earnings, recognition, advancement, challenge, greater work centrality, and achievement defined in terms of wealth. As opposed to quality of life goals, which places a greater emphasis on cooperation, employment, security, a friendly atmosphere, an environment where work is less central, and achievement is defined in human contact (Mark and Elena, 2006). Additionally, "at the individual level of analysis research on psychological gender and gender roles, defined masculinity in terms of self-ascribed instrumental personality traits (i.e., competitive, independent) and femininity in terms of self-ascribed expressive traits (i.e., gentle compassionate)." (Mark and Elena, 2006, p. 683). Our context evaluates the acceptance of an unfamiliar technology. The preferred traits of individuals of feminine values might be overpowered by the preferred traits of individuals of masculine values. Empirical results from Venkatesh et al. (2004) indicated that while technology acceptance intentions of masculine-typed individuals were influenced by attitude (instrumental beliefs), this was not the case for feminine-typed individuals (Venkatesh *et al.*, 2004). As retailing innovations are introduced, customers are becoming more independent as they adapt to self-service technologies. Also, processes are shortening due to the constant search for efficiency, time-saving, and overall satisfaction. Human contact is gradually decreasing as technology continues to provide seamless processes and, by doing so, slowly eliminates traditional routines (i.e., cashier), giving room to more technical or skilled employees. This means that processes are more direct and, in a way, more assertive. Self-service behavior is unlikely among individuals with feminine values, because it is inconsistent with their value system (i.e., nurture, cooperative) (Doney, Cannon and Mullen, 1998). Consequently, we assume that individuals of masculine values will be less sensitive toward levels of familiarity and trust as these individuals are generally more impulsive. Thus the statement below goes as follow:

Hypothesis 1a: *The relationship between familiarity and behavioral intention is negatively moderated by masculinity (MAS).*

Hypothesis 1b: *The relationship between trust and behavioral intention is negatively moderated by masculinity (MAS).*

Long-term Orientation versus Short-term Normative Orientation (LTO) suggests that individuals in these societies prioritize their linkage to the past, present, and future events in different ways. Short-term oriented individuals (low score) are more traditional oriented and have a suspicious or cautious approach to societal changes. In contrast, long-term oriented individuals (high score) are more practical rather than theoretical. Individuals within these societies are more prone to encourage modern efforts (Hofstede, 2010). Hofstede defined LTO as follows: "long-term orientation stands for the fostering of virtues oriented toward future rewards – in particular, perseverance and thrift. Its opposite pole, short-term orientation, stands for the fostering of virtues related to the past and present – in particular, respect for tradition, preservation of "face," and fulfilling social obligations." (Hofstede, Hofstede and Minkov, 2010a, p. 239). In a business context, commonly referred to as normative (short-term) vs. pragmatic (long-term), the low side of this dimension (short-term) has great appreciation of their past and believes that the most important events are in the present. In contrast, the opposite pole (long-term) suggests that the most important events in life are yet to occur (Hofstede, 2011). According to Hofstede et al. (2011), long-term oriented people are open to learning from others. Their traditions can be adaptable to different circumstances. These societies generally have fast economic growth, and higher levels of prosperity when found in developed countries (Hofstede, 2011). "People of high LTO culture have strong beliefs that allow them to take risk during uncertainty." (Yoon, 2009, p. 296). Low levels of familiarity should not inhibit long-term oriented individuals from developing intention to behave given their willingness to learn from others and openness for future events.

Regarding the impact of LTO values on technology acceptance, Yoon (2009) proved the moderating effect of long-term orientation and purchase intention of consumers on the relationship between online trust and the purchase intention of consumers on the TAM model (Yoon, 2009). Baptista et al., (2015); Goularte et al., (2019) have also applied LTO as a moderator on the

UTAUT2 model (Baptista and Oliveira, 2015; Goularte and Zilber, 2019). However, the present thesis proposes different contexts and an unfamiliar concept to test technology acceptance. To our knowledge, LTO has not been applied in a context involving an unfamiliar technology before. Considering low levels of familiarity implies lack of trust among other complexities that may be an inhibiting factor toward technology acceptance. Long-term oriented individuals present greater reward toward future-oriented behaviors such as: planning and future investments (Pearlson, Saunders and Galleta, 2019) which in a way, implies a greater willingness for risk-taking. This study assumes that LTO individuals possess the necessary cultural values to reduce complexities and mitigate the impact of low levels of familiarity, and by doing so, contribute to the acceptance of an unfamiliar technology. This study assumes is that LTO individual should be less sensitive toward low levels of familiarity and trust; the higher the LTO, the less the effect of familiarity and trust on BI. Therefore, we posited.

Hypothesis 2a: *Long-term orientation negatively moderate the relationship between familiarity and behavioral intention.*

Hypothesis 2b**:** *Long-term orientation negatively moderate the relationship between trust and behavioral intention.*

4 Methodologies & Strategies

The term method refers to "techniques and procedures used to obtain and analyze data. This, therefore, includes questionnaires, observation, and interviews as well as both quantitative (statistical) and qualitative (non-statistical) analysis techniques" (Saunders, Lewis and Thornhill, 2009, p. 3). By utilizing appropriate methods, studies can be retested to confirm validation. However, merely reapplying similar methods do not guarantee that the same results will be achieved as the procedures may differ from one study to another. These procedures are referred to as methodology, "the theory of how research should be undertaken" (Saunders, Lewis and Thornhill, 2009, p. 3). "Research methodology is a systematic way to solve a problem, Essentially, the procedure by which researchers go about their study" (Rajasekar, Philominathan and Chinnathambi, 2006, p. 5) and it is the responsibility of the researcher to describe the procedures and techniques used to obtain the results of a given study. The methodology works as the blueprint of a research, and the main methods by which studies are conducted are quantitative and qualitative methods.

This chapter will provide an overview of the most frequently used methods and strategies adopted for academic research. The first portion introduces the research design by describing methods and approaches for research analysis. Followed by the description of the concept & context of this study and the strategies that make up the structure of this thesis and a description of the quantitative analysis techniques used to interpret the results.

4.1 Research Design

Research design refers to the advanced planning of methods to be adopted for collecting the relevant data and the processes and techniques used in the analysis, keeping in mind the overall objective of the research (Inaam, 2016). Ultimately, a research strategy choice will be guided by the research question(s) and objectives, the extent of existing knowledge, the amount of time and other resources a researcher has available, and the researcher's philosophical underpinnings. (Saunders, Lewis and Thornhill, 2009). This is a quantitative study, which implies a deductive approach. A confirmatory method will be applied to explain our hypotheses, which have been logically based on the theories reviewed in chapter two. The relationships between the variables in our model are also relevant to the overall result of this study; therefore, these relationships will also be explained. This section presents the definition of important concepts and methods used in this research, and specific information regarding our survey strategy and data analysis.

Literature Review – "helps to establish the authority and legitimacy of the research, but more importantly it ensures the research ability of the topic before the empirical analysis begins." (Christer, 2010, p. 48). Reviewing existing knowledge is a fundamental part of any academic research. The primary purposes of the literature review are to set up studies within its broader context and present how studies supplement existing knowledge in the field of interest. (Saunders, Lewis and Thornhill, 2009). According to Karlsson Christer (2010), the literature review contributes to the research process and research development broadly in the following areas:

1)Provides an understanding of the existing state of knowledge related to the area of interest.2) Guides the development of the constructs, hypotheses, and questions employed in the study (RQ, survey) and justifies the choice of topic. 3) Justifies the choice of research methodology. 4) Refines skills such as information handling and the ability to employ critical impartial thinking in evaluating existing knowledge. (Christer, 2010)

The literature review stands as the main pillar of this research. It allowed us to identify an initial gap to be studied and further enlightened the originality of this research. Additionally, it has guided us through selecting an appropriate model, methods, approaches, techniques, and strategies used to achieve the overall objective of this thesis. As mentioned previously, this study adopted a quantitative method (deductive approach); therefore, below lies a comparison of these two methods and their respective approaches.

Quantitative research method – is commonly associated with a positivistic research approach as it makes use of mathematical and statistical tools to manage the analysis of numerical data (Christer, 2010). Quantitative research has a deductive approach where hypotheses are developed and tested to build upon an existing body of knowledge in specific fields of interest – here concepts are evaluated and examined through the clear portrait of variables which are well-defined, tangible and observable (Christer, 2010). This method uses structured data, which is generally collected through surveys, and analysis is usually done via descriptive or inferential statistical methods (Emerald Publishing, n.d.).

Deduction: testing theory – commonly related to a positivism approach. "It is the dominant research approach in the natural sciences, where laws present the bases of explanation, allow the anticipation of phenomena, predict their occurrence and therefore permit them to be controlled" (Saunders, Lewis and Thornhill, 2009, p. 124). When using a deductive approach, researchers develop a theory and hypothesis (hypotheses), subsequently design a research strategy to test the hypothesis. Saunders et al. (2009) have described five sequential stages which deductive research progressively goes through:

1)Deducing a hypothesis – a testable proposition about the relationship between concepts or variables from the theory. 2) Indicating exactly how the concepts or variables are to be measured, which denotes a relationship between specific variables or concepts. 3) Testing the hypothesis (data collection). 4) Examining the outcome (confirm, refute, modify). 5)If necessary, adapt the theory in the light of the findings. (Saunders, Lewis and Thornhill, 2009)

Qualitative research methods – as opposed to quantitative methods, which concern lies in the identifying rational and objective truth – qualitative research methods concerns are aligned with interpretation, perception, and constructivism. "Qualitative methods variously recognize and attempt to account for the significance of interpretation, perception, and interaction in the process of defining, collecting, and analyzing research evidence." (Christer, 2010, p. 66). Though qualitative research is more interpretative and experienced-based, numbers can also be attributed to subjective and qualitative variables, and conclusions can be drawn of statistical and mathematical analysis. (Christer, 2010). See table 4.1 for the main characteristics distinguishing these two methods.

Induction: building theory – commonly related to an interpretivist approach inductive method collects data and develops theory as a result of the data analysis. (Saunders, Lewis and Thornhill, 2009). The purpose of this method is to understand better the nature of the problem. The inductive method makes sense of the interview data collected and subsequently formulates a theory. In this method, the "theory follows the data rather than vice versa as with deduction." (Saunders, Lewis and Thornhill, 2009, p. 126).

The importance of research approach choice has been discussed by Easterby-Smith et al. (2008), who suggested three main reasons for selecting the approach accordingly (Saunders, Lewis and Thornhill, 2009).

1)It enables researchers to make informed decisions about the overall configuration of the research, i.e., what type of data to collect and where? How to interpret such data in the way the initial research question is answered (research design). 2) It will make the strategy clearer allowing the researcher to choose what fits best and, most importantly, what does not fit. 3) Knowledge of different research traditions enables the research design to account for constraints, i.e., limited access to data or insufficient understanding of a subject.

Quantitative methods	**Qualitative methods**
Numerical	Non-numerical
Deductive	Inductive
Applies statistics or mathematics and uses numbers.	Applies reasoning and uses words.
Iterative process whereby evidence is evaluated.	Its aim is to get the meaning, feeling and describe the situation.
The results are often presented in tables and graphs.	Data cannot be graphed.

It is conclusive and investigates the what, where and when of decision making.	It is exploratory and investigates the why and how of decision making.

Table 4.1: Adapted from (Rajasekar, Philominathan and Chinnathambi, 2006; Emerald Publishing, n.d.)

Although there are clear differences between deduction and induction approaches, which might convey a misleading impression that these approaches cannot be combined, the reality is quite the contrary. Combining deduction and induction is perfectly possible; in fact, these two approaches can complement each other. The inductive interpretation of data can develop meaningful interpretation to a quantitative data set (Saunders, Lewis and Thornhill, 2009).

4.1.1 Checkout-free Technology an introduction to the concept

Checkout-free Technology (CT) was deployed by a major retailer on December 5, 2016, and open to the public on January 22, 2018. The store is powered by the world's most advanced shopping technology – and it has added convenience to the daily shopping experience. It provides consumers with a seamless journey by eliminating lines, self-checkout stations, registers, and even cash (Wankhede, 2018). This frictionless intelligent store is promised to revolutionize the future of retail. The CT store possesses a combination of a wide variety of AI technologies, including, but not limited to, machine learning, computer vision, and deep learning algorithms. Theoretically speaking, the customer journey is incredibly simple – all users are required to have a personal account with the giant e-commerce retailer, and a recent generation phone supporting applications developed for iOS and Android. Customers gain access to the store by scanning a QR code at the entrance, and once in the store, every item placed in their bags will be automatically added to their virtual cart. The CT detects when items are taken from or returned to the shelves – and when customers are finished shopping, they can simply leave, and their bank account will be charged minutes after they have left the store (Wankhede, 2018).

4.1.2 Checkout-free and self-service technology – existing knowledge

Innovation in retail as a product of infused technology into "everyday services" changes the nature of service offerings. Technology continues to add convenience while offering tremendous potential for cost reduction, and this explains why companies are investing heavily in self-service technologies. Self-service technologies are a growing habit present in our everyday lives so frequently that it goes unnoticed. It is far from being an exclusive convenience for grocery shopping. Self-service technology is present across many industries facilitating services and enabling consumers to complete their orders without direct assistance (Mary Jo *et al.*, 2002). The added value of self-service is two-folded. It enables retailers to optimize their overall services while adding benefit to their customers, thus increasing utility for both customers and service providers. Not surprisingly, a great deal of interest has been placed on the factors contributing to the acceptance and adoption of technology.

From an investment and implementation perspective, it is crucial to identify the drivers contributing to technology acceptance. Scholars have approached this matter from different angles as they have tried to establish a "blueprint" of factors to consider when investigating technology acceptance of self-service technologies (SSTs). Mary Jo et al. (2002) have taken a qualitative approach to identify factors influencing customer satisfaction and issues involved in adopting self-service technologies (Mary Jo *et al.*, 2002). Their results pointed to six lessons to account for: "1) Be very clear on the strategic purpose of the self-service technology (SST). 2) Maintain a customer focus. 3) Actively promote the use of SSTs. 4) Prevent and manage failures. 5) Offer choices, and 6) Be prepared for constant updating and continuous improvement" (Mary Jo *et al.*, 2002, pp. 104 - 105).

Alternatively, Cheng Wang (2017) argued for an overlooked antecedent construct capable of predicting the use of SST. He stressed that SST interaction often requires skills and some level of confidence and that the lack of ability could reduce willingness to use – "that is, consumers' beliefs regarding their ability to use a technology will influence technology adoption independent of their willingness to try." (Wang, 2017, p. 788). Therefore, building a strong case supporting the relevance of both ability and willingness toward technology acceptance.

An experimental analysis focused on using observational technology to study in-store behavior and took an inductive approach to examine key environmental touchpoints throughout the customer journey in grocery retailing. "In-store behavior can be defined as anything that a consumer does in a store, involving action and response to in-store stimuli." (Larsen, Sigurdsson and Breivik, 2017, p. 345). Although this study's contribution concerns the behavioral economic literature as opposed to IS and technology acceptance – "behavior has antecedents and consequences that often influence action." (Larsen, Sigurdsson and Breivik, 2017, p. 346). Therefore, understanding in-store consumer behavior, i.e., interaction with shelves, use or lack of use of shopping carts or baskets, is in-store path, among others. Behavior analysts can build concrete explanations of consumer behavior and, together with marketing scientists, economists, and other professionals, detect problems, adjust inaccuracies, and collect analytics, which can later be used to formulate strategies for the implementation of improved technologies.

Now considering the adoption of checkout-free technology – a journal examining factors influencing the adoption of checkout-free stores in Hong-Kong focused on answering 1) “the internal and external factors that influence the “Hongkongers” adoption intention of checkout-free technologies” and 2) whether or not “facilitation conditions play a significant moderating role in influencing checkout-free technology adoption.” (Qi, 2019, p. 109). The authors claimed that “there is a lack of empirical studies examining context-specific features of technology adoption.” (Qi, 2019, p. 109). Analyzing facilitating condition effects was a strategy to provide retailers with enough insights about consumer’s concerns regarding checkout-free technologies – and by doing so, contribute to future market entry strategies. (Qi, 2019). This conference paper had a total of 13 hypotheses, and 12 of them were supported. Their future research remarks have suggested cultural aspects to be taken into account (Qi, 2019). Lastly, another study concerning the factors influencing the attitudes and behavioral intentions to use checkout-free technology applied an extended version of the TAM model and a quantitative approach to examine technology acceptance in Bangkok, Thailand (Chuawatcharin, 2019). Furthermore, as for the analysis technique, the author opted for multiple regression analysis. This literature review, in its entirety, makes the foundation of the theoretical framework of this study. The choice of model, extension, construct adaptation, moderators, concept, and context have all been influenced by the material reviewed during the construction of this review. Additional influences were obtained by the limitations and future research suggestions of different articles. Together, these have given shape and form to this master thesis.

4.1.3 The context

Characterized as a cross-cultural study, this thesis tests the acceptance of the concept described above in two western European developed countries, namely, Germany and Norway. “Cross-cultural studies are research designs that compare human behaviors across two or more cultures.” (Papayiannis and Anastassiou-Hadjicharalambous, 2011, p. 438). “One of the best-known (and prolific) researches in the area of differences in values across culture is Hofstede. Most studies about the impact of national cultures in IS have used Hofstede’s dimensions of national culture.”

(Pearlson, Saunders and Galleta, 2019, p. 73). Hofstede's dimension definition and its application into technology acceptance models have been addressed earlier in this thesis. Also, the application of cultural dimensions as moderators on the model used in this thesis (UTAUT2) has been tested previously (Baptista and Oliveira, 2015) & (Goularte and Zilber, 2019). The importance of mentioning Hofstede's dimensions in this chapter highlights why these dimensions are taking part in this research, and essentially, how the dimensions have influenced the context selection – in other words, why Germany and Norway as opposed to any other country.

Considering technology acceptance in a cross-cultural context implies acknowledging a variability of human behavior between individuals – and these differences in behavior and cultural value can affect the acceptance of technology in different ways. Therefore, assessing these differences in values among individuals from different countries and applying them to this thesis was an efficient method to identify distinguishing factors between Germany and Norway that could potentially impact the acceptance of CT. Hofstede's MAS and LTO are the means for us to obtain such variation in cultural values among individuals from Germany and Norway.

Germany Overview – Power distance: "The extent to which the less powerful members of institutions and organizations within a country expect and accept that power is distributed unequally" (Hofstede, 2010). Germany *scores 35* on this dimension – it is highly decentralized and has a robust middle class. Participative communication style is encouraged, and control is disliked (Hofstede, 2010).

Individualism – "The degree of interdependence a society maintains among its members." (Hofstede, 2010). Germany *scores 67*, which classifies them as an individualistic society – generally, communication is direct, and honesty and transparency prevail "even if it hurts," allowing individuals to learn from mistakes (Hofstede, 2010).

Masculinity – refers to the dominant values within a society; a high score indicates that a society is driven by competition, achievement, and success, while a low score indicates caring and quality of life as dominant values (Hofstede, 2010). Germany *scores 66*, which classifies them as a masculine society. "Performance is highly valued. Status is often displayed generally in the format of material things. In these societies, people are assertive and decisive (Hofstede, 2010).

Uncertainty Avoidance – refers to “The extent to which the members of a culture feel threatened by ambiguous or unknown situations.” (Hofstede, 2010). With a *score of 65*, Germany is among the uncertainty avoidant countries. “There is a strong preference for deductive rather than inductive approach, and Germany prefers to compensate for their higher uncertainty by strongly relying on expertise.” (Hofstede, 2010).

Long-term Orientation – refers to “how every society has to maintain some links with its past while dealing with the challenges of the present and future.” (Hofstede, 2010). Germany’s *scores 83* and its high score indicate a pragmatic, adaptable, result-oriented society that interprets the situations given time and context. (Hofstede, 2010).

Norway Overview – Power Distance: “The extent to which the less powerful members of institutions and organizations within a country expect and accept that power is distributed unequally” (Hofstede, 2010). Norway *scores 31* on this dimension – here hierarchy is for convenience only, equality is highly encouraged, management structures are flat, superiors are accessible, and attitudes are informal (Hofstede, 2010) .

Individualism – “The degree of interdependence a society maintains among its members.” (Hofstede, 2010). With a *score of 69,* Norway is considered an individualist society. Here, communication is explicit and personal opinions are valued and expressed; however, privacy is important and respected. Work-life balance is present, feedback is encouraged, and job mobility high. (Hofstede, 2010).

Femininity - refers to the dominant values within a society. A high score indicates that a society is driven by competition, achievement, and success. In contrast, a low score indicates caring and quality of life as dominant values (Hofstede, 2010). Norway *scores eight* on this dimension, the second-lowest score just ahead of Sweden, who has the lowest score on this dimension across all nations included in the index. This means that feminine values such as cooperation and sympathy for the underdog prevail in the Norwegian society. “Trying to be better than others is neither socially nor materially rewarded. Societal solidarity in life is important; Focus on well-being and status is not shown.”(Hofstede, 2010).

Uncertainty Avoidance – refers to "The extent to which the members of a culture feel threatened by ambiguous or unknown situations." (Hofstede, 2010). "Norway *scores 50* and thus does not indicate a preference on this dimension." (Hofstede, 2010).

Short-term Orientation – refers to "how every society has to maintain some links with its own past while dealing with the challenges of the present and future." (Hofstede, 2010). With a *score of 35*, Norway is considered a normative society, in other words, short-term oriented – meaning that Norway values traditions and is focused on short-term results having a relatively small propensity to save for the future (Hofstede, 2010).

4.1.4 Survey strategy

Survey is usually associated with the deductive approach (Saunders, Lewis and Thornhill, 2009). It is a method utilized to collect information from a large group of people or a population. "Surveys allow researchers to collect data which can be quantitatively analyzed using descriptive and inferential statistics. In addition, the data collected using a survey strategy can be used to suggest possible reasons for particular relationships between variables and to produce models of these relationships." (Saunders, Lewis and Thornhill, 2009, p. 144). Usually associated with the deductive approach, this method answers to "who," "what," "where," "how much" questions – and when sampling, the process determines information about large populations with a known level of accuracy (Forza, 2002). Some of the strategies for data collection using surveys are: questionnaires, structured observation, and structured interviews. (Saunders, Lewis and Thornhill, 2009). Before getting into the specifics of our survey strategy, this section will describe in a somewhat detailed manner, the processes involved in the development of the survey strategy for data collection of this thesis.

Theoretical Model – The process involved in developing a survey is rather long, and before testing a survey or collecting data, a few sub-processes should be considered. The graph below is adapted from (Forza, 2002).

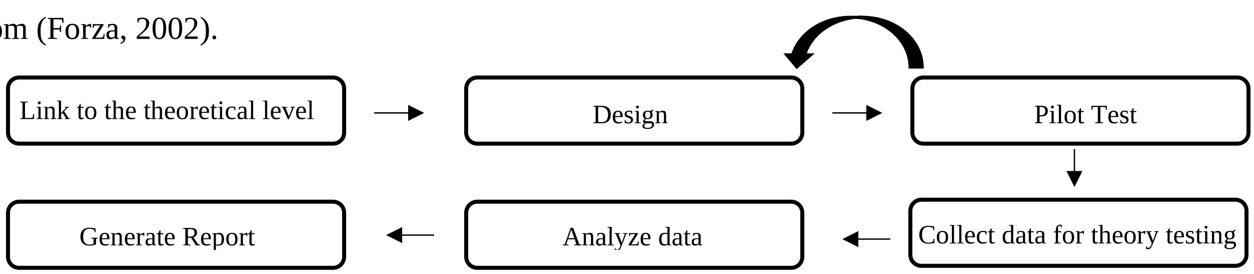


Figure 4-1: Link to theoretical level (Forza, 2002)

Link to theoretical level:

Construct names and nominal definitions – labels and definitions of all the relevant constructs.

Proposition – presentation and discussion of the role each construct, i.e. dependent, independent, moderating. As well as the linkages and direction of the relationship between the variables.

Explanation – essentially why the researcher expects to observe a specific relationship between the variables.

Boundary conditions – definition of conditions under which the research might expect these relationships to hold. (Forza, 2002). See figure (…) for a visual representation of our conceptual model.

The proposed model is an extended version of the original UTAUT2 by (Venkatesh, Thong and Xu, 2012b), containing all the original constructs of the model except for Price Value and Use Behavior (UB). Price value has been replaced by Perceived Value (see chapter three), and UB has been removed. This research examines the acceptance of a technology that has not been introduced (unfamiliar) to Germany and Norway; therefore, actual usage cannot be measured. Additionally, the model incorporates the following constructs, familiarity, trust, and five of Hofstede's national cultural dimensions, namely, Power Distance (PD), Individualism vs. Collectivism (IDV), Masculinity vs. Femininity (MAS), Uncertainty Avoidance Index (UA) and Long Term Orientation vs. Short Term Normative.

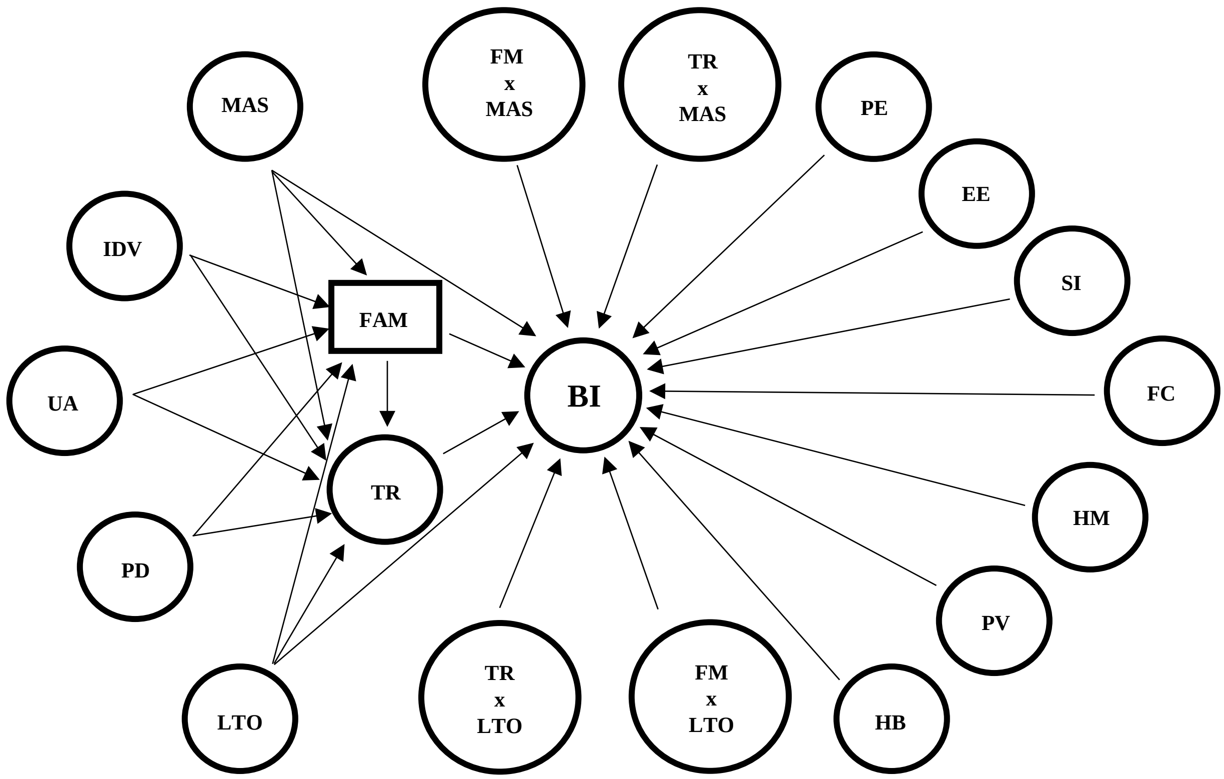


Figure 4-2: Conceptual Model

|Constructs|

UTAUT2 *– Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HB), Behavior Intention (BI).*

Adapted Construct *– Perceived Value (PV).*

Extended Constructs – *Familiarity (FM), Trust (TR).*

Cultural Dimensions – *Masculinity vs. Femininity (MAS), Individualism vs. Collectivism (IDV), Uncertainty Avoidance (UA), Power Distance (PD) and Long-term vs. Short-term Orientation (LTO).*

Hypotheses (moderators*) – Familiarity x Masculinity ⟶ BI, Trust x Masculinity ⟶ BI, Trust x Long-term ⟶ BI and Familiarity x Long-term ⟶ BI.*

See appendix 1 for the questionnaire items used to measure the constructs mentioned above.

Hypothesis – "is a logically conjectured relationship between two or more variables (measures) expressed in the form of testable statements." (Forza, 2002, p. 160). As mentioned earlier in this chapter, out of all Hofstede's dimensions, MAS and LTO were chosen to test our hypotheses. The reason is that both Germany and Norway are relatively similar across all of Hofstede's dimensions, but MAS and LTO, in which Germany is considered masculine and long-term oriented as opposed to Norway, is feminine and short-term oriented. Although this research considers the impact of all five dimensions, only MAS and LTO have been hypothesized. We assume that the differences in these two cultural dimensions might impact the acceptance of an unfamiliar technology. An elaborated discussion of our hypothesis development, including the justification of our choices, has been presented in chapter three, under hypothesis development.

***Design (survey)*:** Our survey adopted a confirmatory approach. According to Forza (2002) confirmatory survey approach aims to test the theorized hypotheses of well-defined concepts (Forza, 2002). The survey was developed in Nettskjema, a reliable survey software available for NTNU students. The survey was available in desktops and smartphones, both iOS and Android, via a link. The questionnaire design included a presentation of the concept and had an estimated duration of 10 minutes. The questions were measured on a 7-point Likert scale expressing "agreement levels," ranging from strongly disagree (1) to strongly agree (7). The questions were based on the literature review of our proposed model UTAUT2 by (Venkatesh, Thong and Xu, 2012b), which included the extended constructs (familiarity and trust). The questionnaire was adapted to the concept and context of this study. Every variable (construct) present in the model depicted above has been measured see appendix 1. Responses were collected from both Germany and Norway (recipients). The original survey was developed in English, and it was later translated to both German and Norwegian. The objective of this survey is to gain enough insight from consumers about Checkout-free Technology in different contexts, establish its familiarity and acceptance levels and by doing so, analyze the relationships of the overall model, which will then allow us to accept or refute the stated hypotheses in order to respond to our research question.

Specific information: translation – The recipients of the survey are average consumers from Germany and Norway. Given that different languages are spoken in Germany and Norway, the survey was first developed in English (common language) and later translated into the respective countries' local languages. Translating the questionnaire was necessary to minimize misinterpretation. Norway's questionnaire was translated from English to Norwegian by a Norwegian native speaker and from Norwegian back to English to ensure translation accuracy. The same procedure was applied to the German survey. In addition, both versions were proofread by two other native speakers to ensure translation reliability. It is important to emphasize that as a precaution, everyone involved in the translation process did not take part in the survey to avoid bias results.

Pilot (testing)**:** The pilot stage took place both in Norway and Germany. The survey was tested in all three languages (English, Norwegian, and German). The respondents were randomly assigned (acquaintances), and the pilot duration took a few days (two or three). The pilot was performed to identify whether the survey was capturing the necessary responses for each of the constructs, confirm estimated duration, eliminate unnecessary questions, overall adaptation and improvement of wording, and correct potential misinterpretation caused due to the translation language barrier, i.e. grammar, interpretation. According to (Malhotra and Grover, 1998), four error components can affect the results of a survey.

1. *Measurement Error* – "the error in measuring latent constructs (i.e., X to x and Y to y)" (Malhotra and Grover, 1998, p. 411)
2. *Sampling Error* – A sample with know or unknown capability of representing the population (Malhotra and Grover, 1998)
3. *Internal Validity Error* – "if other explanations (rival hypothesis) can explain observed relationships. (Malhotra and Grover, 1998)
4. *Statistical Conclusion Error* – "the probability that the null hypothesis has been correctly rejected and that mathematical relationships between hypothesis and variables exist." (Malhotra and Grover, 1998, p. 411).

Data collection took place immediately after the pilot stage, which enabled us to make the necessary adjustments.

Data collection (samples): Our survey collected 230 responses in Norway and 65 responses in Germany, a total of 295 responses. Demographics indicated that the Norwegian sample accounted for every county except for one. The German sample included different counties, but it was not as spread apart as the Norwegian sample was. The age group range in Norway is 18 to 75 years old, and Germany had a range of 18 to 57 years old. A complete description of the sample size will be discussed in chapter 5.

Analyze data & Generate Report: The statistical analysis Partial Least Squares Structural Equation Modelling (PLS-SEM) was chosen to investigate the hypothesis formulated for this research/thesis. Structural equation modeling (SEM) is a multivariate statistical analysis technique that pursues to explain the relationship between multiple variables. It is a family of statistical models used to analyze the structural relationship between measured variables and latent constructs (Hair Jr. *et al.*, 2018). This method will be further explained in chapter 5: Results.

5 Results

The data analysis and results are presented in this chapter. The chapter is segmented into two parts: First, the descriptive statistics will be presented, and second, the data analysis and PLS-SEM estimation procedure will be presented, which includes measurement validation, measurement model assessment, path analysis, and hypotheses testing. Although the cultural differences on an individual-level is of the essence in this paper, the result from the country-level will also be included. The results from the model for the individual-level have been used as a "yardstick" standard for comparison with Germany and Norway on a country-level.

5.1 Descriptive statistics for both Germany and Norway (Combined)

Descriptive analysis illustrates the sample's features and checks the violation of the assumptions underlying the statistical questions. Descriptive statistics include the mean, minimum, maximum, standard deviation, range of scores, distribution of scores (skewness and kurtosis), and number of observations used (Pallant, 2016). The descriptive statistics combined for Norway and Germany are shown in table 5.1 (see Appendix 2). As only closed-ended questions were included in the survey, and all of the questions were obligatory, the respondents could not skip a question or answer more than one option per question. By this, there were no values that fell outside the range of possible values for a variable (1-7), nor any missing values.

5.1.1 Sample characteristics for both Germany and Norway

This section describes the demographic profile of 295 respondents collected from both the survey in Germany and Norway; 230 of the respondents were from Norway, and 65 were from Germany.

Table 5.2 (see Appendix 3) gives an overview of the gender of the different respondents. As shown in the table there are 166 (56,3%) females, 127 (43,1%) males and 2 (0,7%) others. There is a 13,2% difference in female and male respondents.

Table 5.3 (see Appendix 3), shows that the distribution of different age groups among the respondents is presented. The five predominant age groups are 18-25 years, 26-35 years, 36-45 years, 46-55 years, and 56 and older. The most significant percentage of respondents are in the 18-25 group (30,2%), while the next largest group is between 26-35 years (27,5%). The age group of 36-45 has 27 respondents (9,2%); the age group of 46-55 has 65 respondents (22,0%). Lastly, the age group of 56 years and older has 33 respondents (11,2%). This table shows that the majority of the respondents are between 18-35, which together represents a total of 57,7% (See Appendix 3).

As presented in table 5.4 (see Appendix 4), 108 (36,6%) of the respondents are not at all familiar with CT, 66 are unfamiliar (22,4%), and 22 (7,5%) of the respondents are slightly unfamiliar. This shows that 66,6% of the respondents have not heard of or have experience with CT. As shown in table 12 (4,1%) of the respondents were neither familiar nor unfamiliar. The number of moderately familiar respondents was 43 (14,6%); 30 of the respondents were familiar (10,2%), and 14 (4,7%) of the respondents were extremely familiar with CT. Table 5.1 in the Appendix 2 shows that the mean of familiarity is 2,871, which shows that the technology is unfamiliar to the respondents.

5.2 Data analysis and PLS-SEM estimation procedure

As mentioned in the precious chapter, the statistical analysis Partial Least Squares Structural Equation Modelling (PLS-SEM) was chosen to investigate the hypothesis formulated for this research/thesis. Structural equation modeling (SEM) is a multivariate statistical analysis technique that pursues to explain the relationship between multiple variables. It is a family of statistical models used to analyze the structural relationship between measured variables and latent constructs (Hair Jr. *et al.*, 2018). PLS has minimal requirements on measurement scales, sample size, and residual distributions, compared to covariance-based SEM (Vinzi *et al.*, 2010). As covariance-based SEM focus on the reproduction of the theoretical covariance matrix without focusing on explained variance, PLS concentrates on the variance of the endogenous latent construct (dependent variables) explained by the exogenous constructs (independent variables) (Haenlein and Kaplan, 2004). PLS's estimation method has similarities with principle component analysis for reflective indicators or regression analysis with formative indicators. PLS uses latent variable proxies, which are linear composites of the associated observed variables. Parameter estimation is determined through a multistage algorithm in PLS path modeling. The diverse stages involve a string of regressions in terms of weight vectors, with iteration until convergence is reached on a final set of weights (Haenlein and Kaplan, 2004). To sum it up, PLS-SEM was chosen over CB-SEM due to the complexity of the structural model (many constructs and indicators), the small sample size from Germany, and the simplicity of verifying interaction effects with latent variables (Hair, Ringle and Sarstedt, 2011). The software application Smart PLS (3.2.3) was used to estimate the structural equation model (SEM), where Partial Least Square (PLS) and Bootstrapping method were selected. The results from both the measurement model and the structural model will be three folded: the individual result (Individual-level), the result for Norway alone (country-level), and result from Germany alone (country-level). The combined result represents results on an individual level, and the separate results represent the results on a country level.

5.2.1 Measurement Model Results

The measurement model is a theoretically derived model that defines how the indicators correspond to latent constructs and enables an estimate of construct validity (Hair Jr. *et al.*, 2018). The PLS-SEM algorithm calculates the relationship between the latent variables and its indicators (loadings) in the measurement model. By exploring the reliability and validity of the construct measures, the measurement was evaluated. The empirical analysis of the measurement model is based on 45 items (indicators).

Three items measure the primary endogenous construct, which is Behavior Intention (BI). The endogenous construct is predicted by nine (plus two of the cultural dimensions as they are moderators) exogenous constructs that consist of 28 (+ 6 if the cultural dimensions are included (MAS and LTO)), FM, and TR are also included in this number) items. Two of the cultural dimensions (moderators) have a direct link to BI as it moderates the effect of Familiarity and Trust to BI. Familiarity also has a direct link to trust, which makes it an endogenous variable. Trust is measured by four items and is predicted by Familiarity that consist of only one question (How familiar are you with checkout-free technology?).

Before the PLS analysis results are presented, it is necessary to evaluate the convergent and discriminant validity of the measurement indicators (items). It is vital to determine which degree a set of measured variables accurately represents the latent theoretical construct they are designed to measure. The set of indicators of a latent construct is internally consistent with their measurements (Hair Jr. *et al.*, 2018). It is essential for every researcher always to work to increase reliability and validity to get a more precise depiction of the variables of interest, as the influence of measurement error and unfavorable reliability cannot be directly seen as they are entrenched in the observed variables. The existence of measurement error is undoubtedly going to distort the observed relationships and make multivariate techniques less vigorous, even though atrocious results are not always a result of measurement error (Hair Jr. *et al.*, 2018).

PLS standardized coefficients, average variance extracted (AVE), composite reliability, and Cronbach's Alpha were included in assessing the internal consistency and convergent validity of the measurement model. Also, the Fornell-Larcker criterion and cross-loadings were used to assess discriminant validity. In the next section, the convergent – and discriminant validity will be presented.

5.2.1.1 Convergent Validity

According to Hair Jr. et al., (2018) convergent validity is the degree to which a latent construct describes the variance of its indicators, the items that are measures of a particular construct should share a large portion of the variance in common (Hair Jr. *et al.*, 2018). There are several options to estimate the relative amount of convergent validity among item measures, and these options will be represented below.

A critical consideration for convergent validity is the size of the PLS standard coefficients (outer loadings). High loadings on a factor would suggest that they converge on a common point. The factor analysis of each scale shows that each of the latent measures substantially and reliably correlated with the other items - indicating convergent validity (Cunningham, Preacher and Banaji, 2001). As a minimum, all factor loadings should be statistically significant. Even so, significant loading could still be relatively weak in strength. According to Hair Jr. et al., (2018) an acceptable rule of thumb is that standardized loading estimates should be .5 or higher, preferably .7 or higher (Hair Jr. *et al.*, 2018). Table 5.5 (see Appendix 5) presents the links between items and their latent variables (constructs) for the individual level results. The table shows that all of the items have a factor loading of above .7, except from MAS4 (0.696). Table 5.6 and Table 5.7 (see appendix 5) presents the factor loadings for Norway and Germany (country level), respectively.

Here, we can also see that all of the loadings are above .7, apart from MAS2 (.618) and MAS3 (.637) for Norway and IDV3 (.650) for Germany (see Appendix 5). Cross loadings are also presented in table 5.12, 5.13 and 5.14 (see Appendix 5). Some of the items were removed due to poor factor loadings in the combined sample (below .5), and therefore had to be removed in the separate samples too. These factors include: IDV1, LTO2, LTO3, LTO4, UA5, and PD1.

Another indicator for convergent validity is reliability. Every construct in this research consists of at least two indicators. Cronbach's alpha (CA) was used to assess the internal consistency of each scale as CA provides an estimate for the reliability based on the indicator inter correlations (Hair Jr. *et al.*, 2018). A high construct reliability proves the existence of internal consistency. According to (Ursachi, Horodnic and Zait, 2015) a generally accepted rule is valued between .6 and .7 indicates an acceptable level of reliability. If these criteria are fulfilled, all the measures consistently represent the same latent construct (Hair Jr. *et al.*, 2018). The higher the Alpha coefficient, a higher indication of reliability (ranges from 0 to 1). Although CA may underestimate reliability and is sensitive to the number of items in the scale, it is still a commonly applied estimate. Due to the limitation of CA it is suggested to use construct reliability (CR), as this value is often used in convergence with SEM models and is considered a more suitable criterion of reliability in the context of PLS-SEM (Hair Jr. *et al.*, 2018). The CR can be interpreted in the same manner as CA as it is a measure of internal consistency, and it considers that indicators have different loadings. The composite reliability value must not be lower than 0.6 (Cavusgil, Sinkovics and Ghauri, 2009) and calculated as follows:

$$CR_{pc} = \frac{(\sum_{i=1}^{n} \lambda_i)^2}{[(\sum_{i=1}^{n} \lambda_i)^2 + \sum_{i=1}^{n} Var(\varepsilon i)]}$$

$$\lambda_i = the\ outer\ loading\ to\ an\ indicator$$

$$Var(\varepsilon i) = 1 - {\lambda_i}^2\ in\ case\ of\ standardized\ indicators$$

Figure 5-1: : Formula 1(Cavusgil, Sinkovics and Ghauri, 2009)

The average variance extracted (AVE) is another method for estimating convergent validity. AVE is the average percentage of variation explained between the items of a construct. To calculate the AVE, the squared loadings of all components are summated and then divided on the sum of items in each component (Hair Jr. et al., 2018); (Fornell and Larcker, 1981). As reported by (Hair Jr. et al., 2018) (Henseler et al., 2009), a rule of thumb is that AVE should be .5 or higher as this value suggests sufficient convergent validity. If the AVE value is above .5, it means that the latent variable can reason for more than half of the variance of its indicators on average (Henseler, Ringle and Sinkovics, 2009). The AVE value is calculated as follows:

$$AVE = \frac{(\sum \lambda_i{}^2)}{[(\sum \lambda_i{}^2) + \sum Var(\varepsilon i)]}$$

$\lambda_i{}^2 = \textit{the component loading to an indicator}$

$Var(\varepsilon i) = 1 - \lambda_i{}^2$ in case of standardized indicators

Figure 5-2: : Formula 2(Cavusgil, Sinkovics and Ghauri, 2009)

The Cronbach's alpha, Composite reliability, and AVE are presented in table 5.8 (see Appendix 5) for both the individual-level and country-level. The results from the individual level shows that all constructs are above the cut-off level, PD is just below .7 (.663), but still at an acceptable level. For the country level also all of the constructs are above the accepted values, except for PD in Germany as the CA is below .6 (0.516). Although PD did not have an acceptable value for CA, it has been decided to include the construct as it is a construct that has been tested in many researches before (This is further discussed under limitations). Besides PD for Germany, the results show that all values are above the threshold, and convergent validity is achieved for both the individual-level result and the country-level result.

5.2.1.2 Discriminant Validity

According to Hair Jr. et al., (2018), discriminant validity is "the extent to which a construct or variable is truly distinct from other constructs or variables" (Hair Jr. *et al.*, 2018, p. 659). If a construct has a high discriminant validity, it is verified that the construct is distinctive and captures some phenomena other measures do not (Hair Jr. *et al.*, 2018). Current researchers report two methods of measuring discriminant validity: The Fornell-Larcker criterion and the cross-loadings (Henseler, Ringle and Sinkovics, 2009). The Fornell-Larcker criterion claims that a latent variable shares more variance with its assigned indicators than with any other construct (Fornell and Larcker, 1981; Henseler, Ringle and Sinkovics, 2009). The AVE values for any two constructs with the square of the correlation estimate between these two constructs are compared in the Fornell-Larcker tests (correlation table is presented in table 5.21 in Appendix 6). Further, it says that each latent variables' highest squared correlation with any other latent variable (Fornell and Larcker, 1981; Henseler, Ringle and Sinkovics, 2009).

The second measure of discriminant validity says that each indicator's loadings are expected to be higher than all of its other cross-loadings (Henseler, Ringle and Sinkovics, 2009). The Fornell-Larcker criterion is presented in table 5.9 (individual level), 5.10 (country level: Norway), and 5.12 (country level: Germany) (See Appendix 5), which indicates that all construct measurements have adequate discriminant validity.

The second proof of discriminant validity is cross-loading: Each indicator's loading is expected to be higher than all of its loadings on other constructs (cross-loadings). The Fornell-Locker criterion evaluates discriminant validity on the construct level, while the cross-loadings evaluate discriminant validity on the indicator level. A reliable and valid reflective measurement of latent variables should meet these criteria, if not, single indicators should be considered to be removed from the measurement model (Henseler, Ringle and Sinkovics, 2009; Vinzi *et al.*, 2010). The cross-loadings for the individual-level and country-level is presented in table 5.12, 5.13, and 5.14, respectively (see Appendix 5), and indicates that all measurements have satisfactory discriminant validities.

5.2.2 Structural Model Results

Now that the convergent and discriminant validity of the measures have been tested, the next step is to concentrate on the structural model. When assessing the structural model, the prominence will be on the predictive ability of the SEM model and establishing how strong empirical data reinforce the theory and concept. By that, we mean how consistent the structural relationships are with theoretical expectations. PLS analysis emphasizes on the significance of all path estimates along with variance explained. As mentioned before, Smart PLS was used to estimate PLS algorithms. The maximum number of iterations used was 300, and the path weighting scheme was selected. Vinizi et al. (2010) strongly advise researchers to use the path weighting scheme, it provides the highest R^2 value for endogenous latent variables and is universally suitable for plenty of different PLS path model specifications and estimations (Vinzi *et al.*, 2010).

Moderating effect of cultural dimensions

Smart PLS describes moderation as a "situation in which the relationship between two constructs is not constant but depends on the values of a third variable, referred to as a moderator variable" (SmartPLS, n.d.) In this thesis, four moderators are hypothesized: Trust (TR) x Masculinity (MAS) $\rightarrow$ Behavior Intention (TRxMAS$\rightarrow$BI), Trust (TR) x Long-Term orientation $\rightarrow$ Behavior Intention (TRxLTO$\rightarrow$BI), Familiarity (FM) x Masculinity (MAS) $\rightarrow$ Behavior Intention (FMxMAS$\rightarrow$ BI), Familiarity x Long-Term Orientation (LTO) $\rightarrow$ Behavior Intention (FMxLTO$\rightarrow$ BI).

A two-stage calculation method for the moderating effect was chosen. It uses the latent variable scores of the latent predictor and latent moderator variable from the primary effects model (without the interaction term). Standardized product term generation and automatic weighing mode were chosen for the advanced settings (SmartPLS, n.d.). To add a moderating effect on a variable in Smart-PLS, the program creates an interaction term by multiplying all the indicators of the moderating variable with all the indicators of the variable affected by the moderation (SmartPLS, n.d.). The interaction terms were created, and the model was run by (1) calculating the path coefficients using PLS algorithm, and (2) calculate the t-statistics and the significance of the path by using Bootstrapping – when this was done the hypotheses could be tested.

To evaluate the structural model, four measures were used: Assessment of structural model collinearity, assessment of the significance and size of the structural path relationships, assessment of the R^2 level, and an assessment of the effect size f^2.

5.2.2.1 Collinearity assessment

As described above, it is essential to assess the exogenous constructs for collinearity before analyzing the model results. As the path coefficients are based on OLS regressions, it could be biased if multicollinearity is present (Hair Jr. *et al.*, 2018). Tolerance and variance inflation factor (VIF) can be used to assess collinearity. Each set of predictor constructs must be examined individually for each subpart of the structural model. If high levels of multicollinearity is present in the formative measurement model, an indicator`s information can become redundant, which again can result in indicators being nonsignificant (Hair, Ringle and Sarstedt, 2011). As shown in table 5.15 (see Appendix 6) the VIF values for both the individual-level and country-level are below 5.00, in other words, the results of collinearity statistics presented indicates lack of collinearity among construct variables (Hair, Ringle and Sarstedt, 2011).

5.2.2.2 Assessment of significance and size of the structural path relationship

To assess the path coefficients significance, Bootstrapping was used. A path coefficient is considered significant if its t-values are higher than a specified critical value. Path coefficients are evaluating the path relationship between constructs in the structural model (Hair Jr. *et al.*, 2018). The path coefficient symbolizes the hypothesized relationship between the constructs. For each of the hypotheses presented in chapter four, there is a path coefficient. The path coefficients range from -1 to +1, and the further away the value is from 0, the stronger the relationship. Evaluating whether the relationships are significant or not, is not enough to look at the path coefficients; for this, the t-values needs to be calculated with a bootstrapping procedure. A path coefficient is considered significant if its t-value is greater than a particular critical value. Critical t-values for a two-tailed test are 1.65 (significance level = 10% (*)), 1.96 (significance level = 5 percent (**)), and 2.58 (significance level = 1 percent (***)) (Hair, 2014; Hair, Ringle and Sarstedt, 2011; Hair Jr. *et al.*, 2018).

For the individual-level analysis, the bootstrapping option was run using 5.000 subsamples with 295 cases to obtain the significance levels. The significance of relationships is estimated based on a two-tail t-test. The bootstrapping option was run to achieve the country-level results with 230 cases for Norway and 65 for Germany.

The choice of confidence interval estimation method was bias-corrected and accelerated (BCa) bootstrap. This is the most reliable method, and it does not request exaggerated computing time. Figure 5.3 and 5.4, and 5.5 presents the graphical bootstrapping output with path coefficients and R^2 estimated values for the individual-level, and country-level, respectively.

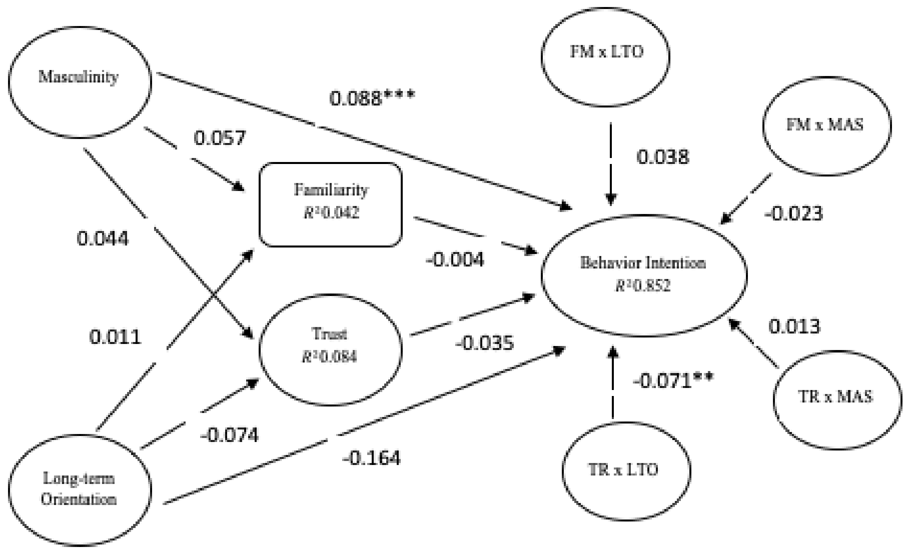


Figure 5-3: Bootstrapping results with PLS path coefficients and R^2 for the individual level result

***Significant at .01 level ** Significant at .05 level * Significant at .10 level

The results presented in figure 5.3 and figure 5.6a (see Appendix 6) support the suggested moderating effect of Long-Term Orientation on trust and behavioral intention (H_{2b}) (t = 2.028, p < 0.05). The results do not support the proposed moderating effect of Long-Term Orientation on familiarity and behavioral intention was not supported (H_{2a}) (t = 1.318, p > 0,10); the moderating effect of Masculinity on familiarity and behavioral intention (H_{1a}) (t = 0.834, p > 0,10); the moderating effect of Masculinity on trust and behavior intention (H_{1b}) (t = 0.410, p > 0,10). As the structural model only shows the hypothesized relationships, only one path is significant TRxLTO→BI on a 5% level. The summary of bootstrapping results with t-values and p-values for each path are presented in table 5.16 in the Appendix 6.

Country-level result Norway

Due to limited space in this thesis, the bootstrapping results with PLS path coefficients and R^2 for the country-level results for Norway are presented in Appendix 6. The results presented in figure 5.4 and 5.7a support the suggested moderating effect of Long-Term Orientation on trust and behavioral intention (H_{2b}) (t = 2.384, p >0.05). The results do not support the proposed moderating effect of Long-Term Orientation on familiarity and behavioral intention (H_{2a}) (t = 1.182, p > 0,10); the moderating effect of Masculinity on familiarity and behavioral intention (H_{1a}) (t = 0.913, p > 0,10); the moderating effect of Masculinity on trust and behavior intention (H_{1b}) (t = 0.154, p

> 0,10). The summary of bootstrapping results with t-values and p-values for each path is presented in Appendix 6, figure 5.17.

Country-level result Germany

The results presented in figure 5.5 and 5.8a (see Appendix 6) show the country-level result for Germany. The results presented do not support the suggested moderating effect of any of the cultural dimensions: The results do not support the proposed moderating effect of Masculinity on familiarity and behavioral intention (H_{1a}) (t = 0.503, p > 0,10); the moderating effect of Masculinity on trust and behavior intention (H_{1b}) (t = 1.180, p > 0,10); Long-Term Orientation on familiarity and behavioral intention (H_{2a}) (t = 0.580, p > 0,10); the moderating effect of Long-Term Orientation on trust and behavioral intention (H_{2b}) (t = 0.687, p > 0.10). The summary of bootstrapping results with t-values and p-values for each path is presented in Appendix 6, table 5.18.

Simple slope analysis

The simple slope analysis for the significant moderating effect of Long-Term Orientation on Trust and Behavioral intention for both the individual result and the result from the country-level for Norway is presented in figure 5.9 and 5.10 in Appendix 6. The figures show that LTO negatively moderates the relationship between trust and behavioral intention, meaning that the relationship between TR and BI will be more negative when individuals are high on LTO. Trust reduces intention for individuals that are high on LTO, in other words, for individuals that are high on LTO do not need to trust checkout-free technology in order to intend to shop in a checkout-free store.

5.2.2.3 Assessment of the R^2 level

The coefficient of determination (R^2) is a measure of the model's predictive accuracy, and it is the primary evaluation criteria for the structural model. An additional way to vision R^2 is that it portrays the exogenous variable`s combined effect on the endogenous variable(s) (F. Hair Jr *et al.*, 2014).

The pivotal target constructs level of R^2 should be high, as the objective of the prediction-oriented PLS-SEM method is to describe the endogenous latent variables variance (Hair, Ringle and Sarstedt, 2011). The assessment of what R^2 level is high, depends on the individual research discipline and the model complexity. As the R^2 values ranges from 0 to 1, high values display higher levels of predictive veracity and low levels lower levels of predictive accuracy (F. Hair Jr *et al.*, 2014). In consumer behavior disciplines, R^2 levels of 0.20 are considered high, while in success driver studies R^2 levels of 0.75 are considered high. According to (Hair, Ringle and Sarstedt, 2011) a rule of thumb in marketing research studies is that R^2 values of 0.75, 0.50 or 0.25 for endogenous latent variables in the structural model can be characterized as substantial, moderate, or weak, respectively (Hair, Ringle and Sarstedt, 2011). PLS also has adjusted R^2 value, like in multiple regression. According to (F. Hair Jr *et al.*, 2014) too much dependence on R^2 can prove problematic, even though it is an important tool in assessing the quality of a PLS model (F. Hair Jr *et al.*, 2014). As an illustration, the R^2 will rise even if a nonsignificant though a slightly correlated construct is added to the model. Correspondingly, if the researcher`s only objective is to improve the R^2 , the researcher would benefit from adding additional exogenous constructs even if the relationships are not purposeful (Hair, 2014).

The adjusted R^2 punish increasing model complexity by reducing the adjusted R^2 when supplementary constructs are added to the model. The determination for a model should, therefore, be based on the adjusted R^2. The result presented in table 5.19 (see Appendix 6), shows that the structural model for the individual-level is adequate to explain 85,2 percent of the variance in behavior intention. The model is able to explain 4,2 percent of the variance in Familiarity (FM) and 8,4 percent of the variance in trust (TR). Both FM and TR are very low and can be characterized as weak R^2 levels. In the present research, it can be concluded that the variance of the main dependent variable is highly predicted by the independent variables. The structural model for the for country-level result for Norway (see table 5.19 in Appendix6) shows that it is able to explain 85,9 percent of the variance in behavior intention, 4,7% of the variance in Familiarity (FM), and 10% of the variance in Trust (TR). The structural model for the for country-level result for Germany (see table 5.19 in Appendix 6) shows that it is able to explain 93,3 percent of the variance in behavior intention, 11,1% of the variance in Familiarity (FM), and 18,7% of the variance in Trust (TR). Overall, the same conclusion can be drawn for the structural models for the country-levels, as for the individual-level; the variance of the main dependent variable is highly predicted by the independent variables, while TR and FM have weak values.

The R^2 and adjusted R^2 estimated values for the structural models are summarized in table 5.19 in the appendix 6.

5.2.2.4 Assessment of the effect size f^2

The change in the R^2 value when a particularized exogenous construct is removed from the structural model can be used to estimate whether the excluded construct has a substantial influence on the endogenous construct (Hair, 2014). This measure is characterized as the effect size f^2 and it can be evaluated for each effect in the path model (Cohen, 1988); (Henseler, Ringle and Sinkovics, 2009). The formula of the effect size f^2 is as follows:

$$f^2 = \frac{R^2 included - R^2 excluded}{1 - R^2 included}$$

Figure 5.11: Formula 3: The effect size of f^2 (Henseler, Ringle and Sinkovics, 2009)

"The effect size f^2 is calculated as the increase in R^2 relative to the proportion of variance of the endogenous latent variable hat remains unexplained" (Henseler, Ringle and Sinkovics, 2009, p. 304). f^2 values of 0.02, 0.15, and 0.35 are according to Cohen (1988), represent small, medium, and large effects, respectively (Cohen, 1988). The f^2 estimated values are presented in table 5.20 (see Appendix 6). For the individual level, we can conclude that MAS (.049), HM (.035), PE (.103), and PV (.111) have a small effect on BI, while HB (.374) has a large effect on BI. The results also show that FM (.065) has a small effect on trust.

The results for the country level (Norway) shows that HM (.04), MAS (.041), PE (.115) and PV (.149) have a small effect size on BI. HB (.23) has a medium effect on BI. FM (.075) has a small effect on TR. The results for the country level (Germany) shows that EE (.048), HM (.124), MAS (.080), and PV (.022) have a small effect on BI, while HB (3.199) has a large effect on BI. IDV (.022) and UA (.048) have a small effect on TR.

5.3 Summary of PLS-SEM path results and hypotheses testing

The results from the hypotheses testing are presented in table 5.21. In the following table, Model 1, represent the results for the individual level, while Model 2 and Model 3 represent the country level results for Norway and Germany. If the path relationships have a p-value below 0.10 they are considered significant, while p-values above 0.10, are considered non-significant. The detailed discussion of the hypothesis, and other findings from the structural model are presented in the next chapter.

Hypothesis		Model 1 (Individual level)	Model 2 (Norway)	Model 3 (Germany)
H_{1a}	The relationship between a familiar technology and behavioral intention is negatively moderated by masculinity (MAS).	Rejected	Rejected	Rejected
H_{1b}	The relationship between trust and behavioral intention is negatively moderated by masculinity (MAS).	Rejected	Rejected	Rejected
H_{2a}	Long-term orientation negatively moderate the relationship between familiarity and behavioral intention.	Rejected	Rejected	Rejected
H_{2b}	Long-term orientation negatively moderate the relationship between trust and behavioral intention.	Supported**	Supported**	Rejected

Table 5.21: Summary of results of hypotheses testing

*** Significant at .01 level, ** Significant at .05 level, * Significant at .10 level.

6 Discussion and Conclusion

The purpose of this master thesis has been to address the following question: ***How do cultural dimensions influence the acceptance of an unfamiliar technology?*** The concept chosen to study technology acceptance is an innovation in retail referred to in this thesis as Checkout-free Technology (CT). CT is unfamiliar to the European market as it has been released in the USA only. Our objective is to account for cultural influences while investigating the acceptance of CT in different contexts. The present study focuses on the impacts of MAS and LTO on technology acceptance, where our intention was to obtain variation among these two dimensions to explore their impact on technology acceptance. An effective way to obtain such variety is by identifying countries that share opposite views on masculinity and long-term orientation. We believed that by achieving such variation, the chances of getting distinct results concerning individuals' intentions based on cultural values would be greater. Although Hofstede's insight score represents an index to the country, levels of national culture also differ among individuals within a society. Selecting two or more countries for data collection is an efficient method for cross-cultural comparison; however, when considering analysis at the individual level, it is also an effective strategy for increasing the variety of cultural differences within the sample. Germany and Norway are two Western European developed countries sharing similarities across most of the cultural dimensions, except for *Masculinity vs. Femininity and Long-term vs. Short-term Orientation.* We assumed that the differences in these two dimensions could have an impact on the acceptance of an unfamiliar technology.

CT has been classified as an unfamiliar technology because upon performing a thorough research in retail technologies, no similar services were identified in both contexts of our study. However, validating such a claim, required the inclusion of familiarity in our proposed model. Adding familiarity, however, raised another question. As Gefen (2000) mentioned, "people's familiarity with a concept can enable them to entertain specific beliefs concerning security" (Gefen, 2000, p. 728), and this indicates that the lack of familiarity could perhaps raise skepticism regarding trust. Therefore, trust was also added to our proposed model. The question of familiarity has been confirmed by our results, which reported a mean of 2.871, confirming our initial assumption that CT is indeed an unfamiliar technology in the contexts of this study. The relationship between familiarity and trust was significant for the individual-level result, and the country-level result for Norway, which means that levels of familiarity increases trust, which is in accordance with Gefen's suggestion mentioned above. This chapter's structure goes as follow: (1) theoretical implications of findings presented in measurement models, (2) Managerial Implications and (3) Limitations and future research (4) Conclusion.

6.1 Theoretical implication of findings presented in the measurement models

Our hypotheses – following our reasoning thus far, it felt logical to elaborate hypotheses that could test the relationships and effects of familiarity, trust, and the two distinct cultural dimensions towards behavior intention. Therefore, interaction terms were created to examine these effects, i.e., Long-term orientation negatively moderates the relationship between trust and BI (TRxLTO-BI). In other words, the interaction term simply means that a third variable is influencing the relationship between an independent and dependent variable, and this effect should interfere in the individuals' intention to accept a new technological concept. The literature review confirmed that the hypotheses formulated in this thesis has, to our knowledge, never been tested in this context or with the UTAUT2 model before. The direction of our hypotheses has been influenced by the following: The work of Hofstede (interpretation of cultural dimensions) and the results, discussion and implications of researches conducting similar studies (Baptista and Oliveira, 2015; Chuawatcharin, 2019; Goularte and Zilber, 2019) to name a few. Our research examines the sample size from a threefold perspective – 1) Individual level (combining both the Norwegian and the German sample), 2) Country-level for Germany, and 3) Country-level for Norway. This enabled us to conclude at both country and individual level. Although the levels of national culture represent a country index, Hofstede's work has been applied to the individual-level previously (Yoo, Donthu and Lenartowicz, 2011).

Hypothesis 1a (Rejected)**:** the first hypothesis assumed that the relationship between familiarity and behavioral intention would be negatively moderated by masculinity (FM x MAS-BI). The direction of the hypothesis was based on the premises of Hofstede's work on national culture values and empirical findings regarding the role of cultural dimensions in technology acceptance. Mark and Elena (2006) associated feminine values to perceived ease of use in their hypotheses justification by stating the following: "the prominence of social/affiliation needs for individuals of feminine values increase the importance placed on the availability of technology support staff for such individuals" (Mark and Elena, 2006, p. 686). In other words, individuals with feminine values place great emphasis on perceived ease of use. However, when considering an unfamiliar technology, the ease of use perception is unknown, as lack of familiarity prevents users from having an experienced-based attitude towards a given product or service. Therefore, masculinity values seemed more appropriate to test the acceptance of CT. Nevertheless, it seems like individuals with masculine values also were affected by low levels of familiarity, given that our result was non-significant.

Our results confirmed a non-significant relationship between FM and BI at the individual level. Perhaps CT is too unfamiliar for individuals to have a formed opinion about it, which in turn, can lead to inhibiting intentions toward behavior. Psailla et al. (2007) stated the following regarding familiarity "in the journalistic sector, it seems logical to point out that readers familiarized with newspaper websites would have a greater predisposition to read them. In this way, the higher familiarity with the website, the higher choice of electronic newspaper." (Psailla *et al.,* 2007, p. 182). Associating this with our context, it would be logical to assume that individuals who are unfamiliar with CT would not have a predisposition to accept or intend to use the technology. Ultimately, this explains the non-significant relationship between FM and BI. However, our results confirmed a significant relationship between MAS (masculine individuals) towards BI. This result is in accordance with our initial assumption that individuals with masculine values (assertive, goal-oriented) were more likely to accept an unfamiliar technology, which is in line with the findings of (Mahfuz, Khanam and Wang, 2016) who reported MAS to have a significant relationship towards BI testing cultural dimension on the UTAUT2 model.

According to our hypothesis, MAS was assumed to moderate the relationship between familiarity and BI. However, our results confirmed the moderating effect to be non-significant. This result is in line with the findings of (Baptista and Oliveira, 2015; Goularte and Zilber, 2019), who applied the cultural dimensions on UTAUT2 and reported a non-significant moderating effect from MAS to BI. However, the findings are contradicting the conclusions of (Mark and Elena, 2006), who found a significant moderating effect of MAS on the relationship between Perceived ease-of-use (PEOU) and BI. These contradictory results may be an indication that values of MAS affect behavioral intention differently, given its interaction with different antecedent constructs. It is also possible that MAS as a dimension (including both extremes) have no moderating effect between familiarity and BI (does not explain). In other words, it makes no difference whether the individual carries modest, caring, or assertive, competitive behavior traits; if the technology is unfamiliar, MAS may have no effect.

More to familiarity –To our knowledge, no empirical studies have examined the moderating effect of Long-term orientation on the relationship between Familiarity and Behavior Intention (FM x MAS - BI). One possible explanation for the non-significant findings may be attributed to levels of familiarity. Our findings did confirm that CT is unfamiliar, and levels of familiarity might be directly related to the non-significance of this result. Limited understanding of technological principles or lack of familiarity can prevent users from having an experienced-based attitude, which, in turn, can influence acceptance. According to (Psailla *et al.*, 2007) several papers have proved that the user's familiarity with websites would affect the individual's final decision. (Gefen, 2000) (Gefen, 2000) examined familiarity in the context of e-commerce – and stated that familiarity reduces uncertainty by generating knowledge structure on individuals, which minimizes complexities through an understanding of how to interact with the given context involved. (Psailla *et al.*, 2007) says that familiarity facilitates decision making by reducing the necessary cognitive efforts, and Niklas Luhmann (2017) stated that familiarity makes it possible to entertain relatively reliable expectations (Luhmann, 2017). Knowledge about the context and understanding of its relevance can be crucial to technology acceptance, and the statements above are supporting this claim. Our initial assumption based on the literature of this thesis was that the moderating effect of MAS would have an impact on the relationship between FM and BI. According to (Luhmann, 2017) familiarity denotes neither favorable nor unfavorable expectations, but the conditions under which both are rendered possible. Therefore, it could be that levels of familiarity (unfamiliarity) with CT prevented people from entertaining specific beliefs regarding how to interact with the store, which in this case might have added unfavorable expectations or uncertainty, negatively impacting acceptance.

How does it differ from the individual level analysis – At the country-level, these relationships were for the most part similar, but somewhat contradictory, especially regarding MAS. Our result reported a significant relationship between MAS and BI in Norway, but a non-significant relationship between MAS and BI in Germany. This result is contrary to Hofstede's dimensions of national culture index. Hofstede reported Germany as a masculine country with a score of (66pts) and Norway as feminine with a score of (8pts) (Insights Hofstede, n.d.). In theory, our result should have been the opposite. We expected to obtain a significant relationship between MAS and BI from Germany as opposed to Norway, given the extreme difference in MAS between these two countries. One possible explanation for the non-significant result of the country-level for Germany, is that the German sample size may have been too heterogeneous, which could have reduced the levels of explained variance. Alternatively, this can be attributed to each individual's cultural value, which might not necessarily correspond to Hofstede's national culture value estimated index. Hofstede himself mentioned the uniqueness of individual behavior by stating the following: "The individual level of human programming is the truly unique part: no two people are programmed exactly alike." (Hofstede, 2001, p. 2). Lastly, an intriguing study by the European Central Bank (ECB) identifies Europeans (Germany included) as cash payers (Skolimowski, 2017) while the Norwegian consumer council has suggested in a public announcement that maintaining cash as a payment solution is non-essential (Blaker, 2018). Section 6.1, in this chapter, discusses "Predominant cash societies vs. Cashless payers" in more depth.

Further, the results showed a non-significant relationship between FM and BI for both Germany and Norway. The discussion for the non-significant relationship between FM and BI at the country-level will be the same as for the individual-level: CT is perhaps too unfamiliar for individuals to have a formed opinion about it, which in turn, can lead to inhibiting intentions toward behavior.

According to our hypothesis, MAS was assumed to moderate the relationship between familiarity and BI. However, our results confirmed the moderating effect to be non-significant for both Germany and Norway. This result is in line with the findings of (Baptista and Oliveira, 2015; Goularte and Zilber, 2019) and contradictory to the results of (Mark and Elena, 2006), as discussed above regarding the same hypothesis for the individual-level. In other words, our results indicate that it does not make any difference whether the country has masculine or feminine (carries modest, caring, or assertive, competitive behavior) traits. If the technology is unfamiliar, MAS may have no moderating effect in both Germany and Norway separately.

Hypothesis 1b: the second hypothesis assumed that the relationship between trust and behavioral intention was negatively moderated by masculinity (TR x MAS - BI). Interacting with processes that are not entirely predictable (unfamiliar) combined with an individual's inherent need to understand actions and procedures can create overwhelming complexities. These complexities, if aggravated due to lack of structured knowledge about the task at hand, can inhibit intentions to perform or behave (Gefen, 2000). Nonetheless, individuals are frequently interacting with unpredictable, complex situations and processes they are not entirely comfortable with. When experiencing such situations, individuals apply a variety of methods for reducing these complexities. Trust is one of the most effective methods to reduce these complexities (Gefen, 2000). "Traditionally, trust has been defined as a group of beliefs held by the consumer that are derived from perceptions the consumer has about determined attributes that characterize the brand, product or services, salespeople, or the establishment." (Psailla *et al.*, 2007, p. 181). Gefen et al. (2000) says that trust is an essential factor in many social and economic interactions – especially those concerning crucial decisions (Gefen, 2000). In this research, the relationship between TR and BI was a byproduct of the interaction term created to apply the moderating effect of masculinity. However, our results confirmed that both the moderating impact of masculinity on the relationship between TR and BI to be non-significant, and the relationship between TR and BI to be non-significant. Numerous studies examining TR in different contexts have confirmed a significant relationship between TR and BI or Use behavior (UB) (Kim, Ferrin and Rao, 2008; Yoon, 2009). Previous studies have proven TR and BI to have a significant relationship; however, in this research, trust is associated with an unfamiliar concept. Therefore, one can reasonably assume that individuals' low levels of familiarity with CT may have affected the significant relationship between TR and BI. Gefen et al. (2000) stated that "familiarity is a precondition for trust." (Gefen, 2000, p. 728) The items measuring trust are related to CT, which has been denoted unfamiliar by our result – and this suggests an implicit influence of familiarity on trust. It does, however, appear that MAS has no moderating impact on the relationship between TR and BI. To our knowledge, the relationship between masculinity and trust has not been examined by previous studies. A possible reason that there was not a moderating effect could be that the sample size is too heterogeneous, which could have reduced the levels of explained variance. An interesting observation, however, when taking a closer look at the conceptual model designed by (Yoon, 2009) for his analysis of e-commerce acceptance in China. Four cultural dimensions were hypothesized from TR to Intention to Use except for masculinity, which was connected to other constructs for apparent no reason. Perhaps masculinity as a dimension (including both poles) have nothing to say regarding an individual's level of trust.

How does it differ from the individual level analysis – The country-level analysis showed the same results. The relationship between TR and BI was non-significant in both Germany and Norway, which denotes that both masculine (Germany) and feminine (Norway) poles of Hofstede's index reacted similarly regarding the acceptance of an unfamiliar technology. However, the issue may also be related to the fact that CT is unfamiliar, and, in this case, low levels of familiarity could have caused the non-significant relationship between these constructs independently of sample size. According to our hypothesis, MAS was assumed to moderate the relationship between trust and BI. However, our results confirmed the moderating effect to be non-significant for both Germany and Norway. This relationship has not been explored before, and this prevents us from comparing our findings with other studies. Srite and Karahanna (2006) applied MAS as a moderator in a different context. They confirmed a significant moderator effect of masculinity on perceived ease of use (PEOU) and intended behavior (Mark and Elena, 2006). However, no studies were found examining the moderating effect of TR x MAS-BI. MAS as a dimension (including both extremes) may not affect the relationship between TR and BI. In other words, it makes no difference whether the national culture in a country is considered Masculine or Feminine as the moderating effect of MAS on the relationship between TR and BI is non-significant. A possible explanation, again, is the unfamiliar concept. If familiarity is a precondition for trust (Gefen, 2000), then low levels of trust could be inhibiting behavior intention across both poles of MAS as a dimension.

Hypothesis 2a (Rejected): *Long-term orientation negatively moderates the relationship between familiarity and behavioral intention.* This hypothesis assumed that the relationship between familiarity and behavioral intention would be negatively moderated by long-term oriented individuals. This relationship has been represented in our proposed model by an interaction term (FM x LTO-BI). The direction of this hypothesis was based on the premises of Hofstede's work on national culture values and empirical findings regarding the role of cultural dimensions in technology acceptance. According to Hofstede, individuals with short-term values are more tradition oriented and have a suspicious or cautious approach to societal changes. In contrast, individuals with long-term values are more practical rather than theoretical and are more likely to encourage modern efforts (Hofstede, 2010). This thesis investigates technology acceptance through the lenses of an unfamiliar technology. As stated previously, familiarity is a precondition for trust (Gefen, 2000) and familiarity when low, can add complexities such as uncertainty and risk which could inhibit intention to behave. "People of high LTO culture have strong beliefs that allow them to take risk during uncertainty" (Yoon, 2009, p. 296). Therefore, LTO individuals seemed to be more adequate to test the acceptance of CT. Our initial assumption was that LTO individuals would have a higher tolerance towards low levels of familiarity. In other words, an unfamiliar technology would not inhibit LTO individuals from intending to use a new and unfamiliar technology, given their tendency to modern efforts and future reward orientation. However, even for LTO individuals, familiarity seemed to be a decisive factor toward BI given the non-significant result.

Our results confirmed a non-significant relationship between FM and BI at the individual level. This is another indication that CT may be too unfamiliar and perhaps it is generating complexities that are indirectly affecting acceptance. According to Idemudia et al., (2014), "familiarity has an indirect positive influence on the intention to adopt." (Idemudia and Raisinghani, 2014, p. 75) and Gefen et al., (2003) says that familiarity increases knowledge, understanding, comprehension; thus, reduces risks (David, Elena and Detmar, 2003; Luhmann, 2017). Given that CT is unfamiliar, one can assume that the lack of knowledge, understanding, and comprehension may indirectly affect individuals' behavior intentions.

However, contrary to our expectations, the relationship between LTO and BI was also non-significant. Our initial assumption was that LTO individuals were likely to accept CT given their tendency to modern efforts and future reward orientation. This result is contrary to similar studies examining the impact of LTO on BI, i.e., (zbilen, 2017; Zhao, 2013), as most studies concerning technology adoption have reported significant correlations between the relationship between these two variables. One possible explanation for the non-significant result is that perhaps most of the individuals who participated in the survey carried short-term orientation values, which is a plausible explanation given that Hofstede himself mentioned that the individual level of human programming is truly unique, no one are programmed exactly alike (Hofstede, 2001), implying the existence of cultural values variety among individuals regardless of the predominant cultural values of their country of origin.

According to our hypothesis, H2a, LTO, was assumed to moderate the relationship between familiarity and BI. However, similar to hypothesis H1a, our result confirmed the moderating effect to be non-significant. This result is contrary to the findings of (Baptista and Oliveira, 2015; Goularte and Zilber, 2019) who applied LTO as a moderator on UTAUT2 and reported a significant result. This finding may be an indication that LTO correlates in different ways with different constructs (antecedents). Although the relationship between LTO and BI has had its significance proven by previous studies, in this context LTO is related to an unfamiliar technology and it may be possible that levels of familiarity are causing an indirect effect leading to a non-significant result. As stated previously "familiarity has an indirect positive influence on the intention to adopt." (Idemudia and Raisinghani, 2014, p. 75) therefore, considering that CT is unfamiliar, it may be causing a negative effect on the individuals' decision concerning technology acceptance.

How does it differ from the individual level analysis – At the country level our result confirmed a non-significant relationship among all the variables in the hypotheses, again a rather controversial result. The analysis confirmed a nonsignificant relationship between LTO and BI for both Germany and Norway. According to Hofstede's insight to national culture dimension (index) Norway scores low on LTO (35pts) meaning that it is a short-term oriented country (Insights Hofstede, n.d.) while Germany sits on the opposite pole with a LTO score of (83pts) (Insights Hofstede, n.d.). Therefore, Norway's non-significant result regarding the relationship between LTO – BI can be explained by Hofstede's index. However, Germany should in theory have had a significant relationship between LTO and BI given Hofstede's index score. A possible explanation is the existence of cultural value variety among individuals regardless of the predominant cultural values of their country of origin. This argument has been used to explain our previous hypothesis and it is being mentioned again as Hofstede himself has acknowledged this statement; it is a reliable way to confirm the existence of variety within cultures among individuals' behavior.

Moving on to the relationship between FM to BI, again, the result confirmed a non-significant relationship for both Germany and Norway – and this relationship seems to be directly related to CT being equally unfamiliar to both Germany and Norway. This argument has been consistently applied throughout this chapter as it concerns all the relationships in which familiarity exerts influence. "Familiarity has an indirect positive influence on the intention to adopt." (Idemudia and Raisinghani, 2014, p. 75). meaning that the higher the familiarity, the higher the chances of interaction and vise-versa. Therefore, one can safely assume that low levels of familiarity can interfere with the acceptance of CT.

Hypothesis H2a assumed that FM moderated the relationship between LTO and BI. However, our result confirmed the moderating effect to be non-significant for both Germany and Norway. This result is contrary to the findings of (Yoon, 2009) who applied the cultural dimensions on the TAM model, LTO included – and contrary to the findings of (Baptista and Oliveira, 2015; Goularte and Zilber, 2019) who have applied the dimensions of national culture on the UTAUT2, LTO included. Considering that the significance of LTO toward BI has been attested previously in different contexts by (zbilen, 2017; Zhao, 2013) one can logically assume that there are other factors influencing this result. Norway's non-significant result can be explained by Hofstede's index score of (35pts) which places Norway on the short-term pole of the dimension (Insights Hofstede, n.d.). Therefore, logically, there could be resistance toward acceptance of an unfamiliar technology in Norway. Germany on the other hand is a LTO country with a score of (83pts) on Hofstede's index (Insights Hofstede, n.d.). This indicates a higher likelihood for Germany to accept CT. Again, the sample size could have been too heterogeneous, which could have reduced the levels of explained variance. This coupled with the possibility of national culture variance within Germany and low levels of familiarity may have caused the moderating effect to report a non-significant result.

Hypothesis 2b (Accepted): *Long-term orientation negatively moderate the relationship between trust and behavioral intention.* (TR x LTO – BI). The hypothesis discussed the role of trust as a complexity reduction method used by individuals when dealing with unpredictable situations. As a byproduct of this moderation effect the path TR x LTO was calculated. Our results confirmed a non-significant relationship between TR-BI. As mentioned previously, while discussing hypothesis H1b, the significant impact of TR on BI has been examined in different contexts, i.e., (Kim, Ferrin and Rao, 2008; Yoon, 2009). However, in this context, the relationship between TR and BI reported a non-significant result. One plausible reason for the non-significant result is that in the present context, trust is associated with an unfamiliar technology. Gefen et al., (2000) said, “familiarity is a precondition for trust.” (Gefen, 2000, p. 728). This implies that low levels of familiarity may reduce levels of trust, which can inhibit individuals’ intention to behave. Nonetheless, as proposed by the interaction term of the present hypothesis, long-term orientation successfully moderated the relationship between TR and BI. In this case, TR x LTO acted as a true moderator, given that it has no direct effect on BI. This result is in line with the findings of (Yoon, 2009) who applied LTO as a moderator on the TAM model, and (Baptista and Oliveira, 2015; Goularte and Zilber, 2019) who applied LTO as a moderator on the UTAUT2 model. It is important to highlight that these studies were conducted in different contexts, used different concepts to test technology acceptance, and had different conceptual models than the one used in the present thesis. The results are in accordance with Hofstede’s acknowledgment that “human programming is truly unique, and no two people are programmed exactly alike.” (Hofstede, 2001, p. 2).

Yoon (2009) stated that “People of high LTO culture have strong beliefs that allow them to take risks during uncertainty.” (Yoon, 2009, p. 296). Individuals who carry high LTO values, and are more comfortable taking risks, may not have placed importance to low levels of familiarity. According to Hofstede, long-term oriented individuals are more likely to encourage modern efforts and future rewards (Hofstede, 2010), which indicates a higher tendency for the acceptance of new technologies. This was also one of the arguments used when developing this hypothesis. We assumed that LTO would moderate the relationship between TR and BI in such a way that individuals who are long-term oriented do not necessarily need to trust to accept a new technology.

How does it differ from the individual level analysis – At the country level, our results confirmed both non-significant and significant relationships. Germany had a non-significant relationship between LTO and BI, and this could be considered controversial, given that Germany is regarded as a long-term oriented society (Insights Hofstede, n.d.). Norway also had a non-significant relationship between LTO and BI. This relationship, however, can be explained by Hofstede's index for Norway (35pts), placing it at the short-term oriented pole (Insights Hofstede, n.d.).

Furthermore, the relationship between trust and behavior intention was also non-significant for both Germany and Norway. Our argument stays consistent with our previous reasoning. The argument of trust and its significance toward intention to behave has been applied consistently in this chapter. Trust plays an essential role in technology adoption and intention to use as confirmed by the results of (Kim, Ferrin and Rao, 2008; Yoon, 2009). This implies that the relationship between trust to behavior intention may have been affected by other factors, which in the present context may be attributed to the interference exerted by low levels of familiarity. An unfamiliar concept can add complexities, which in turn can reduce trust, and this may have caused the relationship between TR and BI to be nonsignificant in both countries.

As for the hypothesis: Long-term orientation negatively moderates the relationship between trust and behavior intention (TR x LTO – BI), was non-significant in Germany. Hofstede's index places Germany on the high pole of this dimension with a score of (83pts). Our expectation was that the moderating effect would have had a significant result in Germany given its high LTO level. Surprisingly, the results confirmed otherwise. This result is contrary to the findings of (Yoon, 2009) who reported LTO to be significant as a moderator between trust and intention to use applying the TAM model in a different context. Also, contrary to the findings of both (Baptista and Oliveira, 2015; Goularte and Zilber, 2019) who hypothesized LTO as a moderator between behavioral intention and use behavior using the UTAUT2. Given that other studies have reported a relationship between LTO and BI to use a technology, it is possible that low levels of familiarity affected the relationship between these variables causing a non-significant result. The reason for this may be that heterogeneous samples from each country are likely to reduce the levels of explained variance in the culture-based models (McCoy, Galletta and King, 2005). Norway however, reported a significant result, which is a somewhat controversial one when considering a country analysis. Contrary to Hofstede's index Norway did not present characteristics of a short-term oriented country. The stated hypothesis posited that long-term orientation would negatively moderate the relationship between trust and behavioral intention. According to Hofstede's index Norway sits on the short-term oriented pole with a score of (35pts) (Insights Hofstede, n.d.). This may be supporting evidence to the existence of variance of cultural value within a given country.

In other worlds, individuals can carry different cultural values, which may or may not be opposite to the predominant cultural values of their country of origin. In a way, this can be related to Hofstede's acknowledgement that "the individual level of human programming is truly unique, and no two people are programmed exactly alike" (Hofstede, 2001, p. 2). Although Norway as a country is predominantly short-term oriented (according to Hofstede's index) LTO acted as a true moderator given that the other relationships were non-significant

6.1.1 Other findings – the impact of UTAUT2 original constructs on behavior intention

Some of the paths of the original UTAUT2 model were found to be significant. Habit, Perceived Value, Performance Expectancy, and Hedonic Motivation directly affect consumer's intention to use Checkout-free technology (CT). The results suggest that Habit has the most substantial influence on behavioral intention to use CT, meaning that the intention to shop in a Checkout-free store is higher for those who think they will use CT frequently. The second most influential factor that affects behavioral intention was Perceived Value, followed by Performance Expectancy, Hedonic Motivation. In other words, an individual's intention to use CT is influenced by how much they feel the use of the technology gives, advantages to their shopping performance, and the fun and enjoyment they get from the shopping experience. Furthermore, individuals that perceive that the benefit (value) of using CT is greater than the sacrifices are more likely to use it. Familiarity on trust was another significant relationship, indicating that the more familiar individuals are with the technology, the more they trust the technology. Trust and familiarity are not original constructs of UTAUT2 but will be discussed in this part of the discussion. The findings will be discussed in depth below.

The results of this study showed that the influence of habit (HB) on behavior intention had the most substantial relationship. HB can be equalized with automaticity, which is to the extent to which people tend to perform behaviors automatically (Venkatesh, Thong and Xu, 2012b). As this technology has not been launched in the European market, customers can not be sure that shopping in a Checkout-free will become a habit for them. For the individual level, we can conclude that for people who think that shopping in Checkout-free stores will become their preferred shopping method, they will be more likely to accept the new technology. In other words, once consumers begin to experience a new way of shopping repeatedly, the technology becomes a routine and a habit that influences the individual to repeat interaction often. This finding is consistent with other studies as a Meta-Analytic evaluation of UTAUT2 done by (Tamilmani, Rana and Dwivedi, 2020) found that habit was the most highly correlated construct to behavioral intention among all UTAUT2 relationships (Tamilmani, Rana and Dwivedi, 2020). Another study using UTAUT2 to predict mobile app-based shopping found that habit was one of the strongest predictors of users' behavioral intention (Tak and Panwar, 2017). Habit was also the most reliable predictor for the country-level, both for Germany and Norway.

The next strongest relationship to behavioral intention (BI) was Perceived value (PV). Price value was excluded as that the costs of the smartphone and its usage were sunk costs. Even though price value was not relevant for this research, we proposed that consumers were still motivated by value. Therefore, PV was included in this study. Moreover, as it turns out, PV was the second most influential factor that affects behavioral intention. This finding is accordant with previous studies of mobile services (Liu *et al.*, 2015; Pura, 2005). This finding suggests that perceived value has an essential role in consumers` adoption decisions and that consumers have an interest in CT since it has value for them. Moving over to the country levels, we see that PV was also the second strongest predictor for BI for Norway (country-level). In contrast, PV did not have a significant impact on BI in Germany (Country-level). According to (dotmagazine, 2017), the European Union (EU) has the strictest requirements for data protection and privacy in the world, and within the EU, German is the strictest. Even though both Norway and Germany have strict regulations and rules regarding data protection and privacy, the German respondents may not see the tradeoff between the value that CT gives and the privacy they have to give up to achieve the value.

Performance Expectancy (PE) was the third strongest factor that affects BI for the individual-level result. According to previous meta-analyses of adoption, performance expectancy (which is equal to perceived usefulness in TAM) is the superior influencing variable (Dwivedi *et al.*, 2011; King and He, 2006). Besides, research on factors influencing the attitudes and behavioral intentions to use Just Walk Out Technology (JWOT) found perceived usefulness (TAM) to have a positive impact on attitude towards using JWOT (source). There was a positive relationship between PE and BI on the country-level for Norway, but not for the country-level for Germany.

Another significant relationship on the individual-level was Hedonic Motivation (HM). The UTAUT2 model (Venkatesh, Thong and Xu, 2012b) anticipated this relationship, and it is compatible with other studies (Alalwan, Dwivedi and Rana, 2017; Tak and Panwar, 2017). This finding may stipulate that consumers get driven by enjoyment of the shopping experience they think they will get from using CT and the consumers` engagement with the activity itself. HD was also significant for Norway and Germany (country-level). Contrarily to HD, Effort Expectancy (EE) and BI did not have a relationship; this is supported by (Mahfuz, Khanam and Wang, 2016). When shopping in a store offering CT, the only effort needed is to install an app and register a user. Features on smartphones are overall similar, and the applications work in the same way. Despite that the technology was unfamiliar for most of the respondents, the expected effort was explained in the introduction to the survey. Also, most of the applications nowadays are intuitive and easy to use. EE was not significant for either the individual-level result nor the country-level result. The non-significant result for EE could also be explained because of the level of familiarity with the technology. Maybe the technology is too unfamiliar for people to know what kind of effort is expected and needed to use the technology (despite the explanation in the introduction to the survey).

In this study, several of the original constructs of UTAUT2 were not significant, including Social influence (SI). Venkatesh et al. (2003) found that there was an essential difference across studies emanating from the voluntary vs. mandatory context, where they discovered that SI was significant in mandatory settings, but not in voluntary settings (Venkatesh *et al.*, 2003a). Consumer adoption of CT is voluntarily and generally administered and operated alone. This result proposes that the possibility of people fulfilling the presumption of others is greater for those who are rewarded or disciplined for their behavior. Our result is also acknowledged by other researchers (Alalwan, Dwivedi and Rana, 2017; Owusu Kwateng, Osei Atiemo and Appiah, 2019). SI was non-significant both for the individual-level, and the country-level.

Another construct that was not significant was Facilitating Conditions (FC). This result is in accordance with Venkatesh et al. (2003), who expressed that FC becomes nonsignificant in predicting intention when PE and EE constructs are present (Venkatesh *et al.*, 2003a). As mentioned before, a smartphone is the only tool necessary (including the application) to shop in a Checkout-free store. Smartphones and applications are easy to use: smartphone providers create sound products, network suppliers provide stable connectivity, and app developers produce intuitive apps. That said, the usage of the product requires hardly any assistance. As a consequence, the app used for this particular technology is just an additional app on the smartphone, which rarely calls for the need for a help desk or any kind of help. If there were a problem with the technology required, there would be personnel in the stores to help the customers. This is also stated in the introduction to the survey so that the respondents could get a real picture of the technology presented. Contradicting to our result, a meta-analysis of UTAUT showed that facilitating conditions was one of the constructs that showed the highest number of significant relations with behavioral intention (Dwivedi *et al.*, 2011). In our result, facilitating conditions and BI were not significant for neither the individual-level nor the country-level analysis

Familiarity and Trust - the extended constructs

Furthermore, the results showed that there was a positive relationship between familiarity (FM) and trust (TR) for both the individual-level and country-level for Norway. The relationship between familiarity and trust has been explored and proved by many studies from various contexts (Alraja, Farooque and Khashab, 2019). Our findings are supported by (Mittendorf, 2018) as they found that FM positively affects TR in their study about loT-based healthcare (Alraja, Farooque and Khashab, 2019). By validating the positive impact of familiarity on users' trust in CT, this work created evidence of the importance of familiarity to highlight the effective role of overall grocery chain providers. For the country-level of Germany, FM did not have a positive impact on TR – this will be further discussed below under Predominant Cash Society versus Cashless Payers.

6.1.2 Predominant Cash Society versus Cashless Payers

The Norwegian consumer council has suggested the discontinuance of cash as the only form of payment. In 2014, the council stated that maintaining cash as a payment solution is non-essential – and this created a debate concerning the possibility of allowing companies to opt-out of cash payment solutions by removing a statutory obligation for Norwegian companies to accept cash as a form of payment. However, the Norwegian minister of finance says that time is yet to come. The Norwegian government sees tradition, privacy, and security as challenges associated with new technologies that currently prevent Norway from eliminating cash overnight (Blaker, 2014). Instead, innovations in payment solution systems have introduced user-friendly payment methods, allowing continued use of cash as a form of payment while familiarizing individuals with new electronic payment solutions such as mobile payment (Apple Pay/Google Pay/Vipps) and contactless payment methods. Innovation in payment solutions are gradually decreasing the use of cash over the years and making the transition from physical cash to new payment systems an endogenous process.

According to NorgesGruppen, “revenue share for cash on groceries decreased by approximately three percentage points in 2017 than 2016. This implies a decrease from 14-15 to 11-12, percent” – and one of Norway’s largest wholesale retailers stated that in 2017, only 10.9 percent of sales in the company’s stores were in cash (Blaker, 2018). Besides, Statistics Norway, has pointed to a decline in cash flow since 2016, ranging from 50 billion NOK to 46 billion – and according to Norges Bank, the increase in money supply is steady; however, money in the form of cash has become less common partially due to the sharp decrease in cash withdraw and cashback in store purchases. While cash withdrawal numbers plummeted from 81.8 million to 35.2 million from 2006 to 2016, card payments doubled, going from 907 to 1920 million transactions (Blaker, 2018). This is an indication of a predisposition to use other means of payment rather than cash for purchases of any value – including purchases of relatively small values, which would have been paid in cash before.

According to Finance Norway, cash accounts for a small percentage of payments in Norway, and the costs associated with cash handling are disadvantageous. Therefore, the availability of electronic payment systems are an excellent alternative to introduce innovative cash-free payment methods and further transition to a cashless society (Fåne, 2017). However, though cash usage contributes to a small percentage in the Norwegian economy and the emergence of new payment solutions gradually leads Norway towards becoming a cashless society, Norwegian authorities have emphasized the importance of ensuring familiar payment solutions to those who are not quite comfortable with digital payment instruments (Blaker, 2018). This is an indication that although Norwegians have access to cash as a form of payment, individuals in this society have a predisposition to use electronic payment solutions – and this is what characterizes Norway as a cashless society.

Although electronic payment solutions are gradually increasing as the preferred payment habit mostly due to its convenience – in the eurozone a study by the European Central Bank (ECB) showed that even though most people say that they prefer to use electronic payment solutions for everyday purchases, the results indicated that “notes and coins still reign supreme in most of Europe.” In 2016, most point-of-sale payments were made in cash – according to ECB, 79% of everyday payments across the eurozone were made in cash. This figure increases in countries like

Germany, Austria, and Slovenia, with transactions at point-of-sale and 80% of all payments (Skolimowski, 2017). Using Germany as an example – cash is commonly used as a form of payment for purchases no higher than 20 euros – most people fail to remember how often they make purchases of small value. ECB has highlighted that nearly two-thirds of all transactions in the eurozone are below 15 euros (Skolimowski, 2017). According to Forbes, customers spend an average of $10 per visit at checkout-free stores (Cheng, 2019). This raises a question of how a predominant cash society such as Germany would react to a retail technology in which payments can only be made electronically. In addition to Germany being a predominant cash society according to statistics, the fact that we only were able to collect 65 respondents from Germany could also have affected the results. This will be elaborated under Limitations and future research.

6.2 Managerial Implications

It may be only a matter of time before CT is introduced to the European market. Considering that this event takes place soon it is important to know how the European consumers will react to an unfamiliar technology. To date, there are only a few empirical studies concerning CT. Thus, this study contributes to finding the factors retailers should be taking into consideration before introducing this new technology to the European market.

The most essential job for a retailer is to provide its customer better than the competition by responding effectively to the customers changing needs, desires, and demands. It is also proven that having perceived value as a strategic imperative for retailers is important (Forester, 1999; Vantrappen, 1992; Woodruff, 1997). The retailers who focus their offers toward the consumer categories that 1) emphasize on value and 2) those for whom time pressure is the key, are successful retailers (Sweeney and Soutar, 2001). This has further been confirmed by this research as consumers who intend to use Checkout-free technology want to receive value. They appreciate saving time, in addition to having fun and feel enjoyment while shopping for their groceries. By sharing information, the customer can receive personalized promotions and offers directly on their smartphone, which could be both useful and time saving for the customer. By registering and storing card information with the retailer, preventing the customer to enter card details for each visit to the store, will increase convenience and minimize effort for the customers. As productivity and time saving is an important aspect for the customers, a fast checkout is key. Retailers should emphasize the fun and pleasure derived from shopping in Checkout-free stores as this increases the intention of the customers to do their shopping in a checkout-free store rather than a traditional grocery store.

This study confirms the important aspect of familiarity for individuals to trust new technology. Confirming Gefen (2000) findings that say levels of familiarity increases trust. Individuals' levels of familiarity can enable them to entertain specific beliefs concerning security, which underpin the importance of making individuals familiar with the new technology. Considering that it may be easier to establish familiarity through marketing and exposure than it is to build trust through frequent suitable communication and interactions, increasing familiarity with CT may be an option the industry should consider. Through marketing efforts, it is of course also important to ensure customers that the technology is safe and trustworthy. As mentioned before, by validating the positive impact of familiarity on users' trust in CT, this work created evidence of the importance of familiarity to highlight the effective role of overall grocery chain providers.

All of the aspects mentioned above are important to take into account when launching CT in the European market. The retailer`s marketing strategy should be mainly focused on factors that contribute to potential customers' enjoyment, benefits, and value of using CT. An additional consideration, cultural differences at the individual level, given that this research has shown that cultural values may vary in between countries, as well as within countries. From this specific research, we have found that individuals that have masculinity values are more likely to accept an unfamiliar technology. In addition, individuals with long-term values do not necessarily need to trust an unfamiliar technology before intending to use it.

6.3 Limitation and future research

The preeminent limitation of this study is related to the difficulties in capturing enough respondents from Germany. According to Hair Jr. et al. (2018), sample sizes, both small and large, are essential to achieving statistical significance. The effects of multivariate technique may cause one of two things: (1) It can weaken the statistical power of the analysis making the results non-significant, or, (2) the data can "overfit" in such a way where the results are unnaturally positive fitting the sample but preventing the application of the findings in a different research setting and different context (Hair Jr. *et al.*, 2018). This could be an explanation for the non-significant findings of the country-level for Germany.

Due to limited resources and time, we could not collect more samples from Germany. We could not be physically present in Germany, which made it more difficult to collect a sufficient sample size. Also, COVID-19 was a factor for not collecting a sufficient sample size. The original translator could not help translate the survey due to unexpected circumstances from the pandemic – this resulted in a time-consuming process of finding a new translator with the skills and time required to translate the survey.

Additionally, the collected sample from Germany consists mostly of young people. We collected the respondents through friends and social media, which may not present the general public and represent a more homogenous sample size. Therefore, a suggestion for future research is to repeat the research based on a larger sample size from Germany, and stricter qualification requirements concerning the respondents as our sample size from Germany may be too homogenous. The new sample size qualification criteria are suggested to be over 200 respondents from all over Germany with a broad range of age differences. This would also help to generalize findings.

A Multi-Group Analysis (MGA) was supposed to be conducted in SmartPLS to analyze the country levels. However, due to the significant gap between Norway and Germany and the complexity of the model, it was not possible as the significant differences between the groups were not calculated. The results were therefore analyzed using the PLS algorithm and Bootstrap analysis on both the individual-level and country-level, using the combined dataset as a yardstick. The study would have been more refined if both country comparison could have been done with MGA. Another consequence of the gap between Norway and Germany was that we could not measure all of the paths we intended to measure. Due to the model's complexity in proportion to the German sample size, it was not possible to test all of the cultural dimensions as moderators between trust and familiarity, and behavior intention, as there were more parameters than respondents.

Country-level vs. individual-level: Even though our thesis is based on an individual-level analysis a country-level analysis has been included. We are aware of the shortcomings when it comes to the country-level analysis as we do not have a sufficient sample size for Germany. Also, that the best way of predicting individual behavior is to use individual-level analysis.

Moreover, regarding the reliability of the scales used in this research, the construct Power Distance (PD) for Germany had a Cronbach`s alpha below .6. The scales adopted for this research has been tested before and well known. Among others, (Merhi, Hone and Tarhini, 2019; Yoo, Donthu and Lenartowicz, 2011) and (Mustafa, Glavee-Geo and Rice, 2017) have proved this construct valid, and also, for the exact model used in this research the scale has been validated by (Baptista and Oliveira, 2015), showing a Cronbach's alpha of .795 for PD. Besides, Consistency Reliability (CR) is a better method to assess reliability and the CR of PD in Germany showed a value of .799. As the scale only consisted of three items, and one item already was removed due to poor factor loading, it was not possible to remove any further items.

Next, there is a lack of previous research on the topic. Only a few research papers have been found on this exact technology, none of them in the same context as this research. None of these researchers have included cultural dimensions, UTAUT2 or familiarity in their research (Chuawatcharin and Gerdsri, 2019; Ives, Cossick and Adams, 2019; Qi, 2019).

The scale used to measure cultural values is designed to measure cultural values at the individual and not on a country level. This could also influence our results from the country-level analysis.

Cultural- and personal bias can also lead to a misunderstanding of a word or sentence in the survey. A cultural bias is the likelihood of interpreting a word or action in line with the culturally attained meaning assigned to it and is a result of cultural variation (Haddad, Doherty and Purtilo, 2019). Regarding personal bias, it is the tendency to interpret actions or words relating to personal importance assigned to it. Personal experience and culturally defined interpretations can result in personal bias (Haddad, Doherty and Purtilo, 2019).

Initially, we exchanged emails with the product manager of Coop Norway, trying to establish a partnership to collect relevant data and valuable insight for our research purpose. A partnership like this would have enabled us to collect more respondents, target Coop`s customers directly, and get more insight into the retail industry and technology development. Unfortunately, the effects of COVID-19 made this partnership impossible. Another recommendation for future research is to initiate a partnership with one of the big grocery chains. Especially now, after COVID-19 hit the world, a checkout-free store may be more relevant than ever to prevent infections among people.

The original model includes moderators such as age, gender, and experience. In this study, it has been decided not to include the moderators because of the sample size and the fact that people of different ages and genders have different preferences. Some might be over 60 years and be updated on the latest technology, while a 20-year-old might not be interested in new technology at all. This also might have limited the generalizability of this study.

Furthermore, a conjoint analysis of self-checkout, checkout-free technology, and maybe even a regular cashier to determine how people value the different attributes (feature, function, benefits) of the different services a grocery store can offer. To estimate the impact of selected service characteristics on customer preferences for services, conjoint analysis has been widely used in market research (Cattin and Wittink, 1982).

Lastly, elements from the Privacy calculus can be included in the theory as it can be an important factor for accepting a new technology. People highly appreciate privacy, but few would disagree that complete privacy is futile. Individuals make certain choices where they relinquish their privacy to some degree in exchange for outcomes that are anticipated to be worth the risk of exposing such information. In ecommerce for example, consumers are averse to giving personal information because of their privacy concerns, which negatively affect their disposition to make online purchases (Dinev and Hart, 2006). Organizations analyze consumer’s transactional data to help them understand purchase patterns, consumer behavior and preferences to optimize their advertisement, increase retention and customer acquisition (McKinsey&Company, 2015). Sheehan and Hoy (2000) suggested that consumers want to be aware of what type of data is collected and how it will be used beyond the original transaction. Their study confirmed other dimensions such as sensitivity of information, familiarity with the entity collecting the data and what are the associated benefits of sharing this information. Therefore, the tradeoff between benefit and perceived privacy is likely to cause an impact in technology acceptance. Due to limited resources for collecting enough respondents, and a complex model, we did not include this in our thesis. The survey could also have been too longitudinal which might had resulted in respondents giving up before finishing.

6.4 Conclusions

This study has examined the moderating effect of Masculinity and Long-term Oriented individuals from the lenses of an unfamiliar technology. A cross-cultural approach enabled us to attain a variation in cultural values among MAS and LTO at the individual level. Our purpose was to examine the acceptance of Checkout-free Technology while and by doing so answer to the following question:

How do cultural dimensions influence the acceptance of an unfamiliar technology?

Upon concluding the literature review we were able to confirm that CT is an unfamiliar technology to both contexts of the present thesis. This was later confirmed by the mean reported in our descriptive analysis resulting from the 295 responses obtained from the survey. The literature review also indicated that low levels of familiarity could raise concerns regarding trust which could then inhibit behavior intention. Our results are also pointing toward the same direction as it appears that low levels of familiarity are adding complexities which may have influenced individuals trust and thus, affecting behavior intention. It seems that familiarity does indeed exert an indirect influence on adoption as posited by (Idemudia and Raisinghani, 2014).

The only cultural dimensions to demonstrate a significant moderating effect on the acceptance of an unfamiliar technology was LTO. MAS did report any significant results. Upon reviewing LTO it was our belief that long-term oriented individuals would place less importance on low levels of familiarity and trust given that they are generally future oriented and more comfortable at taking risks. Thus, our hypothesis (H2b) posited a negative relationship between trust and BI meaning that LTO individuals would still develop intention even when trust is low.

LTO also presented a significant result at the country level for Norway. This was a rather controversial finding given that Norway has been classified as a short-term oriented country by Hofstede. However, this shows evidence of differences in cultural values within countries. In other worlds, individuals can carry different cultural values, which may or may not be opposite to the predominant cultural values of their country of origin. Given that such variation exists - when considering cultural dimensions for technology acceptance it is recommended to an individual level approach.

As to how cultural dimensions influence the acceptance of an unfamiliar technology. The cultural values pertaining to LTO individuals (i.e., risk taking, future reward oriented) may have worked as complexity reduction mitigating the impact of unfamiliarity and low levels of trust allowing individuals to develop behavior intention.

References

Abrahão, R. d. S., Moriguchi, S. N. and Andrade, D. F. (2016) 'Intention of adoption of mobile payment: An analysis in the light of the Unified Theory of Acceptance and Use of Technology (UTAUT)', *RAI Revista de Administração e Inovação,* 13(3), pp. 221-230.

Ajzen, I. (1991) 'The theory of planned behavior', *Organizational Behavior and Human Decision Processes,* 50(2), pp. 179-211.

Ajzen, I. (2002) 'Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior', *Journal of Applied Social Psychology,* 32(4), pp. 665-683.

Ajzen, I. (2005) *Attitudes, Personality, and Behavior.* Open University Press.

Ajzen, I., Joyce, N., Sheikh, S. and Cote, N. (2011) 'Knowledge and the Prediction of Behavior: The Role of Information Accuracy in the Theory of Planned Behavior', *BASIC AND APPLIED SOCIAL PSYCHOLOGY,* 33, pp. 101-117.

Alalwan, A. A., Dwivedi, Y. K. and Rana, N. P. (2017) 'Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust', *International Journal of Information Management,* 37(3), pp. 99-110.

Alalwan, A. A., Dwivedi, Y. K. and Williams, M. D. (2016) 'Customers' Intention and Adoption of Telebanking in Jordan', *Information Systems Management*, 33(2), pp. 154-178.

Alba, J. W. and Hutchinson, J. W. (1987) 'Dimensions of consumer expertise', *Journal of consumer research : JCR ; an interdisciplinary bimonthly,* 13(4), pp. 411-442.

Alraja, M. N., Farooque, M. M. J. and Khashab, B. (2019) 'The Effect of Security, Privacy, Familiarity, and Trust on Users' Attitudes Toward the Use of the IoT-Based Healthcare: The Mediation Role of Risk Perception', *IEEE Access,* 7, pp. 111341-111354.

Altman Klein, H. 2004. COGNITION IN NATURAL SETTINGS: THE CULTURAL LENS MODEL. Emerald Group Publishing Limited.

Baptista, G. and Oliveira, T. (2015) 'Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators', *Computers in Human Behavior,* 50, pp. 418-430.

Beyo Global (2019) *Collectivist vs Individualist Societies: How do these impact upon retail?* https://beyo.global/. Available at: https://beyo.global/thinking/collectivist-vs-individualist-societies-how-do-these-impact-upon-retail (Accessed: 07/04/2020 2020).

Blaise, R., Halloran, M. and Muchnick, M. (2018) 'Mobile Commerce Competitive Advantage: A Quantitative Study of Variables that Predict M-Commerce Purchase Intentions', *Journal of Internet Commerce,* 17(2), pp. 96-114.

Blaker, M. (2014) *Will remove cash as a means of payment*: Netttavisen.no. Available at: https://www.nettavisen.no/na24/vil-fjerne-kontanter-som-betalingsmiddel/8484790.html (Accessed: 05/05/2020 2020).
Blaker, M. (2018) *Use of Cash Plunges in Norway*. nettavisen.no: nettacisen.no. Available at: https://www.nettavisen.no/na24/bruk-av-kontanter-stuper-i-norge/3423405137.html (Accessed: 5/5/2020 2020).
Cattin, P. and Wittink, D. R. (1982) 'Commercial Use of Conjoint Analysis: A Survey', *Journal of Marketing,* 46(3), pp. 44-53.
Cavusgil, T., Sinkovics, R. R. and Ghauri, P. N. (2009) *New Challenges to International Marketing* Bingley: Bingley: Emerald Publishing Limited. *Advances in international marketing*.
Cheng, A. (2019) *Why Amazon Go May Soon Change The Way We Shop* Retail forbes.com: Forbes. Available at: https://www.forbes.com/sites/andriacheng/2019/01/13/why-amazon-go-may-soon-change-the-way-we-want-to-shop/#34bfc5bf6709 (Accessed: 5/15/2020 2020).
Chhabra, S. (2012) *ICT Influences on Human Development, Interaction, and Collaboration.* United States of America: Information Science Reference (an imprint of IGI Global), p. 29.
Christer, K. (2010) *Researching Operations Management.* Taylor and Francis, p. 66.
Chu, T.-H. and Chen, Y.-Y. (2016) 'With Good We Become Good: Understanding e-learning adoption by theory of planned behavior and group influences', *Computers & Education,* 92-93, pp. 37-52.
Chuawatcharin, R. and Gerdsri, N. (2019) 'Factors influencing the attitudes and behavioural intentions to use just walk out technology among Bangkok consumers'.
Chuawatcharin, R. a. G., N. (2019) 'Factors influencing the attitudes and behavioural intentions to use just walk out technology among Bangkok consumers ', *Int. J. Public Sector Performance Management,* Vol. 5 No. 2,, pp. 146-163.
Cohen, J. (1988) *Statistical power analysis for the behavioral sciences.* 2nd ed. edn. Hillsdale, N. J: Laurence Erlbaum.
Compeau, D. R. and Higgins, C. A. (1995) 'Application of Social Cognitive Theory to Training for Computer Skills', *Information Systems Research,* 6(2), pp. 118-143.
Conner, M., Godin, G., Sheeran, P. and Germain, M. (2012) 'Some Feelings Are More Important: Cognitive Attitudes, Affective Attitudes, Anticipated Affect, and Blood Donation', *Health psychology : official journal of the Division of Health Psychology, American Psychological Association,* 32.
Cunningham, W. A., Preacher, K. J. and Banaji, M. R. (2001) 'Implicit Attitude Measures: Consistency, Stability, and Convergent Validity', *Psychological Science,* 12(2), pp. 163-170.
David, G., Elena, K. and Detmar, W. S. (2003) 'Trust and TAM in Online Shopping: An Integrated Model', *MIS Quarterly,* 27(1), pp. 51-90.
Davis, F. D. 'A technology acceptance model for empirically testing new end-user information systems : theory and results'.
Davis, F. D. (1989) 'Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information

Technology', Vol. 13, No. 3, pp. 319-340.
Davis, F. D., Bagozzi, R. P. and Warshaw, P. R. (1989) 'User Acceptance of Computer Technology: A Comparison of Two Theoretical Models', *Management Science,* 35(8), pp. 982-1003.

Davis, F. D., Bagozzi, R. P. and Warshaw, P. R. (1992) 'Extrinsic and Intrinsic Motivation to Use Computers in the Workplace1', *Journal of Applied Social Psychology,* 22(14), pp. 1111-1132.
Dezdar, S. (2017) 'Green information technology adoption: Influencing factors and extension of theory of planned behavior', *Social Responsibility Journal*, 13, pp. 292-306.
Dinev, T. and Hart, P. (2006) 'An Extended Privacy Calculus Model for E-Commerce Transactions', *Information Systems Research*, 17(1), pp. 61-80,100.
Dodds, W. B., Monroe, K. B. and Grewal, D. (1991) 'Effects of Price, Brand, and Store Information on Buyers' Product Evaluations', *Journal of Marketing Research*, 28(3), pp. 307-319.
Doney, P. M., Cannon, J. P. and Mullen, M. R. (1998) 'UNDERSTANDING THE INFLUENCE OF NATIONAL CULTURE ON THE DEVELOPMENT OF TRUST', *Academy of Management Review*, 23(3), pp. 601-620.
Dorfman, P. and Howell, J. (1988) 'Dimension of national culture and effective leadership patterns: Hofstede revisited', pp. 127-149.
dotmagazine (2017) 'GERMANY: LAND OF DATA PROTECTION AND SECURITY – BUT WHY?'. Available at: https://www.dotmagazine.online/issues/security/germany-land-of-data-protection-and-security-but-why.
Dwivedi, Y. K., Rana, N. P., Chen, H. and Williams, M. D. 2011. A Meta-analysis of the Unified Theory of Acceptance and Use of Technology (UTAUT). Berlin, Heidelberg: Berlin, Heidelberg: Springer Berlin Heidelberg.
Emerald Publishing (n.d.) *How to... conduct empirical research* https://www.emeraldgrouppublishing.com/: Emeralc Publishing Limited (Accessed: 6/7/2020 2020).
F. Hair Jr, J., Sarstedt, M., Hopkins, L. and G. Kuppelwieser, V. (2014) 'Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research', *European Business Review*, 26(2), pp. 106-121.
Faaeq, M., Ismail, N. A., Osman, W., Al-Swidi, A. and Faieq, A. (2013) 'A meta-analysis of the unified theory of acceptance and use of technology studies among several countries', *Electronic Government*, 10, pp. 343-360.
Fåne, J. E. (2017) *Future-oriented about cash-free*. Finansnorge.no: Finans Norge. Available at: https://www.finansnorge.no/aktuelt/nyheter/2017/01/fremtidsrettet-om-kontantfritt/ (Accessed: 05/08/2020 2020).
Farley, J. U. and Lehmann, D. R. (1994) 'Cross-National "Laws" and Differences in Market Response', *Management Science*, 40(1), pp. 111-122.
Feindt, P. H. and Poortvliet, P. M. (2020) 'Consumer reactions to unfamiliar technologies: mental and social formation of perceptions and attitudes toward nano and GM products', *Journal of Risk Research*, 23(4), pp. 475-489.
Fishbein, M. and Ajzen, I. (1975) *Belief, attitude, intention and behavior : an introduction to theory and research. Addison-Wesley series in social psychology* Reading, Mass: Addison-Wesley.
Forester, M. (1999) 'Deja vu discussion delivers message emphasizing value', *Chain Store Age*, 75(4), pp. 12.
Fornell, C. and Larcker, D. (1981) 'Evaluating Structural Equation Models with Unobservable Variables and Measurement Error', *JMR, Journal of Marketing Research*, 18(1), pp. 39.

Forza, C. (2002) 'Survey research in operations management: a process-based perspective', *International Journal of Operations & Production Management*, 22(2), pp. 152-194.
Gao, B., Li, X., Liu, S. and Fang, D. (2018) 'How power distance affects online hotel ratings: The positive moderating roles of hotel chain and reviewers� travel experience', *Tourism Management*, 65, pp. 176-186.
Garfinkel, S. and Cranor, L. F. (2005) *Security and usability : designing secure systems that people can use. Theory in practice* Beijing,Sebastopol, Calif: O'Reilly, p. 88.
Gefen, D. (2000) 'E-commerce: the role of familiarity and trust', *Omega*, 28(6), pp. 725-737.
Gharaibeh, M. and Mohd Arshad, M. (2018) 'Determinants of Intention to Use Mobile Banking Services in the North of Jordan: Extending UTAUT2 with Mass Media and Trust', *Journal of Engineering and Applied Sciences*, 13.
Glanz, K., Rimer, B. and Viswanath, K. K. (2015) *Health Behavior: Theory, Research, And Practive.* Jossey-Bass, p. 95,96,97.
Goularte, A. D. C. and Zilber, S. N. (2019) 'The moderating role of cultural factors in the adoption of mobile banking in Brazil', *International Journal of Innovation Science*, 11(1), pp. 63-81.
Haddad, A., Doherty, R. and Purtilo, R. (2019) 'Chapter 5 - Respect in a Diverse Society', in Haddad, A., Doherty, R. and Purtilo, R. (eds.) *Health Professional and Patient Interaction (Ninth Edition)*: W.B. Saunders, pp. 60-76.
Haenlein, M. and Kaplan, A. M. (2004) 'A Beginner's Guide to Partial Least Squares Analysis', *Understanding Statistics*, 3(4), pp. 283-297.
Hair, J. F. (2014) *A primer on partial least squares structural equation modeling (PLS-Sem).* Los Angeles, Calif: Sage, p. 177,178,195,196,198.
Hair, J. F., Ringle, C. M. and Sarstedt, M. (2011) 'PLS-SEM: Indeed a Silver Bullet', *Journal of Marketing Theory and Practice*, 19(2), pp. 147,.
Hair Jr., J. F., Black, W. C., Babin, B. J. and Anderson, R. E. (2018) *Multivariate Data Analysis.* Cengage Learning, EMEA, p. 12, 21, 124, 607, 661, 662, 663, 664, 665, 666, 667, 668, 669, 676, 760.
Harrison, D. A., Mykytyn, P. P., Jr. and Riemenschneider, C. K. (1997) 'Executive Decisions About Adoption of Information Technology in Small Business: Theory and Empirical Tests', *Information Systems Research*, 8(2), pp. 171-195.
Hatch, C. (2020) *Be in the Know: Ecommerce Statistics You Should Know*. https://www.disruptiveadvertising.com/: Disruptive Advertising. Available at: https://www.disruptiveadvertising.com/ppc/ecommerce/2018-ecommerce-statistics/ (Accessed: 23/4/2020 2020).
Hazen, B., Weigel, F., Hall, D. and Cegielski, C. (2014) 'Diffusion of Innovations and the Theory of Planned Behavior in Information Systems Research: A Metaanalysis', *Communications of the Association for Information Systems*, 34.
Henseler, J., Ringle, C. M. and Sinkovics, R. R. (2009) *The use of partial least squares path modeling in international marketing.* Emerald Group Publishing Limited.
Hillier, M. (2003) 'The role of cultural context in multilingual website usability', *Electronic Commerce Research and Applications*, 2(1), pp. 2-14.
Hofstede, G. (2001) *Culture's consequences : comparing values, behaviors, institutions, and organizations across nations.* 2nd ed. edn. Thousand Oaks, Calif: Sage, p. 2, 148.
Hofstede, G. (2010) *National Culture*. hofstede-insights.com. Available at: https://hi.hofstede-insights.com/national-culture (Accessed: 30/3/2020 2020).

Hofstede, G. (2011) 'Dimensionalizing Cultures: The Hofstede Model in Context', *The Online Readings in Psychology and Culture (ORPC)*, pp. 9,10,11,12.
Hofstede, G. and Eckhardt, G. (2002) 'Culture's consequences: comparing values, behaviors, institutions and organisations across nations: book review'.
Hofstede, G., Hofstede, G. J. and Minkov, M. (2010a) *Cultures and organizations : software of the mind : intercultural cooperation and its importance for survival.* 3rd ed. edn. New York: McGraw-Hill, p. 34,61,90,91,92,102,103,139,140,189,239,410,411.
Hofstede, G., Hofstede, G. J. and Minkov, M. (2010b) *Cultures and Organizations, software on the mind.* The McGraw-Hill Companies, Inc.
Idemudia, E. C. and Raisinghani, M. S. (2014) 'The influence of cognitive trust and familiarity on adoption and continued use of smartphones: an empirical analysis', *Journal of International Technology and Information Management*, 23(2), pp. 69.
Inaam, A. D. M. (2016) 'Research Design', pp. 17, *https://papers.ssrn.com/* [Research in Social Science: Interdisciplinary Perspectives]. Available at: https://ssrn.com/abstract=2862445 (Accessed 6/9/2020).
Insights Hofstede (n.d.) *Country Comparison*. https://www.hofstede-insights.com/country-comparison/. Available at: https://www.hofstede-insights.com/country-comparison/germany,norway/ (Accessed: 7/5/2020 2020).
Ives, B., Cossick, K. and Adams, D. (2019) 'Amazon Go: Disrupting retail?', *Journal of Information Technology Teaching Cases*, 9, pp. 204388691881909.
Jacobs, K., Tolido, R., Himmelreich, A., Buvat, J., KVJ, S., B., A. and Khemka, Y. (2018) *Building the retail superstar: How unleashing AI across functions offers a multi-billion dollar opportunity*, https://www.capgemini.com/: Capgemini. Available at: https://www.capgemini.com/wp-content/uploads/2018/12/Report-%E2%80%93-Building-the-Retail-Superstar-Digital1.pdf.
Kim, D. J., Ferrin, D. L. and Rao, H. R. (2008) 'A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents', *Decision Support Systems*, 44(2), pp. 544-564.
Kim, S.-H., Kim, M.-S., Holland, S. and Han, H.-S. (2018) 'Hospitality employees' citizenship behavior: the moderating role of cultural values', *International Journal of Contemporary Hospitality Management*, 30(2), pp. 662-684.
Kim, S. S., Malhotra, N. K. and Narasimhan, S. (2005) 'Research Note—Two Competing Perspectives on Automatic Use: A Theoretical and Empirical Comparison', *Information Systems Research*, 16(4), pp. 418-432.
Kim, Y. and Zhang, Y. (2014) 'The Impact of Power-Distance Belief on Consumers' Preference for Status Brands', *Journal of Global Marketing*, 27(1), pp. 13-29.
Kim, Y. H., Kim, D. J. and Wachter, K. (2013) 'A study of mobile user engagement (MoEN): Engagement motivations, perceived value, satisfaction, and continued engagement intention', *Decision Support Systems*, 56(1), pp. 361-370.
Kinard, B. R., Capella, M. L. and Kinard, J. L. (2009) 'The Impact of Social Presence on Technology Based Self-Service Use: The Role of Familiarity', *Services Marketing Quarterly*, 30(3), pp. 303-314.
King, W. R. and He, J. (2006) 'A meta-analysis of the technology acceptance model', *Information & Management*, 43(6), pp. 740-755.

Lancelot Miltgen, C., Popovič, A. and Oliveira, T. (2013) 'Determinants of end-user acceptance of biometrics: Integrating the “Big 3” of technology acceptance with privacy context', *Decision Support Systems,* 56, pp. 103-114.
Larsen, N. M., Sigurdsson, V. and Breivik, J. r. (2017) 'The Use of Observational Technology to Study In-Store Behavior: Consumer Choice, Video Surveillance, and Retail Analytics', *Behav Anal,* 40(2), pp. 343-371.
Lee, M.-C. (2009) 'Understanding the behavioural intention to play online games', *Online Information Review,* 33(5), pp. 849-872.
Li, X., Hess, T. J., McNab, A. L. and Yu, Y. (2009) 'Culture and acceptance of global web sites: a cross-country study of the effects of national cultural values on acceptance of a personal web portal', *SIGMIS Database,* 40(4), pp. 49–74.
Li, X., Hess, T. J. and Valacich, J. S. (2008) 'Why do we trust new technology? A study of initial trust formation with organizational information systems', *The Journal of Strategic Information Systems,* 17(1), pp. 39-71.
Limayem, M., Hirt, S. G. and Cheung, C. M. K. (2007) 'How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance', *MIS Quarterly,* 31(4), pp. 705-737.
Liu, F., Zhao, X., Chau, P. Y. K. and Tang, Q. (2015) 'Roles of perceived value and individual differences in the acceptance of mobile coupon applications', *Internet Research,* 25(3), pp. 471-495.
Luhmann, N. (2017) *Trust and Power.* first english edition edn., p. 22.
Magni, M., Susan Taylor, M. and Venkatesh, V. (2010) '‘To play or not to play’: A cross-temporal investigation using hedonic and instrumental perspectives to explain user intentions to explore a technology', *International Journal of Human - Computer Studies,* 68(9), pp. 572-588.
Mahfuz, M. A., Khanam, L. and Wang, H. 2016. The influence of culture on m-banking technology adoption: An integrative approaches of UTAUT2 and ITM. Portland International Conference on Management of Engineering and Technology, Inc.
Malhotra, M. K. and Grover, V. (1998) 'An assessment of survey research in POM: from constructs to theory', *Journal of Operations Management,* 16(4), pp. 407-425.
Mark, S. and Elena, K. (2006) 'The Role of Espoused National Cultural Values in Technology Acceptance', *MIS Quarterly,* 30(3), pp. 679-704.
Mary Jo, B., Amy, L. O., Matthew, L. M. and Clancy, J. A. (2002) 'Implementing Successful Self-Service Technologies [and Executive Commentary]', *The Academy of Management Executive (1993-2005),* 16(4), pp. 96-109.
Mayer, R., Davis, J. and Schoorman, F. (1995) 'An Integrative Model of Organizational Trust', *The Academy of Management Review,* 20(3), pp. 709.
McCoy, S., Galletta, D. and King, W. (2005) 'Integrating National Culture into IS Research: The Need for Current Individual Level Measures', *Communications of the Association for Information Systems,* 15.
McCoy, S., Galletta, D. F. and King, W. R. (2007) 'Applying TAM across cultures: the need for caution', *European Journal of Information Systems,* 16(1), pp. 81-90.
McDougall, G. H. G. and Levesque, T. (2000) 'Customer satisfaction with services: putting perceived value into the equation', *Journal of Services Marketing,* 14(5), pp. 392-410.
McEachan, R. R. C., Conner, M., Taylor, N. J. and Lawton, R. J. (2011) 'Prospective prediction of health-related behaviours with the Theory of Planned Behaviour: a meta-analysis', *Health Psychology Review,* 5(2), pp. 97-144.

McKinsey&Company (2015) *Marketing & Sales Big Data, Analytics, and the Future of Marketing & Sales*, mckinsey.com: McKinsey&Company. Available at: https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/Marketing%20and%20Sales/Our%20Insights/EBook%20Big%20data%20analytics%20and%20the%20future%20of%20marketing%20sales/Big-Data-eBook.ashx.
Merhi, M., Hone, K. and Tarhini, A. (2019) 'A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: Extending UTAUT2 with security, privacy and trust', *Technology in Society*, 59, pp. 101,151.
Mittendorf, C. (2018) 'Collaborative consumption: the role of familiarity and trust among Millennials', *Journal of Consumer Marketing*, 35(4), pp. 377-391.
Mohamamd Alamgir, H., Mohammad Imran, H., Caroline, C. and Jashim Uddin, A. (2017) 'Predicting User Acceptance and Continuance Behaviour Towards Location-based Services: The Moderating Effect of Facilitating Conditions on Behavioural Intention and Actual Use', *Australasian Journal of Information Systems*, 21.
Momani, A. and Jamous, M. (2017) 'The Evolution of Technology Acceptance Theories', *International Journal of Contemporary Computer Research (IJCCR)*, 1, pp. 50-58.
Moore, G. C. and Benbasat, I. (1991) 'Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation', *Information Systems Research*, 2(3), pp. 192-222.
Mulaomerovic, E. and Trappey, C. V. 'THE ROLE OF CULTURAL DIMENSIONS IN THE ACCEPTANCE OF RETAIL INNOVATIONS ', *Active Citizenship by Knowledge Management & Innovation: Management Knowledge and Learning International Conference*, Zadar, Croatia, 19/06/2013, 6.
Mustafa, G., Glavee-Geo, R. and Rice, P. M. (2017) 'Teamwork orientation and personal learning: The role of individual cultural values and value congruence.(Report)', *South African Journal of Industrial Psychology*, 43(3).
Oliveira, T., Thomas, M., Baptista, G. and Campos, F. (2016) 'Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology', *Computers in Human Behavior*, 61, pp. 404-414.
Orbell, S. and Sheeran, P. (1998) '‘Inclined abstainers’: A problem for predicting health-related behaviour', *The British journal of social psychology / the British Psychological Society*, 37 (Pt 2), pp. 151-65.
Owusu Kwateng, K., Osei Atiemo, K. A. and Appiah, C. (2019) 'Acceptance and use of mobile banking: an application of UTAUT2', *Journal of Enterprise Information Management*, 32(1), pp. 118-151.
Pallant, J. (2016) *SPSS survival manual : a step by step guide to data analysis using IBM SPSS.* 6th ed. edn. Maidenhead: McGraw Hill Education.
Papayiannis and Anastassiou-Hadjicharalambous, S. X. 2011. Cross-Cultural Studies.
Park, N., Jung, Y. and Lee, K. M. (2011) 'Intention to upload video content on the internet: The role of social norms and ego-involvement', *Computers in Human Behavior*, 27(5), pp. 1996-2004.
Pearlson, K. E., Saunders, C. S. and Galleta, D. F. (2019) *Managing and Using Information Systems: A Strategic Approach.* (7th edition vols). Wiley, p. 73, 74.
Peter, C. and Bryan, M. (2008) 'NATIONAL CULTURE AND TECHNOLOGY ACCEPTANCE: THE IMPACT OF UNCERTAINTY AVOIDANCE', *Issues in Information Systems*, 9(2), pp. 103-110.

Png, I. P. L., Tan, B. C. Y. and Khai-Ling, W. (2001) 'Dimensions of national culture and corporate adoption of IT infrastructure', *IEEE Transactions on Engineering Management*, 48(1), pp. 36-45.
Psailla, G., Wagner, R., International Conference on Electronic, C. and Web, T. (2007) *E-Commerce and Web Technologies : 8th International Conference, EC-Web 2007, Regensburg, Germany, September 3-7, 2007, Proceedings* Berlin, Heidelberg: Springer Berlin Heidelberg : Imprint: Springer. *Information Systems and Applications, incl. Internet/Web, and HCI*. Available at: https://books.google.no/books?id=0zxuCQAAQBAJ&pg=PA188&lpg=PA188&dq=technology+acceptance+the+role+of+familiarity&source=bl&ots=6Z-AB5DKft&sig=ACfU3U30FUJDwgz0JjoOdSeoOy8c5DI_4A&hl=en&sa=X&ved=2ahUKEwikk8yjmNnpAhVK1qYKHUmvBwsQ6AEwBXoECAsQAQ#v=onepage&q=familiarity&f=false.
Pura, M. (2005) 'Linking perceived value and loyalty in location-based mobile services', *Managing Service Quality: An International Journal*, 15(6), pp. 509-538.
Qi, C. 'Is checkout- free store a flash in the pan? Factors influencing Hong Kong people's adoption intention of checkout-free stores ', *Australiasian Conference on Information Systems* Perth, Western Australia. Perth, 7.
Rajasekar, S., Philominathan, P. and Chinnathambi, V. (2006) 'Research Methodology'.
Rogers, E. M. (1995) *Diffusion of innovations.* New York: Free Press, p. 11, 22.
Rondan-Cataluña, F. J., Arenas-Gaitán, J. and Ramírez-Correa, P. E. (2015) 'A comparison of the different versions of popular technology acceptance models', *Kybernetes*, 44(5), pp. 788-805.
Ruvio, A. A. B., Russell W. (2013) *The Routledge Companion to Indentity and Consumption.* USA, Canada: Routledge, p. 207.
Samaradiwakara, G. D. M. and Chandra, G. (2014) 'Comparison of existing technology acceptance theories and models to suggest a well improved theory/model', *International Technical Sciences Journal*, 1, pp. 21-36.
Saunders, M. N. K., Lewis, P. and Thornhill, A. (2009) *Research methods for business students.* 5th ed. edn. Essex: Pearson Education, p. 3, 124, 126, 138, 139, 142, 534.
Schepers, J. and Wetzels, M. (2007) 'A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects', *Information & Management*, 44(1), pp. 90-103.
Shaw, N. and Sergueeva, K. (2019) 'The non-monetary benefits of mobile commerce: Extending UTAUT2 with perceived value', *International Journal of Information Management*, 45, pp. 44-55.
Sheeran, P., Gollwitzer, P. M. and Bargh, J. A. (2013) 'Nonconscious processes and health', *Health Psychology*, 32(5), pp. 460-473.
Sheppard, B., Hartwick, J. and Warshaw, P. (1988) 'The Theory of Reasoned Action: A Meta-Analysis of Past Research with Recommendations for Modifications and Future Research', *Journal of Consumer Research*, 15.
Skolimowski, P. (2017) *Europeans Still Love Paying Cash, Even if They Don't know It*. Becnhmark. Bloomberg.com: European Central Bank (ECB). Available at: https://www.bloomberg.com/news/articles/2017-11-26/europeans-still-love-paying-cash-even-if-they-don-t-know-it (Accessed: 5/15/2020 2020).
Slade, E. L., Dwivedi, Y. K., Piercy, N. C. and Williams, M. D. (2015) 'Modeling Consumers' Adoption Intentions of Remote Mobile Payments in the United Kingdom: Extending UTAUT with Innovativeness, Risk, and Trust', *Psychology & Marketing*, 32(8), pp. 860-873.

SmartPLS (n.d.) 'Moderation'. Available at: https://www.smartpls.com/documentation/algorithms-and-techniques/moderation.
Srite, M. and Karahanna, E. (2006) 'The Role of Espoused National Cultural Values in Technology Acceptance', *MIS Quarterly,* 30(3), pp. 679-704.
SSB (2019) 'FAKTA OM Internett og mobil'. Available at: https://www.ssb.no/teknologi-og-innovasjon/faktaside.
Sweeney, J. C. and Soutar, G. N. (2001) 'Consumer perceived value: The development of a multiple item scale', *Journal of Retailing,* 77(2), pp. 203-220.
Taiwo, A. A. and Downe, A. G. (2013) 'The theory of user acceptance and use of technology (UTAUT): A meta-analytic review of empirical findings', *Journal of Theoretical and Applied Information Technology,* 49(1), pp. 48-58.
Tak, P. and Panwar, S. (2017) 'Using UTAUT 2 model to predict mobile app based shopping: evidences from India', *Journal of Indian Business Research,* 9(3), pp. 248-264.
Tamilmani, K., Rana, N., Dwivedi, Y., Sahu, G. and Roderick, S. (2018) *Exploring the Role of 'Price Value' for Understanding Consumer Adoption of Technology: A Review and Meta-analysis of UTAUT2 based Empirical Studies.*
Tamilmani, K., Rana, N. P. and Dwivedi, Y. K. (2020) 'Consumer Acceptance and Use of Information Technology: A Meta-Analytic Evaluation of UTAUT2', *Information Systems Frontiers*.
Tarhini, A., Hone, K., Liu, X. and Tarhini, T. (2017) 'Examining the moderating effect of individual-level cultural values on users' acceptance of E-learning in developing countries: a structural equation modeling of an extended technology acceptance model', *Interactive Learning Environments,* 25(3), pp. 306-328.
Taylor, S. and Todd, P. (1995) 'Assessing IT Usage: The Role of Prior Experience', *Management Information Systems Quarterly - MISQ,* 19.
Thompson, R. L., Higgins, C. A. and Howell, J. M. (1991) 'Personal computing: toward a conceptual model of utilization. (technical)', *MIS Quarterly,* 15(1), pp. 125.
Udo, G. J., Bagchi, K. K. and Kirs, P. J. (2012) 'Exploring the role of espoused values on e-service adoption: A comparative analysis of the US and Nigerian users', *Computers in Human Behavior,* 28(5), pp. 1768-1781.
Ursachi, G., Horodnic, I. A. and Zait, A. (2015) 'How Reliable are Measurement Scales? External Factors with Indirect Influence on Reliability Estimators', *Procedia Economics and Finance,* 20, pp. 679-686.
Vantrappen, H. (1992) 'Creating customer value by streamlining business processes', *Long Range Planning,* 25(1), pp. 53-62.
Venkatesh, V. (2000) 'Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model', *Information Systems Research,* 11(4), pp. 342-365.
Venkatesh, V. and Bala, H. (2008) 'Technology Acceptance Model 3 and a Research Agenda on Interventions', *Decision Sciences,* 39(2), pp. 273-315.
Venkatesh, V. and Davis, F. (2000) 'A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies', *Management Science,* 46(2), pp. 186-204.
Venkatesh, V., Morris, M. G., Davis, G. B. and Davis, F. D. (2003a) 'User acceptance of information technology: Toward a unified view', *MIS Quarterly,* 27(3), pp. 425-478.
Venkatesh, V., Morris, M. G., Davis, G. B. and Davis, F. D. (2003b) 'User acceptance of information technology: Toward a unified view1', *MIS Quarterly,* 27(3), pp. 425-478.

Venkatesh, V., Morris, M. G., Sykes, T. A. and Ackerman, P. L. (2004) 'Individual Reactions to New Technologies in the Workplace: The Role of Gender as a Psychological Construct', *Journal of Applied Social Psychology*, 34(3), pp. 445-467.
Venkatesh, V., Thong, J. Y. L. and Xu, X. (2012a) 'Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology', *MIS Quarterly*, 36(1), pp. 157-178.
Venkatesh, V., Thong, J. Y. L. and Xu, X. (2012b) 'Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology.', *MIS Quarterly*, 36(1), pp. 157.
Vinzi, V. E., Chin, W. W., Henseler, J. and Wang, H. (2010) *Handbook of Partial Least Squares: Concepts, Methods and Applications* DE: DE: Springer. *Springer handbooks of computational statistics*.
Walczuch, R. and Seelen, J. L., Henriette (2001) 'Psychological Determinants for Consumer Trust in

E-Retailing'. *Proceedings of the Eighth Research Symposium on Emerging Electronic Markets (RSEEM 01)* Maastricht, The Netherlands, September 16-18, 2001.
Wang, C. (2017) 'Consumer Acceptance of Self-service Technologies: An Ability - Willingness Model', *International Journal of Market Research*, 59(6), pp. 787-802.
Wankhede, K. e. a. (2018) 'Just Walk-Out Technology and its Challenges: A case of Amazon Go'. *International Conference on Inventive Research in Computing Applications (ICIRCA 2018)*, India, 07/11/ 2018: IEEE Xplore, 4.
Webb, T. and Sheeran, P. (2006) 'Does Changing Behavioral Intentions Engender Behavior Change? A Meta-Analysis of the Experimental Evidence', *Psychological bulletin*, 132, pp. 249-68.
Webster, J. and Martocchio, J. J. (1992) 'Microcomputer Playfulness: Development of a Measure with Workplace Implications', *MIS Quarterly*, 16(2), pp. 201-226.
Woodruff, R. (1997) 'Customer value: The next source for competitive advantage', *Official Publication of the Academy of Marketing Science*, 25(2), pp. 139-153.
Xu, X. (2014) 'Understanding users' continued use of online games: An application of UTAUT2 in social network games', *MMEDIA - International Conferences on Advances in Multimedia*, pp. 58-65.
Yoo, B., Donthu, N. and Lenartowicz, T. (2011) 'Measuring Hofstede's Five Dimensions of Cultural Values at the Individual Level: Development and Validation of CVSCALE', *Journal of International Consumer Marketing: International/Global Perspectives in Cross-Cultural and Cross-National Consumer Research in the Twenty-First Century*, 23(3-4), pp. 193-210.
Yoon, C. (2009) 'The effects of national culture values on consumer acceptance of e-commerce: Online shoppers in China', *Information & Management*, 46(5), pp. 294-301.
Yousafzai, S., Foxall, G. and Pallister, J. (2007) 'Technology acceptance: A meta-analysis of the TAM: Part 1', *Journal of Modelling in Management*, 2.
Zakour, A. (2004) 'Cultural differences and information technology acceptance'.
zbilen, P. n. (2017) 'The Impact of Natural Culture on New Technology Adoption by Firms: A Country Level Analysis', *International journal of innovation, management and technology*, pp. 299-305.
Zeithaml, V. (1988) 'Consumer Perceptions of Price, Quality and Value: A Means-End Model and Synthesis of Evidence', *Journal of Marketing*, 52, pp. 2-22.

Zhao, F. (2013) 'An empirical study of cultural dimensions and e-government development: implications of the findings and strategies', *Behaviour & Information Technology*, 32(3), pp. 294-306.

Appendix

Appendix 1: Survey

Independent variables	
Hedonic Motivation (HM) HM1: I believe it would be fun to shop in a Checkout-free store HM2: I believe it would be enjoyable to shop in a Checkout-free store HM3: I believe it would be entertaining to shop in a Checkout-free store	**Performance Expectancy (PE)** PE1: A Checkout-free store would be useful in my daily life PE2: Using Checkout-free store increases my productivity PE3: Using Checkout-free store would help me accomplish my grocery shopping more quickly
Facilitating Conditions FC1: I have the resources necessary to shop in a Checkout-free store. FC2: I have the knowledge necessary to use Checkout-free services. FC3: Checkout-free services are compatible with other technologies I use FC4: I can get help from others when I have difficulties using the technology a Checkout-free store requires	**Social Influence (SI)** SI1: I would shop in a Checkout-free store if people who are important to me think I should do it SI2: I would shop in a Checkout-free store if family and friends think I should do it SI3: I think that shopping in a Checkout-free store would be a status symbol in my environment
Habit (HB) HB1: Shopping in a Checkout-free store would probably become a habit for me HB2: It will be a must for me to shop in a Checkout-free store HB3: Shopping in a Checkout-free store will become natural for me	**Effort Expectancy (EE)** EE1: I believe it would be easy for me to learn how to shop in a Checkout-free store EE2: I believe it would be clear and understandable for me how to shop in a Checkout-free store EE3: I believe I will find Checkout-free services easy to use
BI, PE, EE, SI, FC, HM, and HB are all adopted from: (Venkatesh, Thong and Xu, 2012a)	
Perceived Value (PV) PV1: I believe shopping in a Checkout-free store would be worthwhile PV2: I believe shopping in a Checkout-free store overall would deliver good value PV3: I believe shopping in a Checkout-free store would be valuable PV4: I believe shopping in a Checkout-free store would be beneficial to me	**Trust (TR)** TR1: I believe I would trust Checkout-free stores TR2: I believe Checkout-free shopping is reliable TR3: I believe Checkout-free stores keep their promises and commitments regarding data protection TR4: I believe Checkout-free stores have a high level of security protection in the online payment system.
PV adopted from: (Liu et al., 2015)	**TR adopted from: (Alalwan et al., 2017),**
Moderating variables	

Collectivism/Individualism (IDV)	Power Distance (PD)
IDV1: Individuals should remain with their group even through difficult times IDV2: Individual rewards are not as important as group prosperity IDV3: Group accomplishment is more important than individual accomplishment IDV4: Being loyal to a group is more important than individual achievements	PD1: Mangers should make most decisions without consulting other people in lower positions. PD2: Managers should not ask the opinions of people in lower positions too frequently PD3: Managers should avoid social interaction with people in lower positions
Masculinity (MAS) MAS1: It not as important for women to have a professional career, as it is for men. MAS2: Men usually solve problems with logical analysis; women usually solve problem with intuition. MAS3: Solving complex problems usually requires the active, forcible approach, which is typical for men. MAS4: There are some jobs that a man will perpetually do better than a woman.	**Uncertainty Avoidance (UA)** UA1: It is important for me to have instructions spelled out in detail UA2: It is important to abide by instructions and procedures UA3: It is helpful to have standardized work procedures UA4: Rules and regulations are important because they inform me of what is anticipated of me UA5: To fulfill work activities it is important with instructions
IDV, MAS, PD, and UA adapted from: (Yoo, Donthu and Lenartowicz, 2011)	
Long-Term Orientation (LTO) LT1: It is important for me to have respect for traditions LT2: I plan for the long run LT3: Family heritage is important to me LT4: I work hard for success in the future LT5: Traditional values are important to me	LTO adapted from: (Yoo, Donthu and Lenartowicz, 2011)
Dependent variable	
Behavior Intention BI1: I intend to shop in Checkout-free stores if available in the future BI2: I will always try to shop in Checkout-free stores in my daily life if available BI3: I plan to shop in Checkout-free stores frequently in the future if available **Adopted from (Venkatesh, Thong and Xu, 2012a)**	

- Footnote: Some of the items was removed from the analysis due factor loadings below .5: IDV1, LTO2, LTO3, LTO4, UA5, and PD1.

Appendix 2: Descriptive Statistics from Smart-PLS

Table 5.1: Descriptive statistics from SmartPLS

	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness
FM	2,871	2,000	1,000	7,000	1,992	-1,016	0,683
BI	4,318	4	1	7	1,664	-0,744	-0,262
PE	4,988	5	1	7	1,584	-0,488	-0,635
EE	6,021	6	1	7	0,984	3,109	-1,475
SI	3,534	4	1	7	1,578	-0,814	0,088
FC	4,379	5	2	7	0,693	1,026	-0,823
HD	4,657	5	1	7	1,728	-0,459	-0,562

HB	4,513	5	1	7	1,468	-0,309	-0,511
PV	4,465	5	1	7	1,601	-0,460	-0,506
TR	4,832	5	1	7	1,174	0,889	-0,789
IDV	4,784	5	1	7	1,193	0,078	-0,401
MAS	2,827	3	1	7	1,270	-0,431	0,422
PD	1,830	2	1	7	1,004	2,176	1,461
UA	5,404	6	1	7	0,885	1,823	-0,762
LTO	4,957	5	1	7	1,289	0,729	-0,860
Valid N	**295**						

Appendix 3: Socio-Demographic Statistics

Table 5.2: Gender of respondents

Gender of respondents		
Category	Frequency	Percent (%)
Female	166	56,3
Male	127	43,1
Other	2	,7
Total	295	100,0

Table 5.3: Age of respondents

Age of respondents		
Age group	Frequency	Percent (%)
18-25	89	30,2
26-35	81	27,5
36-45	27	9,2
46-55	65	22
56 and older	33	11,2
Total	295	100

Appendix 4: Descriptive Statistics of Familiarity

Table 5.4: Respondents level of familiarity with CT

Level of familiarity with CT		
Familiarity with CT	Frequency	Percent (%)
Not at all familiar	108	36,6
Unfamiliar	66	22,4
Slightly unfamiliar	22	7,5
Neither familiar nor unfamiliar	12	4,1
Moderately familiar	43	14,6
Familiar	30	10,2
Extremely familiar	14	4,7
Total	295	100,0

Appendix 5: Measurement Model Results

Table 5.5: Outer loadings combined result (individual level)

	BI	EE	FC	HB	HD	IDV	LTO	MAS	PD	PE	PV	SI	TR	UA
BI1	0,908													
BI2	0,889													
BI3	0,915													
EE1		0,872												
EE2		0,887												
EE3		0,913												
FC1			0,87											
FC2			0,828											
FC3			0,811											
HB1				0,878										
HB2				0,770										
HB3				0,930										
HD1					0,964									
HD2					0,965									
HD3					0,906									
IDV2						0,882								
IDV3						0,856								
IDV4						0,906								
LTO1							0,998							
LTO4							0,729							
MAS1								0,878						
MAS2								0,718						
MAS3								0,736						
MAS4								0,696						
PD2									0,711					
PD3									0,963					
PE1										0,900				
PE2										0,925				
PE3										0,929				
PV1											0,945			
PV2											0,938			
PV3											0,944			
PV4											0,951			
SI1												0,955		
SI2												0,950		
SI3												0,772		
TR1													0,881	
TR2													0,900	
TR3													0,886	
TR4													0,763	
UA1														0,748
UA2														0,856
UA3														0,732
UA4														0,840

Table 5.6: Outer loadings for Norway (country-level)

	BI	EE	FC	HB	HD	IDV	LTO	MAS	PD	PE	PV	SI	TR	UA
BI1	0,923													
BI2	0,925													
BI3	0,925													
EE1		0,872												
EE2		0,884												
EE3		0,927												
FC1			0,898											
FC2			0,845											
FC3			0,786											
HB1				0,878										
HB2				0,770										
HB3				0,930										
HD1					0,962									
HD2					0,964									
HD3					0,904									
IDV2						0,878								
IDV3						0,861								
IDV4						0,930								
LTO1							0,897							
LTO4							0,886							
MAS1								0,884						
MAS2								0,618						
MAS3								0,637						
MAS4								0,744						
PD2									0,703					
PD3									0,981					
PE1										0,909				
PE2										0,954				
PE3										0,955				
PV1											0,956			
PV2											0,955			
PV3											0,948			
PV4											0,958			
SI1												0,954		
SI2												0,950		
SI3												0,779		
TR1													0,885	
TR2													0,912	
TR3													0,899	
TR4													0,793	
UA1														0,711
UA2														0,871
UA3														0,717
UA4														0,808

Table 5.7: Outer loadings for Germany (country-level)

	BI	EE	FC	HB	HD	IDV	LTO	MAS	PD	PE	PV	SI	TR	UA
BI1	0,840													
BI2	0,836													
BI3	0,857													
EE1		0,855												
EE2		0,889												
EE3		0,917												
FC1			0,712											
FC2			0,758											
FC3			0,929											
HB1				0,845										
HB2				0,846										
HB3				0,902										
HD1					0,964									
HD2					0,972									
HD3					0,911									
IDV2						0,789								
IDV3						0,65								
IDV4						0,946								
LTO1							0,967							
LTO4							0,916							
MAS1								0,767						
MAS2								0,787						
MAS3								0,800						
MAS4								0,743						
PD2									0,890					
PD3									0,736					
PE1										0,828				
PE2										0,841				
PE3										0,818				
PV1											0,904			
PV2											0,860			
PV3											0,927			
PV4											0,929			
SI1												0,960		
SI2												0,950		
SI3												0,753		
TR1													0,856	
TR2													0,872	
TR3													0,826	
TR4													0,705	
UA1														0,844
UA2														0,85
UA3														0,813
UA4														0,904

Table 5.8: Cronbach's alpha (CA), Composite reliability (CR), and average variance extracted (AVE)

	Individual-level			Country-level: Norway			Country-level: Germany		
	CA	**CR**	**AVE**	**CA**	**CR**	**AVE**	**CA**	**CR**	**AVE**
BI	0,888	0,931	0,817	0,915	0,946	0,855	0,799	0,882	0,713
EE	0,870	0,920	0,794	0,875	0,923	0,801	0,868	0,918	0,788
FC	0,785	0,875	0,699	0,797	0,881	0,713	0,756	0,845	0,648
HB	0,826	0,896	0,743	0,836	0,901	0,754	0,831	0,899	0,748
HD	0,94	0,962	0,894	0,939	0,961	0,891	0,945	0,965	0,901

IDV	0,866	0,913	0,777	0,881	0,920	0,792	0,814	0,843	0,647
LTO	0,81	0,863	0,764	0,742	0,886	0,795	0,878	0,940	0,887
MAS	0,781	0,845	0,579	0,775	0,816	0,531	0,785	0,857	0,600
PD	0,663	0,832	0,716	0,709	0,839	0,728	0,516	0,799	0,667
PE	0,907	0,942	0,843	0,933	0,958	0,883	0,773	0,868	0,687
PV	0,96	0,971	0,892	0,967	0,976	0,911	0,927	0,948	0,820
SI	0,873	0,924	0,803	0,876	0,925	0,806	0,867	0,921	0,797
TR	0,881	0,918	0,738	0,896	0,928	0,763	0,831	0,889	0,668
UA	0,806	0,873	0,633	0,788	0,860	0,608	0.878	0.915	0.728

The Fornell-Larcker criterion

Table 5.9: Fornell-Larcker criterion individual result

	BI	EE	FC	HB	HD	IDV	LTO	MAS	PD	PE	PV	SI	TR	UA
BI	**0,904**													
EE	0,432	**0,891**												
FC	0,337	0,569	**0,836**											
HB	0,188	0,449	0,352	**0,862**										
HD	0,849	0,428	0,350	0,710	**0,946**									
IDV	0,785	0,125	0,067	0,149	0,048	**0,882**								
LTO	0,113	-0,031	-0,069	-0,026	-0,071	0,201	**0,874**							
MAS	-0,057	-0,008	-0,065	0,099	0,037	-0,019	0,101	**0,761**						
PD	0,133	-0,136	-0,100	0,115	0,050	-0,125	-0,043	0,365	**0,846**					
PE	0,086	0,483	0,367	0,715	0,713	0,097	-0,174	-0,008	0,045	**0,918**				
PV	0,798	0,473	0,383	0,750	0,790	0,106	-0,079	0,009	0,069	0,776	**0,945**			
SI	0,831	0,281	0,214	0,552	0,600	0,188	0,034	0,100	0,171	0,528	0,539	**0,896**		
TR	0,592	0,458	0,453	0,569	0,588	0,131	-0,034	0,045	-0,005	0,525	0,684	0,444	**0,859**	
UA	0,574	-0,027	-0,052	0,008	0,038	0,129	0,238	0,080	-0,151	-0,043	0,010	0,034	0,015	**0,796**

Table 5.10: Fornell-Larcker criterion country-level; Norway

	BI	EE	FC	HB	HD	IDV	LTO	MAS	PD	PE	PV	SI	TR	UA
BI	**0,925**													
EE	0,477	**0,895**												
FC	0,374	0,583	**0,844**											
HB	0,215	0,191	0,288	**1,000**										
HD	0,839	0,487	0,390	0,215	**0,868**									
IDV	0,814	0,449	0,360	0,179	0,754	**0,944**								
LTO	0,124	0,166	0,098	0,031	0,158	0,105	**0,890**							
MAS	-0,026	-0,001	-0,019	0,013	-0,015	0,063	0,159	**0,892**						
PD	0,131	0,019	-0,065	0,070	0,084	0,092	-0,080	-0,035	**0,729**					
PE	0,049	-0,149	-0,097	0,119	0,082	0,055	-0,161	-0,054	0,337	**0,853**				
PV	0,818	0,533	0,373	0,202	0,732	0,731	0,135	-0,140	0,030	0,026	**0,940**			
SI	0,859	0,501	0,413	0,255	0,776	0,807	0,161	0,005	0,049	0,076	0,785	**0,954**		
TR	0,607	0,327	0,238	0,186	0,562	0,660	0,190	0,097	0,101	0,170	0,554	0,603	**0,898**	
UA	0,597	0,474	0,470	0,272	0,590	0,603	0,145	0,044	0,086	0,004	0,546	0,693	0,490	**0,873**

Table 5.11: Fornell-Larcker criterion country-level; Germany

	BI	EE	FC	HB	HD	IDV	LTO	MAS	PD	PE	PV	SI	TR	UA
BI	**0,844**													
EE	0,216	**0,888**												
FC	0,222	0,514	**0,805**											
HB	0,948	0,278	0,226	**0,865**										
HD	0,665	0,372	0,347	0,603	**0,949**									
IDV	0,117	-0,049	0,030	0,116	-0,042	**0,804**								
LTO	-0,044	-0,138	-0,189	-0,059	-0,203	0,291	**0,942**							
MAS	0,242	-0,096	-0,037	0,201	-0,032	0,150	0,368	**0,775**						
PD	0,296	-0,076	-0,037	0,296	-0,022	-0,013	0,131	0,535	**0,817**					
PE	0,684	0,259	0,436	0,686	0,608	0,083	-0,133	0,023	0,129	**0,829**				
PV	0,690	0,356	0,289	0,666	0,717	-0,035	-0,200	-0,025	0,056	0,730	**0,905**			
SI	0,546	0,125	0,174	0,535	0,398	0,221	-0,097	0,136	0,212	0,431	0,297	**0,893**		
TR	0,504	0,386	0,390	0,480	0,622	0,071	-0,316	-0,108	0,076	0,515	0,706	0,301	**0,817**	
UA	0,226	-0,089	0,103	0,165	0,213	0,033	0,165	0,167	-0,044	0,136	0,219	0,049	0,073	**0,853**

Table 5.12: Cross-loadings individual result

	BI	EE	FC	HB	HD	IDV	LTO	MAS	PD	PE	PV	SI	TR	UA
BI1	**0,908**	0,419	0,355	0,804	0,755	0,075	-0,119	0,070	0,055	0,784	0,788	0,550	0,553	0,034
BI2	**0,889**	0,349	0,247	0,746	0,636	0,152	0,053	0,142	0,114	0,632	0,677	0,535	0,472	0,032
BI3	**0,915**	0,398	0,306	0,751	0,731	0,084	-0,079	0,153	0,067	0,741	0,783	0,521	0,528	0,018
EE1	0,393	**0,872**	0,414	0,390	0,379	0,055	-0,014	-0,003	-0,121	0,469	0,431	0,246	0,375	-0,011
EE2	0,374	**0,887**	0,521	0,396	0,391	0,157	-0,063	-0,025	-0,122	0,417	0,435	0,244	0,410	-0,027
EE3	0,385	**0,913**	0,588	0,413	0,374	0,123	-0,008	0,005	-0,120	0,404	0,397	0,261	0,439	-0,034

FC1	0,294	0,490	**0,870**	0,301	0,290	0,037	-0,047	-0,088	-0,151	0,311	0,338	0,171	0,374	-0,066
FC2	0,248	0,524	**0,828**	0,233	0,241	0,026	-0,027	-0,043	-0,103	0,276	0,298	0,131	0,358	-0,064
FC3	0,297	0,422	**0,811**	0,340	0,337	0,099	-0,094	-0,031	0,000	0,327	0,321	0,226	0,401	-0,003
HB1	0,770	0,406	0,311	**0,878**	0,689	0,145	-0,093	0,039	0,034	0,675	0,708	0,479	0,507	0,038
HB2	0,579	0,238	0,172	**0,770**	0,423	0,101	0,071	0,201	0,233	0,394	0,446	0,403	0,353	-0,030
HB3	0,820	0,482	0,395	**0,930**	0,688	0,135	-0,023	0,049	0,068	0,732	0,744	0,534	0,582	0,004
HD1	0,770	0,467	0,345	0,690	**0,964**	0,047	-0,088	0,016	0,009	0,719	0,776	0,562	0,573	0,048
HD2	0,767	0,421	0,350	0,710	**0,965**	0,050	-0,054	0,030	0,049	0,702	0,770	0,578	0,596	0,029
HD3	0,686	0,316	0,294	0,612	**0,906**	0,039	-0,060	0,062	0,088	0,593	0,692	0,565	0,496	0,030
IDV2	0,106	0,104	0,041	0,135	0,030	**0,882**	0,196	-0,009	-0,123	0,031	0,083	0,164	0,102	0,141
IDV3	0,042	0,106	0,013	0,089	-0,034	**0,856**	0,106	-0,075	-0,143	0,024	0,024	0,094	0,070	0,100
IDV4	0,124	0,117	0,094	0,152	0,088	**0,906**	0,201	0,004	-0,087	0,153	0,135	0,203	0,148	0,103
LTO1	-0,061	-0,030	-0,067	-0,030	-0,074	0,195	**0,998**	0,093	-0,049	-0,176	-0,081	0,034	-0,034	0,229
LTO4	-0,003	-0,032	-0,064	0,019	-0,023	0,201	**0,729**	0,151	0,025	-0,111	-0,037	0,023	-0,023	0,259
MAS1	0,133	0,033	-0,065	0,119	0,071	-0,009	0,047	**0,878**	0,308	0,032	0,026	0,124	0,075	0,057
MAS2	0,050	-0,015	-0,091	-0,002	-0,049	-0,016	0,129	**0,718**	0,208	-0,091	-0,050	0,022	-0,044	0,064
MAS3	0,076	-0,078	-0,096	0,052	0,009	-0,038	0,162	**0,736**	0,322	-0,059	-0,015	0,080	0,019	0,013
MAS4	0,097	-0,011	0,017	0,055	-0,001	-0,008	0,053	**0,696**	0,246	-0,005	0,009	0,020	0,006	0,111
PD2	0,088	-0,059	-0,005	0,108	0,030	-0,115	-0,056	0,344	**0,711**	0,049	0,052	0,132	0,054	-0,108
PD3	0,072	-0,145	-0,122	0,101	0,050	-0,110	-0,032	0,319	**0,963**	0,037	0,065	0,160	-0,026	-0,145
PE1	0,768	0,454	0,360	0,692	0,704	0,054	-0,167	-0,034	0,013	**0,900**	0,764	0,500	0,531	-0,032
PE2	0,702	0,442	0,348	0,641	0,588	0,102	-0,122	0,040	0,096	**0,925**	0,660	0,471	0,457	-0,089
PE3	0,726	0,434	0,300	0,634	0,665	0,113	-0,190	-0,026	0,017	**0,929**	0,707	0,481	0,455	0,000
PV1	0,787	0,428	0,349	0,710	0,744	0,100	-0,088	0,006	0,014	0,747	**0,945**	0,483	0,638	0,010
PV2	0,803	0,460	0,379	0,728	0,738	0,100	-0,093	0,016	0,044	0,732	**0,938**	0,509	0,653	-0,008
PV3	0,762	0,445	0,365	0,689	0,743	0,101	-0,042	0,006	0,097	0,710	**0,944**	0,526	0,661	0,013
PV4	0,787	0,453	0,353	0,705	0,760	0,099	-0,075	0,007	0,106	0,740	**0,951**	0,519	0,631	0,022
SI1	0,566	0,302	0,244	0,532	0,554	0,210	0,028	0,064	0,139	0,522	0,505	**0,955**	0,450	0,071
SI2	0,568	0,270	0,235	0,530	0,554	0,216	0,054	0,065	0,143	0,509	0,519	**0,950**	0,448	0,045
SI3	0,450	0,171	0,074	0,412	0,507	0,058	0,002	0,154	0,187	0,375	0,420	**0,772**	0,278	-0,038
TR1	0,556	0,398	0,415	0,540	0,547	0,053	-0,059	0,074	0,042	0,484	0,635	0,418	**0,881**	-0,013
TR2	0,525	0,433	0,416	0,510	0,553	0,066	-0,102	0,016	-0,026	0,474	0,645	0,379	**0,900**	0,007
TR3	0,468	0,418	0,378	0,492	0,503	0,170	-0,001	0,000	-0,021	0,447	0,555	0,385	**0,886**	-0,005
TR4	0,409	0,312	0,341	0,398	0,400	0,188	0,074	0,070	-0,017	0,393	0,499	0,340	**0,763**	0,079
UA1	0,110	-0,007	-0,044	0,039	0,123	0,079	0,106	0,022	-0,082	0,084	0,106	0,067	-0,008	**0,748**

UA2	-0,051	-0,075	-0,054	-0,048	-0,059	0,151	0,306	0,029	-0,198	-0,121	-0,083	-0,006	-0,020	**0,856**
UA3	-0,016	0,010	-0,050	0,003	0,005	0,051	0,122	0,098	-0,074	-0,031	0,009	-0,029	0,016	**0,732**
UA4	0,072	0,002	-0,019	0,045	0,075	0,110	0,184	0,111	-0,102	-0,036	0,030	0,076	0,062	**0,840**

Table 5.13: Cross-loadings country-level: Norway

	BI	**EE**	**FC**	**HB**	**HD**	**IDV**	**LTO**	**MAS**	**PD**	**PE**	**PV**	**SI**	**TR**	**UA**
BI1	**0,923**	0,481	0,397	0,813	0,802	0,098	-0,042	0,095	0,034	0,801	0,818	0,591	0,608	-0,018
BI2	**0,925**	0,394	0,302	0,738	0,713	0,142	-0,002	0,091	0,061	0,705	0,764	0,554	0,502	-0,012
BI3	**0,925**	0,446	0,333	0,772	0,739	0,105	-0,025	0,175	0,042	0,758	0,799	0,538	0,541	-0,069
EE1	0,436	**0,872**	0,416	0,430	0,409	0,061	-0,029	0,024	-0,147	0,510	0,460	0,298	0,405	-0,003
EE2	0,415	**0,884**	0,547	0,436	0,392	0,232	0,022	-0,003	-0,128	0,456	0,444	0,286	0,418	-0,004
EE3	0,430	**0,927**	0,606	0,441	0,404	0,155	0,006	0,031	-0,124	0,462	0,441	0,294	0,448	-0,024
FC1	0,350	0,536	**0,898**	0,353	0,328	0,078	0,016	-0,090	-0,140	0,359	0,381	0,221	0,414	-0,112
FC2	0,285	0,505	**0,845**	0,266	0,236	0,062	0,005	-0,054	-0,110	0,286	0,324	0,150	0,353	-0,075
FC3	0,307	0,434	**0,786**	0,364	0,341	0,109	-0,071	-0,016	0,009	0,293	0,335	0,226	0,419	-0,059
HB1	0,760	0,465	0,338	**0,896**	0,724	0,182	-0,015	0,048	0,003	0,674	0,721	0,502	0,547	-0,013
HB2	0,556	0,249	0,205	**0,767**	0,452	0,078	0,034	0,165	0,208	0,424	0,482	0,393	0,349	-0,081
HB3	0,833	0,512	0,439	**0,934**	0,743	0,138	-0,043	0,035	0,045	0,759	0,776	0,550	0,603	-0,051
HD1	0,805	0,507	0,365	0,734	**0,962**	0,102	0,049	0,076	0,015	0,738	0,789	0,623	0,584	-0,004
HD2	0,790	0,447	0,368	0,746	**0,964**	0,101	0,062	0,083	0,054	0,720	0,783	0,623	0,606	-0,031
HD3	0,706	0,304	0,279	0,650	**0,904**	0,093	0,068	0,105	0,092	0,605	0,710	0,627	0,514	-0,046
IDV2	0,114	0,117	0,081	0,143	0,072	**0,878**	0,147	-0,107	-0,163	0,085	0,131	0,152	0,104	0,160
IDV3	0,042	0,123	0,032	0,098	0,004	**0,861**	0,052	-0,134	-0,177	0,063	0,054	0,093	0,069	0,118
IDV4	0,137	0,179	0,115	0,159	0,144	**0,930**	0,176	-0,027	-0,121	0,167	0,189	0,214	0,170	0,125
LTO1	-0,039	-0,002	-0,021	-0,020	0,052	0,116	**0,897**	-0,062	-0,063	-0,136	0,011	0,112	0,039	0,270
LTO4	-0,006	0,002	-0,012	-0,007	0,060	0,169	**0,886**	0,002	-0,034	-0,113	-0,002	0,059	0,040	0,303
MAS1	0,133	0,034	-0,093	0,106	0,108	-0,058	-0,038	**0,884**	0,315	0,060	0,051	0,131	0,084	0,027
MAS2	0,040	0,022	-0,126	-0,022	-0,030	-0,049	0,066	**0,618**	0,164	-0,103	-0,064	0,002	-0,052	0,022
MAS3	0,052	-0,097	-0,110	0,012	0,048	-0,104	0,103	**0,637**	0,250	-0,068	-0,004	0,074	0,019	-0,009
MAS4	0,084	0,035	0,031	0,033	0,034	-0,057	-0,067	**0,744**	0,213	0,010	0,041	0,010	0,067	0,067
PD2	0,044	-0,067	-0,021	0,068	0,053	-0,134	-0,152	0,336	**0,703**	0,030	0,048	0,110	0,021	-0,169
PD3	0,045	-0,156	-0,108	0,078	0,050	-0,152	-0,022	0,304	**0,981**	0,023	0,077	0,170	-0,001	-0,164
PE1	0,808	0,532	0,368	0,739	0,738	0,112	-0,110	0,015	0,008	**0,909**	0,793	0,553	0,574	-0,103

PE2	0,736	0,458	0,356	0,655	0,642	0,117	-0,155	0,036	0,059	**0,954**	0,698	0,480	0,475	-0,143
PE3	0,754	0,507	0,326	0,663	0,673	0,153	-0,131	0,034	0,009	**0,955**	0,714	0,523	0,485	-0,045
PV1	0,835	0,464	0,379	0,760	0,759	0,160	-0,007	0,047	0,009	0,761	**0,956**	0,555	0,660	-0,063
PV2	0,846	0,498	0,409	0,765	0,791	0,134	-0,022	0,045	0,033	0,763	**0,955**	0,560	0,674	-0,075
PV3	0,796	0,469	0,397	0,720	0,760	0,166	0,025	0,045	0,131	0,729	**0,948**	0,610	0,664	-0,061
PV4	0,800	0,482	0,388	0,714	0,768	0,156	0,026	0,051	0,123	0,742	**0,958**	0,578	0,645	-0,053
SI1	0,578	0,347	0,268	0,532	0,606	0,201	0,100	0,064	0,116	0,540	0,561	**0,954**	0,487	0,063
SI2	0,586	0,315	0,254	0,540	0,611	0,210	0,098	0,045	0,143	0,527	0,582	**0,950**	0,487	0,022
SI3	0,464	0,205	0,099	0,434	0,565	0,088	0,059	0,182	0,215	0,415	0,475	**0,779**	0,330	-0,050
TR1	0,608	0,421	0,425	0,595	0,580	0,090	0,027	0,116	0,048	0,512	0,667	0,485	**0,885**	0,004
TR2	0,552	0,426	0,403	0,544	0,534	0,084	0,035	0,086	0,029	0,495	0,652	0,420	**0,912**	-0,012
TR3	0,491	0,409	0,399	0,512	0,529	0,157	0,051	0,040	-0,024	0,466	0,573	0,418	**0,899**	0,016
TR4	0,403	0,401	0,420	0,380	0,450	0,199	0,046	0,046	-0,059	0,426	0,508	0,380	**0,793**	-0,024
UA1	0,104	0,026	-0,061	0,049	0,099	0,112	0,179	0,071	-0,081	0,062	0,097	0,081	0,023	**0,711**
UA2	-0,108	-0,052	-0,079	-0,104	-0,105	0,138	0,340	-0,046	-0,248	-0,166	-0,142	-0,020	-0,029	**0,871**
UA3	-0,065	0,005	-0,128	-0,050	-0,052	0,080	0,167	0,097	-0,053	-0,076	-0,063	-0,051	-0,031	**0,717**
UA4	0,033	0,017	-0,042	-0,001	0,048	0,127	0,262	0,080	-0,106	-0,059	-0,012	0,079	0,045	**0,808**

Table 5.14: Cross-loadings country-level: Germany

	BI	**EE**	**FC**	**HB**	**HD**	**IDV**	**LTO**	**MAS**	**PD**	**PE**	**PV**	**SI**	**TR**	**UA**
BI1	**0,840**	0,152	0,238	0,845	0,497	0,101	-0,187	0,126	0,201	0,661	0,632	0,395	0,404	0,187
BI2	**0,836**	0,187	0,093	0,840	0,520	0,118	0,066	0,261	0,327	0,441	0,422	0,526	0,336	0,105
BI3	**0,857**	0,210	0,237	0,706	0,676	0,075	0,013	0,228	0,219	0,635	0,704	0,461	0,547	0,288
EE1	0,175	**0,855**	0,402	0,215	0,255	0,015	0,022	-0,057	-0,029	0,257	0,304	0,056	0,266	-0,037
EE2	0,145	**0,889**	0,386	0,207	0,352	-0,119	-0,188	-0,019	-0,063	0,170	0,365	0,083	0,383	-0,125
EE3	0,235	**0,917**	0,543	0,297	0,375	-0,041	-0,189	-0,147	-0,099	0,248	0,296	0,171	0,377	-0,083
FC1	0,098	0,359	**0,712**	0,121	0,203	-0,084	-0,208	-0,062	-0,104	0,174	0,212	0,029	0,253	0,038
FC2	0,110	0,590	**0,758**	0,100	0,307	-0,084	-0,192	0,026	-0,059	0,277	0,231	0,078	0,365	-0,039
FC3	0,255	0,394	**0,929**	0,256	0,320	0,115	-0,127	-0,045	0,008	0,481	0,260	0,221	0,342	0,159
HB1	0,840	0,152	0,238	**0,845**	0,497	0,101	-0,187	0,126	0,201	0,661	0,632	0,395	0,404	0,187
HB2	0,827	0,220	0,106	**0,846**	0,516	0,081	0,031	0,274	0,355	0,440	0,440	0,504	0,347	0,093
HB3	0,787	0,356	0,244	**0,902**	0,550	0,119	0,008	0,118	0,208	0,680	0,657	0,490	0,497	0,146
HD1	0,616	0,341	0,317	0,582	**0,964**	-0,029	-0,189	-0,074	-0,054	0,611	0,717	0,356	0,642	0,197
HD2	0,644	0,326	0,310	0,589	**0,972**	-0,059	-0,209	-0,047	-0,026	0,594	0,705	0,409	0,619	0,199

HD3	0,632	0,393	0,359	0,544	**0,911**	-0,032	-0,180	0,029	0,018	0,526	0,619	0,366	0,510	0,211
IDV2	0,131	0,070	-0,048	0,095	0,024	**0,789**	0,218	0,173	-0,067	-0,074	-0,004	0,234	0,057	0,085
IDV3	0,061	0,041	-0,012	0,049	-0,126	**0,650**	0,264	0,080	-0,001	-0,113	-0,069	0,105	0,056	0,036
IDV4	0,091	-0,104	0,066	0,109	-0,067	**0,946**	0,279	0,114	0,016	0,154	-0,044	0,179	0,066	0,001
LTO1	-0,103	-0,128	-0,186	-0,127	-0,255	0,322	**0,967**	0,306	0,050	-0,202	-0,275	-0,131	-0,340	0,143
LTO4	0,053	-0,134	-0,169	0,055	-0,094	0,201	**0,916**	0,414	0,240	-0,007	-0,055	-0,030	-0,237	0,176
MAS1	0,183	0,029	0,018	0,161	0,044	0,113	0,128	**0,767**	0,374	0,003	-0,014	0,129	-0,005	0,106
MAS2	0,117	-0,144	-0,030	0,072	-0,065	0,074	0,278	**0,787**	0,366	-0,005	0,026	0,093	-0,029	0,158
MAS3	0,226	-0,015	-0,045	0,207	-0,035	0,135	0,297	**0,800**	0,590	0,066	0,001	0,125	-0,020	0,051
MAS4	0,182	-0,183	-0,050	0,136	-0,052	0,116	0,397	**0,743**	0,289	-0,008	-0,063	0,071	-0,233	0,213
PD2	0,283	-0,032	0,044	0,268	-0,049	-0,050	0,126	0,428	**0,890**	0,136	0,071	0,205	0,169	0,025
PD3	0,189	-0,110	-0,142	0,210	0,028	0,046	0,083	0,465	**0,736**	0,065	0,010	0,132	-0,095	-0,128
PE1	0,541	0,128	0,420	0,522	0,509	-0,057	-0,214	-0,053	0,040	**0,828**	0,616	0,291	0,426	0,200
PE2	0,554	0,371	0,391	0,581	0,423	0,082	0,011	0,145	0,247	**0,841**	0,523	0,445	0,390	0,032
PE3	0,602	0,148	0,282	0,599	0,574	0,169	-0,128	-0,032	0,040	**0,818**	0,671	0,335	0,462	0,109
PV1	0,581	0,296	0,248	0,553	0,664	0,006	-0,094	0,011	0,040	0,688	**0,904**	0,233	0,629	0,173
PV2	0,569	0,303	0,274	0,559	0,523	-0,035	-0,238	-0,020	0,091	0,581	**0,860**	0,312	0,602	0,168
PV3	0,594	0,340	0,277	0,564	0,690	-0,103	-0,180	-0,059	-0,008	0,643	**0,927**	0,223	0,676	0,207
PV4	0,731	0,344	0,251	0,712	0,705	-0,002	-0,207	-0,021	0,075	0,720	**0,929**	0,303	0,651	0,237
SI1	0,540	0,148	0,215	0,545	0,399	0,270	-0,116	0,088	0,256	0,478	0,304	**0,960**	0,330	0,067
SI2	0,504	0,113	0,226	0,502	0,369	0,286	-0,096	0,136	0,206	0,450	0,278	**0,950**	0,319	0,090
SI3	0,407	0,066	-0,008	0,368	0,287	-0,005	-0,037	0,148	0,085	0,189	0,203	**0,753**	0,131	-0,042
TR1	0,347	0,320	0,400	0,316	0,519	-0,084	-0,406	-0,094	0,117	0,440	0,565	0,205	**0,856**	-0,071
TR2	0,402	0,464	0,446	0,376	0,635	0,014	-0,419	-0,187	-0,117	0,396	0,626	0,240	**0,872**	0,054
TR3	0,388	0,448	0,305	0,410	0,472	0,174	-0,177	-0,154	0,053	0,422	0,525	0,282	**0,826**	-0,095
TR4	0,506	0,018	0,107	0,466	0,388	0,136	-0,010	0,088	0,214	0,427	0,582	0,258	**0,705**	0,341
UA1	0,104	-0,142	0,050	0,028	0,092	0,044	0,136	0,007	-0,107	0,076	0,073	-0,005	-0,057	**0,844**
UA2	0,205	-0,157	0,033	0,149	0,160	0,134	0,236	0,191	0,009	0,124	0,166	0,047	0,008	**0,850**
UA3	0,181	0,021	0,180	0,170	0,217	-0,025	0,153	0,163	-0,059	0,163	0,274	0,039	0,168	**0,813**
UA4	0,262	-0,053	0,085	0,204	0,239	0,001	0,092	0,209	0,004	0,114	0,229	0,077	0,110	**0,904**

Appendix 6: Structural Model Result

Collinearity assessment

Table 5.15: Inner VIF values for Individual-level and Country-level

	Individual-level		Country-level: Norway		Country-level: Germany	
	BI	**TR**	**BI**	**TR**	**BI**	**TR**
BI						
EE	1,783		1,900		2,114	
FC	1,709		1,831		1,467	1,125
FM	1,145	1,044	1,158	1,049	1,830	
FMxLTO	1,167		1,226		1,459	
FMxMAS	1,147		1,239		1,401	
HB	2,967		3,207		2,953	
HD	3,31		3,870		2,507	
IDV		1,063		1,064		1,130
LTO	1,085	1,105	1,124	1,139	1,460	1,265
MAS	1,076	1,193	1,085	1,152	1,444	1,694
PD		1,221	1,385			1,469
PE	3,234			1,203	3,319	
PV	4,524		3,514		4,417	
SI	1,719		4,893		1,705	
TR	2,248		1,913		2,744	
TRxLTO	1,187		2,347		1,400	
TRxMAS	1,232		1,215		1,592	
UA		1,132		1,211		1,119

- Footnote: The constructs without any values has been removed to fit both the individual analysis and country analysis in one table
- **Assessment of significance and size of the structural path relationship**

Figure 5.4: Bootstrapping results with PLS path coefficients and R^2 for the country-level result (Norway):

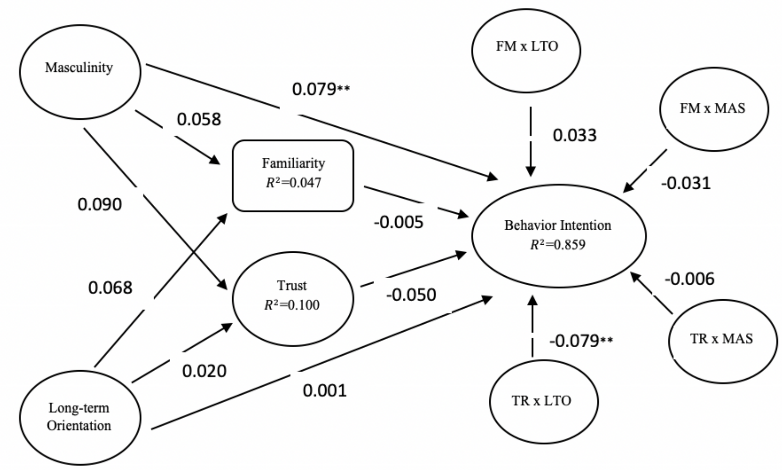


Figure 5.5: Bootstrapping results with PLS path coefficients and R^2 for the country-level result (Germany):

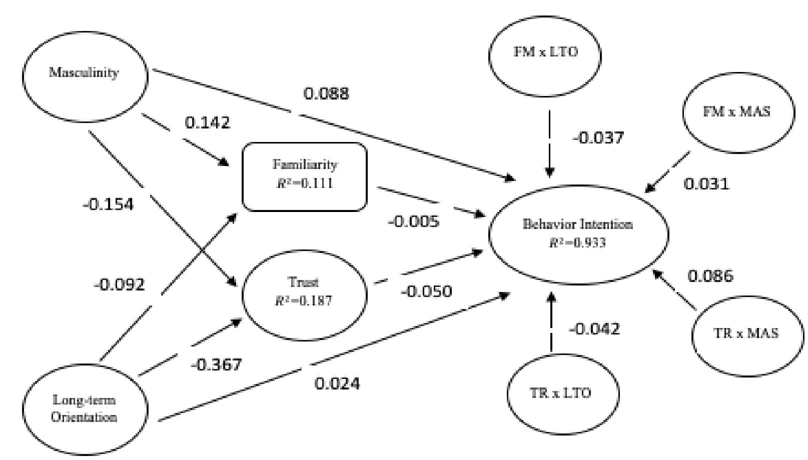


Table 5.16: Test of PLS path with bootstrapping Individual-level result

Path	**(Path) Coefficients**	**T Statistics**	**P values**
Effort Expectancy→Behavior Intention	-0,032	1,083	0,279
Facilitating Conditions→Behavior Intention	-0,002	1,083	0,955
Familiarity→Behavior Intention	-0,004	1,083	0,883
Familiarity→Trust	0,249	4,405	0,000
Familiarity x Long-Term Orientation→Behavior Intention	0,038	1,307	0,191

Familiarity x Masculinity→Behavior Intention	-0,023	0,815	0,415
Habit→Behavior Intention	0,405	9,188	0,000
Hedonic Motivation→Behavior Intention	0,131	3,077	0,002
Individualism→Familiarity	0,035	0,526	0,599
Individualism→Trust	0,135	1,947	0,052
Long-Term Orientation→Behavior Intention	0,013	0,503	0,615
Long-Term Orientation→Familiarity	0,011	0,154	0,877
Long-Term Orientation→Trust	-0,074	1,000	0,317
Masculinity→Behavior Intention	0,088	2,825	0,005
Masculinity→Familiarity	0,057	0,692	0,489
Masculinity→Trust	0,044	0,523	0,601
Power Distance→Familiarity	0,087	1,212	0,225
Power Distance→Trust	-0,032	0,420	0,675
Performance Expectancy→Behavior Intention	0,222	4,634	0,000
Perceived Value→Behavior Intention	0,273	5,384	0,000
Social Influence →Behavior Intention	0,049	1,587	0,113
Trust→Behavior Intention	-0,035	0,974	0,330
Trust x Long-Term Orientation →Behavior Intention	-0,071	2,012	0,044
Trust x Masculinity →Behavior Intention	0,013	0,402	0,687
Uncertainty Avoidance →Familiarity	-0,164	2,480	0,013
Uncertainty Avoidance →Trust	0,049	0,653	0,514
R^2 for BI = 0.852, R^2 for FM = 0.042, R^2 for TR = 0.084			

Table 5.17: Test of PLS path with bootstrapping Norway

Path	**(Path) Coefficients**	**T Statistics**	**P values**
Effort Expectancy→Behavior Intention	-0,026	0,771	0,441
Facilitating Conditions→Behavior Intention	0,018	0,544	0,586
Familiarity→Behavior Intention	-0,005	0,195	0,845
Familiarity→Trust	0,265	4,486	0,000
Familiarity x Long-Term Orientation→Behavior Intention	0,033	1,207	0,227
Familiarity x Masculinity→Behavior Intention	-0,031	0,947	0,343
Habit→Behavior Intention	0,323	6,745	0,000
Hedonic Motivation→Behavior Intention	0,147	2,792	0,005
Individualism→Familiarity	0,066	0,871	0,384
Individualism→Trust	0,134	1,628	0,104
Long-Term Orientation→Behavior Intention	0,001	0,033	0,974
Long-Term Orientation→Familiarity	0,068	0,784	0,433
Long-Term Orientation→Trust	0,020	0,240	0,810
Masculinity→Behavior Intention	0,079	2,020	0,043
Masculinity→Familiarity	0,058	0,566	0,572

Masculinity→Trust	0,090	0,847	0,397
Trust x Masculinity →Behavior Intention	-0,006	0,153	0,879
Power Distance→Familiarity	0,080	0,948	0,343
Power Distance→Trust	-0,035	0,480	0,631
Performance Expectancy→Behavior Intention	0,239	4,257	0,000
Perceived Value→Behavior Intention	0,321	5,494	0,000
Social Influence →Behavior Intention	0,028	0,773	0,439
Trust→Behavior Intention	-0,050	1,271	0,204
Trust x Long-Term Orientation →Behavior Intention	-0,079	2,375	0,018
Uncertainty Avoidance →Familiarity	-0,183	2,363	0,018
Uncertainty Avoidance →Trust	0,003	0,037	0,971
R^2 for BI = 0.859, R^2 for FM = 0.047, R^2 for TR = 0.100			

Table 5.18: Test of PLS path with bootstrapping Germany

Path	(Path) Coefficients	T Statistics	P values
Effort Expectancy→Behavior Intention	-0,082	1,294	0,196
Familiarity→Behavior Intention	-0,006	0,114	0,909
Familiarity→Trust	0,111	0,724	0,469
Facilitating Conditions→Behavior Intention	0,031	0,460	0,645
Familiarity x Long-Term Orientation→Behavior Intention	-0,037	0,580	0,562
Familiarity x Masculinity→Behavior Intention	0,031	0,503	0,615
Habit→Behavior Intention	0,795	12,291	0,000
Hedonic Motivation→Behavior Intention	0,144	1,906	0,057
Individualism→Familiarity	-0,146	0,743	0,457
Individualism→Trust	0,214	1,511	0,131
Long-Term Orientation→Behavior Intention	0,024	0,399	0,690
Long-Term Orientation→Familiarity	-0,092	0,576	0,565
Long-Term Orientation→Trust	-0,367	2,509	0,012
Masculinity→Behavior Intention	0,088	1,530	0,126
Masculinity→Familiarity	0,142	0,896	0,370
Masculinity→Trust	-0,154	0,838	0,402
Power Distance→Familiarity	0,101	0,601	0,548
Power Distance→Trust	0,197	0,870	0,385
Performance Expectancy→Behavior Intention	-0,025	0,291	0,771
Perceived Value→Behavior Intention	0,081	0,852	0,394
Social Influence →Behavior Intention	0,025	0,404	0,686
Trust→Behavior Intention	0,035	0,411	0,681
Trust x Long-Term Orientation →Behavior Intention	-0,042	0,687	0,492
Trust x Masculinity →Behavior Intention	0,086	1,180	0,238
Uncertainty Avoidance →Familiarity	-0,214	1,057	0,291
Uncertainty Avoidance →Trust	0,184	0,931	0,352

R^2 for BI = 0.933, R^2 for FM = 0.111, R^2 for TR = 0.187

Figure 5.6a: SmartPLS output: Structural model with path estimates (Individual result)

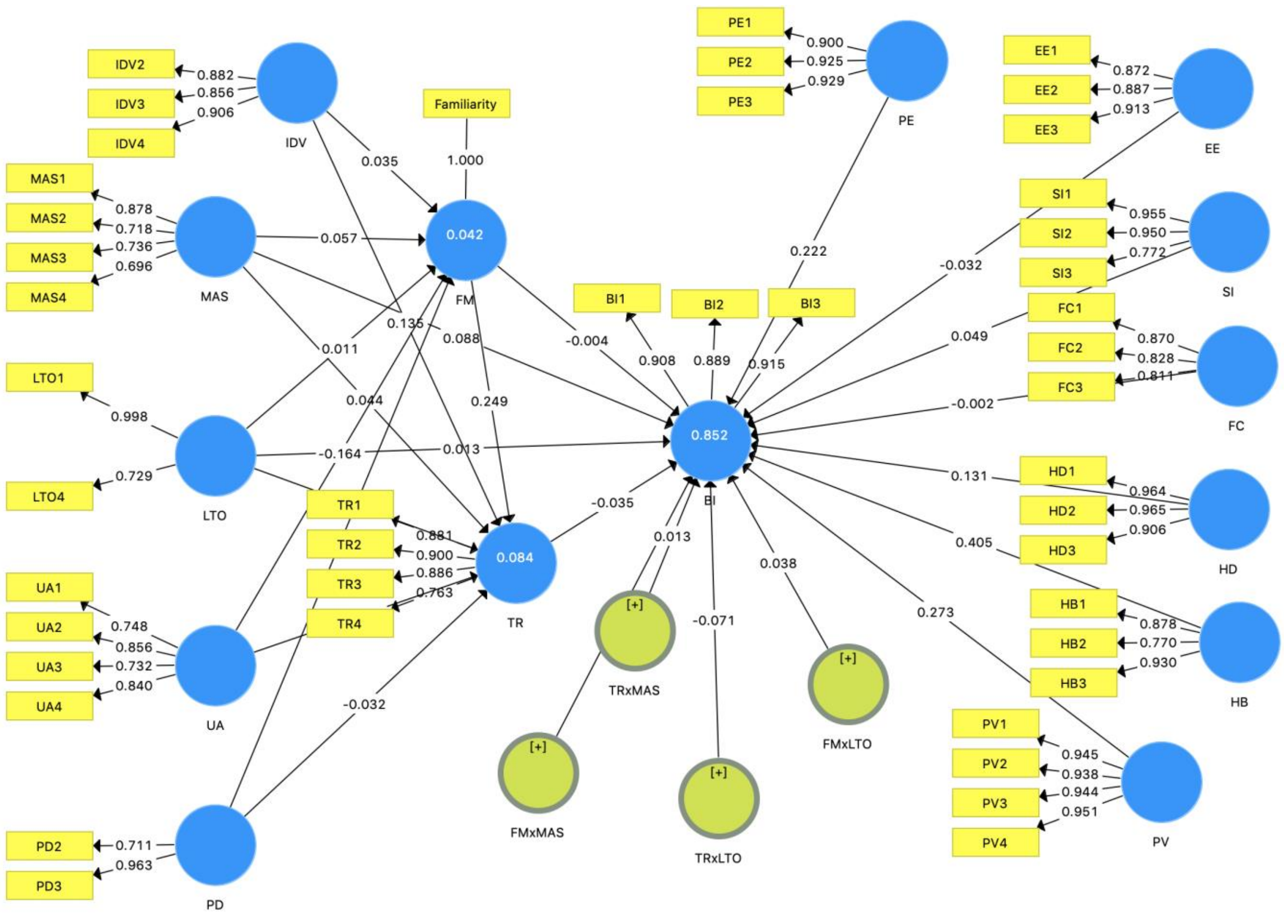


Figure 5.6b: SmartPLS output: Structural model with t-values (Individual result)

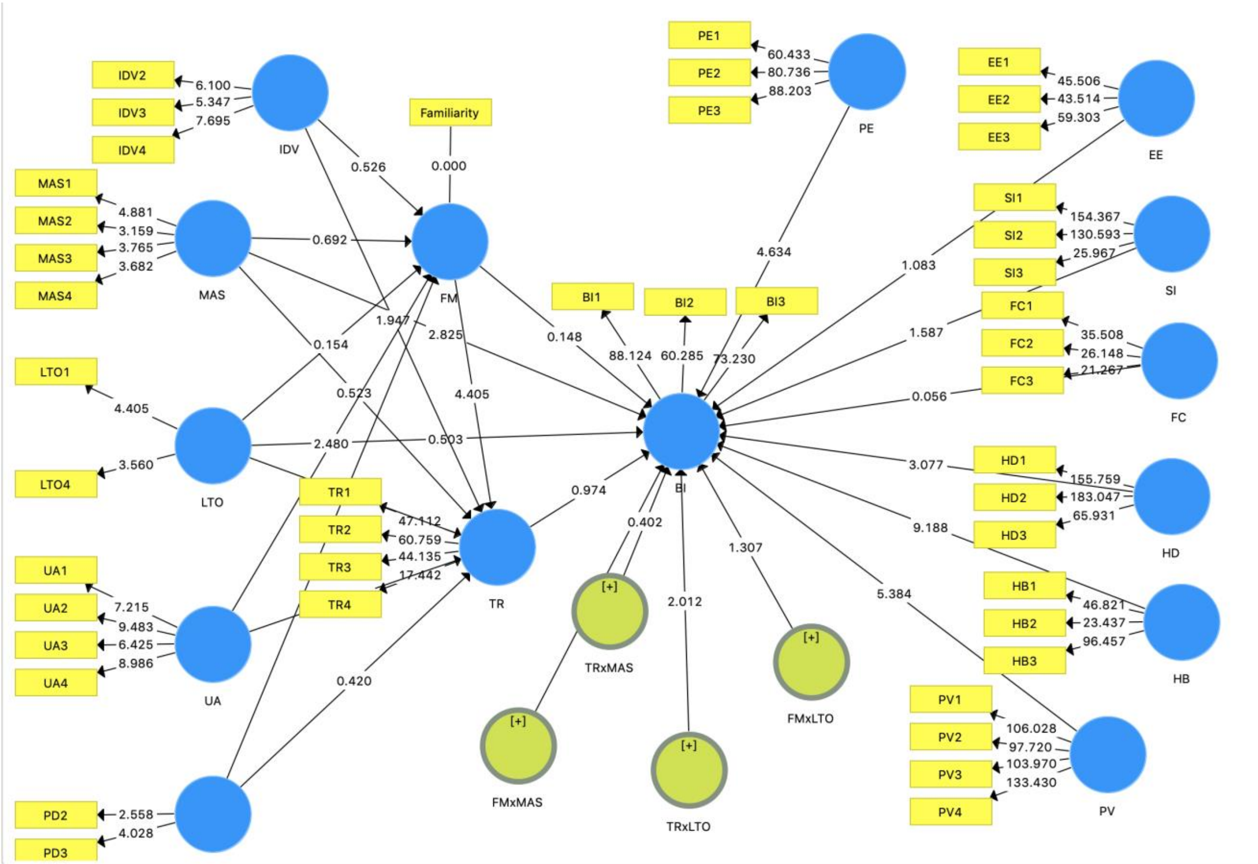


Figure 5.7a: SmartPLS output: Structural model with path estimates (Country-level: Norway)

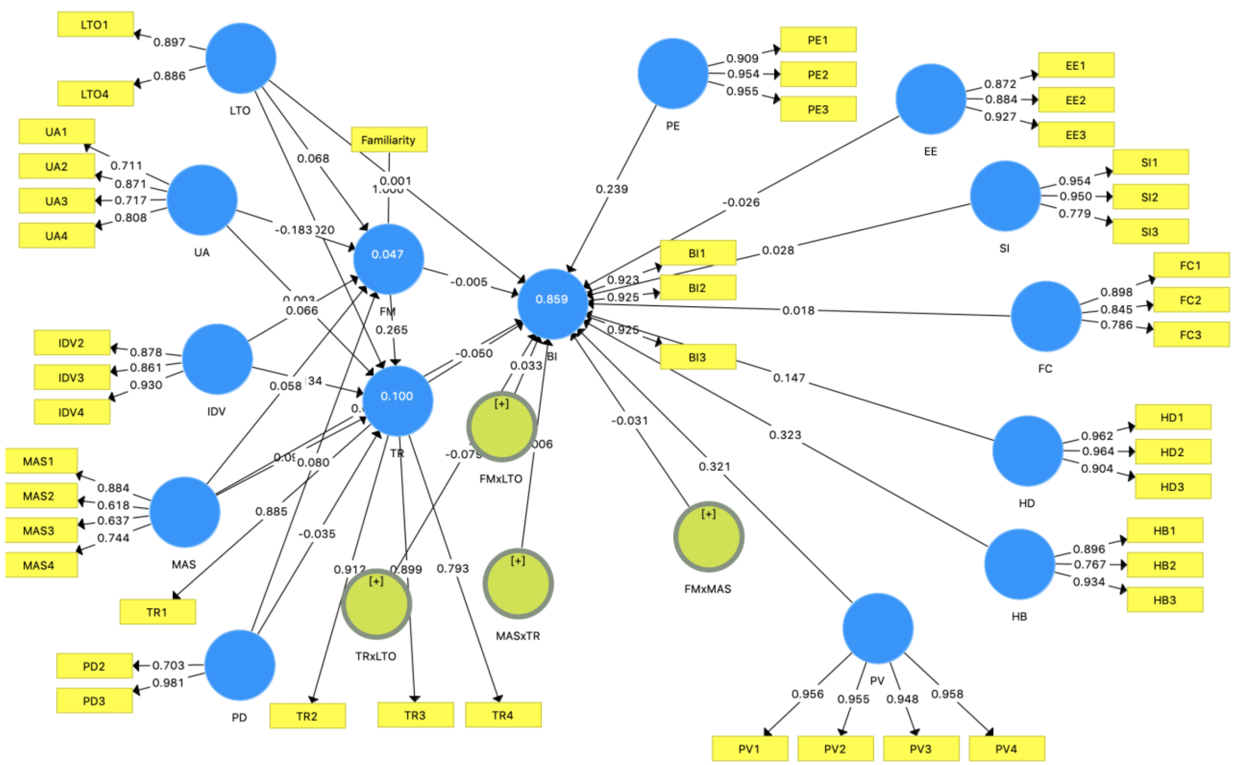


Figure 5.7b: SmartPLS output: Structural model with t-values (Country-level: Norway)

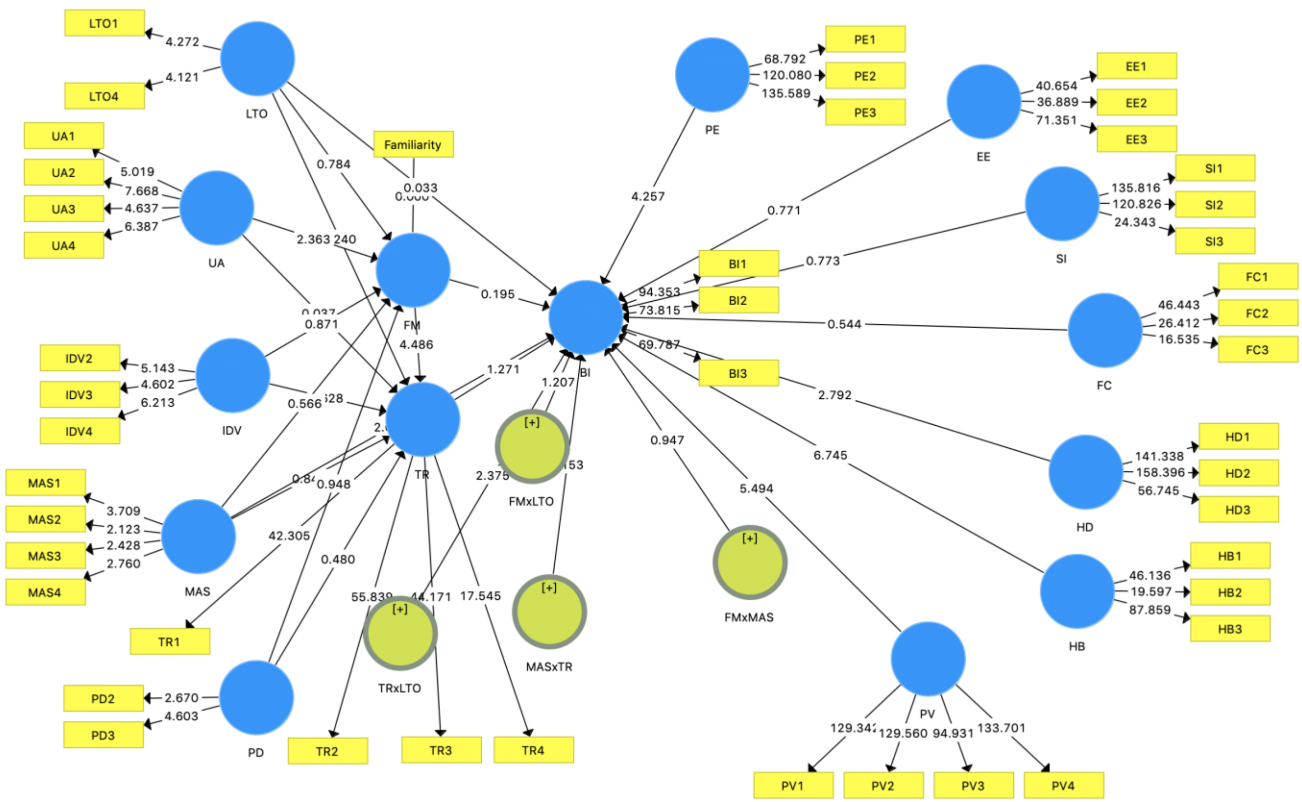


Figure 5.8a: SmartPLS output: Structural model with path estimates (Country-level: Germany)

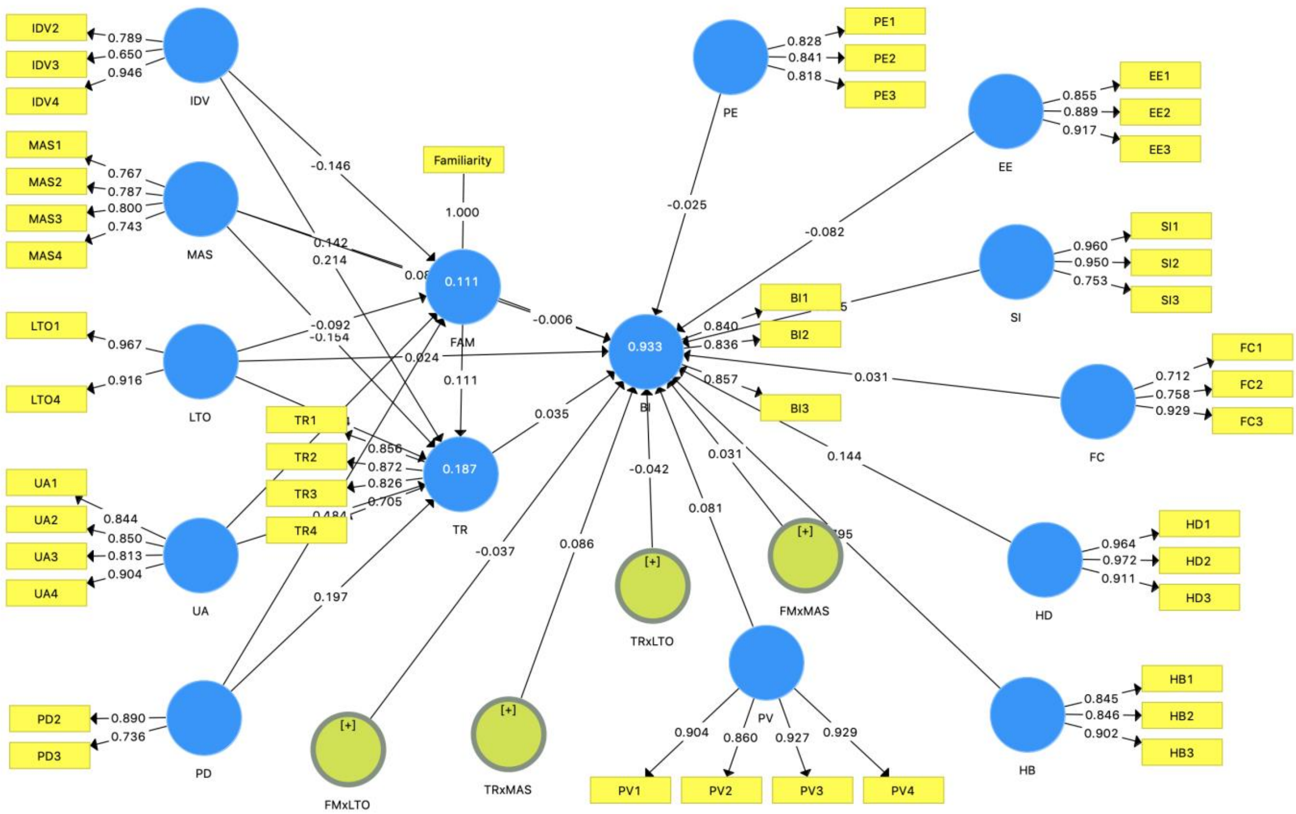
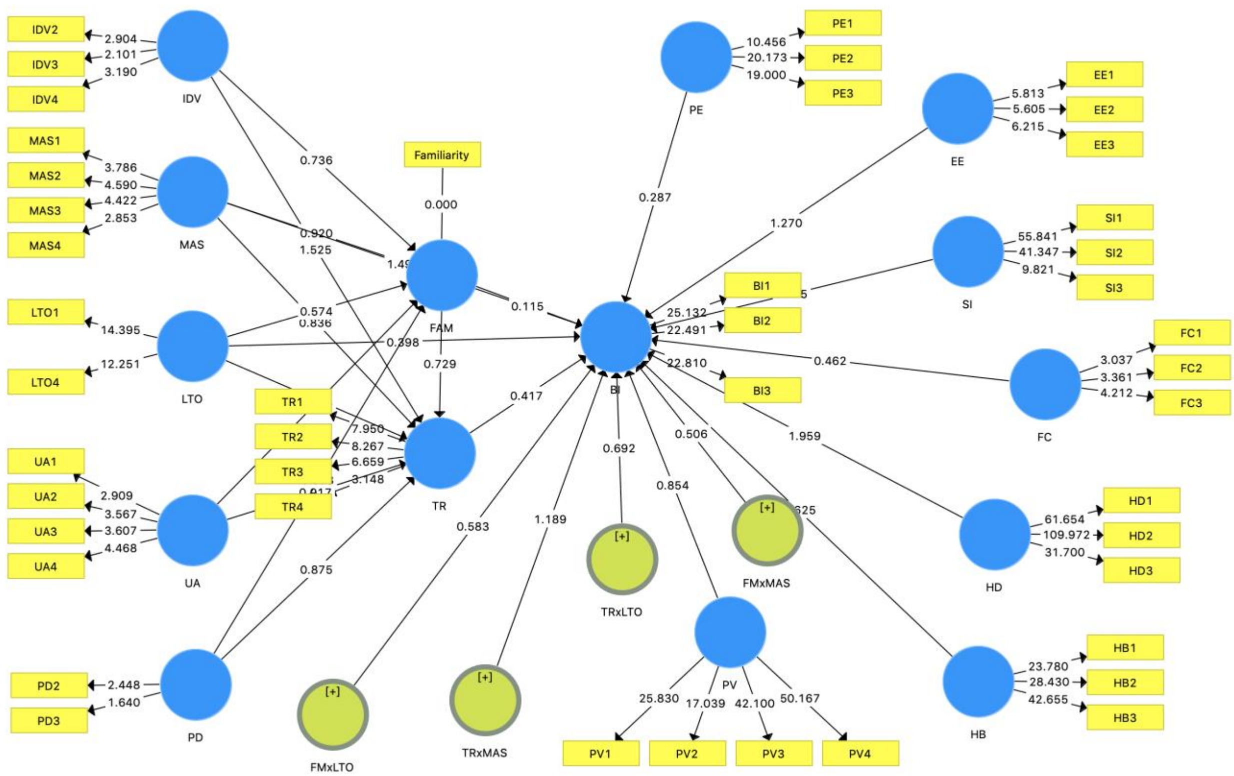


Figure 5.8b: SmartPLS output: Structural model with t-values (Country-level: Germany)



Simple Slope Analysis

Figure 5.9: Simple slope analysis (Individual-level)

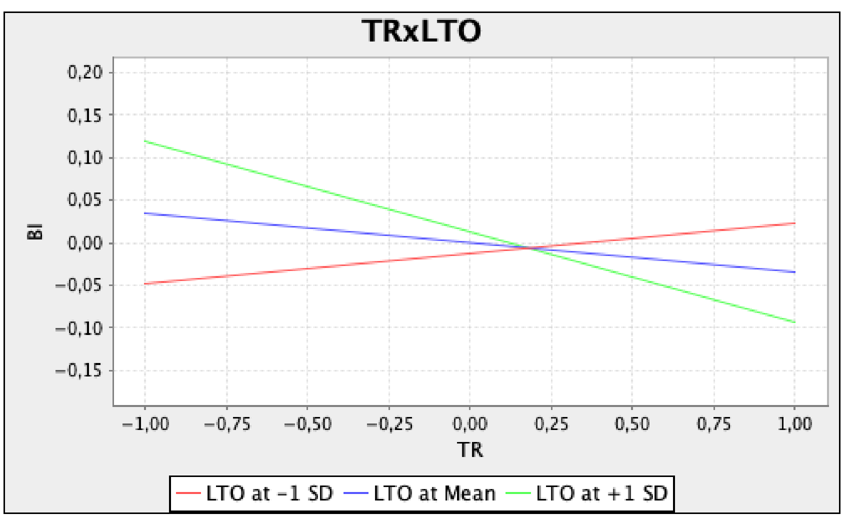
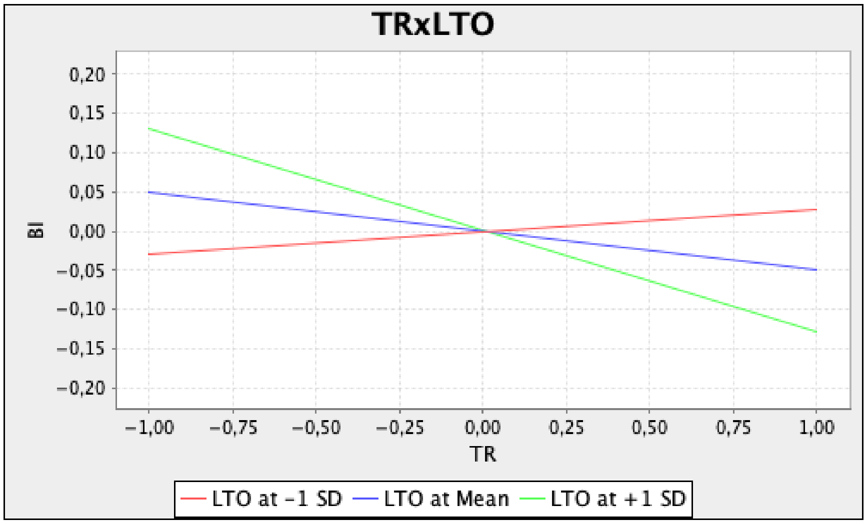


Figure 5.10: Simple slope analysis (Country-level: Norway)



Assessment of the R^2 level

Table 5.19: Coefficients of determination: Individual-level and Country-level

	Individual-level		**Country-level: Norway**		**Country-level: Germany**	
	R^2	R^2 Adjusted	R^2	R^2 Adjusted	R^2	R^2 Adjusted
BI	0,852	0,844	0,859	0,849	0,933	0,913
FM	0,042	0,026	0,047	0,025	0,111	0,036
TR	0,084	0,063	0,100	0,076	0,187	0,102

Assessment of the f^2 effect size

Table 5.20: Assessment of the f^2 effect size: Individual-level and Country-level

	Individual-level			**Country-level: Norway**			**Country-level: Germany**		
	BI	FM	TR	BI	TR	FM	BI	TR	FM
BI									
EE	0.004			0.002			0,048		
FM	0.000		0.065	0.000		0.075	0.000		0.013
FC	0.000			0.001			0.008		
FMxLTO	0.008			0.007			0.015		
FMxMAS	0.004			0.006			0.013		
HB	0.374			0.230			3.199		
HD	0.035			0.040			0.124		
IDV		0.001	0.019		0.004	0.019		0.022	0.050
LTO	0.001	0.000	0.005	0.000	0.004	0.000	0.006	0.008	0.131
MAS	0.049	0.003	0.002	0.041	0.003	0.008	0.080	0.014	0.017
PD		0.007	0.001		0.006	0.001		0.008	0.033
PE	0.103			0.115			0.003		
PV	0.111			0.149			0.022		
SI	0.009			0.003			0.005		
TR	0.004			0.007			0.007		
TRxLTO	0.032			0.044			0.023		
TRxMAS	0.001			0.000			0.058		
UA		0.025	0.002		0.030			0.048	

Fabio Alves Pena, Therese Hide

NTNU
Norwegian University of
Science and Technology