Stockholm School of Economics

MSc Thesis in Business and Management

The Impact of Network Externalities and Trust on User Adoption of Mobile Peer-to-Peer Payment Technologies

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Abstract

Mobile peer-to-peer payment technologies are receiving growing attention on a global scale, from consumers to banks, large tech companies, and startups, as an alternative payment method. They are one of the factors driving the cashless transformation with a potential global market value of over €900 billion. The potential of this new way of transferring money is immense, some researchers even see it as the trigger for a rearrangement of major players in the financial services ecosystem. This study aims to determine the main factors behind the user intention to adopt mobile peer-to-peer payment technologies. The authors extend the technology adoption model Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) by incorporating Network Externalities and Trust. Based on the model's constructs, hypotheses were formalized and empirically tested by collecting data through an online survey in Sweden (N = 545). Data was analyzed by applying the Structured Equation Modeling (SEM). The extended model proves to explain 62.8 % of the variation in behavioral intention to adopt mobile peer-to-peer payment technologies, with Network Externalities and Trust having a positive influence on the explanatory power of the model. The results further showed that Performance Expectancy, Effort Expectancy, and Habit have a significant and positive influence on behavioral intention. The study contributes to an advanced theoretical understanding of user behavioral intention to adopt technology and by providing practitioners with constructive guidelines for effectively designing, developing and marketing mobile peer-to-peer payment technologies that achieve high consumer acceptance. Additionally, discussion of the results and limitations of the study open up for suggestions for further research.

Keywords: user adoption of technology, UTAUT2, mobile peer-to-peer payment, network externalities, trust

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Definitions

Technology adoption	The stage in which a technology is selected for use by an individual or an organization.
Technology diffusion	The stage in which the technology spreads to general use and application.
Unified Theory of Acceptance and Use of Technology (UTAUT)	The UTAUT was formulated by Venkatesh et al. (2003) and is a unification of previous technology adoption models. It aims to explain user intentions to use a technology and subsequent usage behavior.
Peer-to-peer (P2P)	Peer-to-peer is a decentralized communications model in which each party has the same capabilities and either party can initiate a communication session.
Mobile device	A mobile device (or handheld computer) is a computing device small enough to hold and operate in the hand.
Mobile payment	Any payment that utilizes a mobile device to make a financial transaction in return for goods and services.
Mobile P2P payment	Financial transactions made from one mobile device to another mobile device through an intermediary which is referred to as the mobile peer-to-peer payment application.
Swish	Launched in 2012, Swish is a mobile peer-to-peer payment application owned by GetSwish AB, a joint venture between Sweden's largest banks.
Network externalities	Network externalities are present when the perceived value of the product or service increases as the number of users increase.
Trust	Trust reflects a willingness to be in vulnerability based on the positive expectation towards another party's future behavior.

Abbreviations

m-payment	mobile payment
m-commerce	mobile commerce
m-P2P	mobile peer-to-peer
NFC	Near Field Communication
PE	Performance Expectancy
EE	Effort Expectancy
SI	Social Influence
H	Habit
HM	Hedonic Motivation
NE	Network Externalities
NET	Network Externalities Theory
T	Trust
BI	Behavioral Intention
SEM	Structural Equation Model
CR	Construct Reliability
AVE	Average Variance Extracted

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1. Introduction

"Swish has pretty much killed cash for most people." - Niklas Arvidsson
(Professor, Royal Institute of Technology, Stockholm, specialising in payment systems innovation)

Mobile peer-to-peer payment technologies are on the rise. This new payment method has attracted the attention from some of the largest and most prominent organizations in the world. Significant investments are made to introduce new technologies that have the potential of disrupting how financial transactions occur. Yet, little is known of how consumers adopt and intend to use these technologies. The below section introduces the thesis, the subsequent theoretical and empirical problematization, and finally the aim, purpose, and contribution of this thesis.

Around 300 years ago paper money was introduced as legal tender. Since then the way consumers pay for goods and services has changed significantly. However, cash has so far resisted any major changes. A study conducted by MasterCard in 2013 revealed that cash still accounts for approximately 85 % of consumer transactions worldwide (Chakravorti & Chaturvedi, 2016). Only recently has the road toward a cashless society started to take shape with signs that cash is following the same road as other consumption products, by being replaced by digital solutions (Chakravorti & Chaturvedi, 2016).

A technology that plays a major role in driving the transformation towards a more cashless society is mobile peer-to-peer (m-P2P) payments. These applications are considered among the most disruptive innovations that the payment industry has seen in a decade (Windh, 2011). M-P2P transactions are electronic money transfers made from one person's mobile device to another person's through an intermediary m-P2P application.

M-P2P payments have opened new dimensions for daily transactions, from the casual splitting of a restaurant bill to international remittances of payments transferring funds cross-borders. M-P2P payments create increased customer efficiency, convenience, and accessibility (Windh, 2011). Furthermore, m-P2P payment is a more cost-effective method of financial transactions in comparison to traditional cash payments. Cash is an expensive instrument with high infrastructure, upkeep and usage costs. The total cost of cash in EU is approximately 1 % of GDP, and in the US over $200 billion is spent to keep cash in circulation (Piscini et al., 2015). Especially in the context of developing markets, it is predicted that opportunities will arise for m-P2P payments due to underdeveloped financial infrastructures and lower penetration of financial institutions. In Kenya, the m-P2P payment technology *M-Pesa* has significantly changed the financial eco-system, with 92% of all Kenyans having sent or received a m-P2P payment in 2015 (Zafar et al, 2016).

It comes as no surprise that m-P2P payment is believed to play a major role in financial transactions in the future. Some researchers even consider it as a trigger for the rearrangement of major players in the financial sector (Koenig-Lewis et al., 2015). M-P2P payments are estimated to have a CAGR of 45-50% between 2016-2018 and represents a potential global market value of €900 billion (Heggestuen, 2015). An example of m-P2P's potential is *WeChat*, a messaging application in China that has over 550 million active users and since they have activated a m-P2P payment feature it has been used by over 80% of the user base (Zafar et al., 2016).

The seemingly massive potential has made Social Media corporations, card networks, banks, and other payment companies eager to take part in this emerging market. Alongside the long-time dominant P2P payment platform PayPal, major players like MasterCard and Google have all introduced m-P2P payment solutions to the market. The Social Media giants Facebook and Snap (former Snapchat) have just recently launched a m-P2P payment application in the U.S. (Rosenberg, 2016). The European Central Bank (ECB) revealed that by the end of 2017 it will be possible for consumers to make m-P2P payments across European countries by only inputting the payee's mobile number (Boden, 2017). Both organizations and governments are investing heavily in payment technologies that have the potential of disrupting the financial transaction market. The expectations in m-P2P payments are high, yet these investments will not yield the intended results if diffusion rates of these technologies will be low (Sharma & Mieshra, 2014).

1.1. Problematization

According to a survey by Edgar Dunn & Company (2007), the mobile payment industry perceives consumer adoption as the greatest barrier to mobile payment diffusion. Product development and extensive marketing campaigns become irrelevant if the actual product or service is not being adopted by the intended user base. However, as research has revealed, technology adoption is not only related to the aspects of technology, but also includes much more complex processes such as hedonic motivation (Venkatesh et al., 2012), social influence (Ajzen & Fishbein, 2000) or habit (Limayem et al., 2007).

To understand consumer adoption behavior, theorists have set out to determine what drives users to adopt a technology. Research in the domain of *technology adoption* has evolved over time, resulting in the development of several theories and models (Sharma & Mieshra, 2014). However, current theories are inadequate in offering a satisfactory framework that explains the driving factors behind user adoption in the context of m-P2P payment technologies. Research that has been conducted has primarily been on *mobile payment*. While m-P2P payment can be considered as part of mobile payment, it differs greatly from other solutions in this category both in terms of the *nature of the transaction* and the *network architecture*. This, in turn, has significant impact on the intention why consumers use such a technology and for what purposes.

In terms of the *nature of the transaction*, the participating parties are almost always consumers while other mobile payment solutions are regular customer-to-business (C2B) offerings. Furthermore, with regards to the *network architecture*, m-P2P networks are closed (payer and payee need to have the same specific application), while other forms of mobile payments are open networks (e.g. mobile wallets can be used with a variety of different merchant payment terminals).

Therefore, the number of users in a m-P2P network directly influences the transaction possibilities and thereby the value of such a network. In this context, *network externalities* play a much more important role in m-P2P payment networks. Network externalities are present when the perceived value of a service or product increases as the number of users increases (Economides, 1996). Consequently, network externalities should influence users' decision to join such a network by adopting the m-P2P payment technology.

There is also reason to believe that *trust* plays a substantial role in the adoption of m-P2P payment solutions. Research in fields related to financial transactions has shown that trust plays an imperative role in the adoption and intention to use financial technologies (Slade et al, 2013). The uncertainties that are present in financial transactions due to the vulnerability to financial loss demand that the user has trust in the technology, service provider and counterparty (Gefen et al., 2003; Lu et al., 2011; Zhou, 2011). M-P2P payments add additional uncertainties to the financial transaction due to the potential spatial separation between sender and receiver as well as the sharing of personal information, i.e. mobile phone number (Grabner-Kräuter & Kaluscha, 2003).

1.2. Purpose, Aim & Contribution

The purpose and aim of this study are to determine to which degree different factors impact users' behavioral intention to adopt m-P2P payment technologies. The thesis further aims to establish a greater understanding of how relationships between independent variables and the dependent variable are moderated.

The contribution of this study is threefold:

1. Providing insight into the factors that lead users to adopt m-P2P payment applications by adjusting and extending an existing model to this specific context.
2. Contributing knowledge to the rather scarce field of consumer technology adoption.
3. Providing financial institutions, trusted third parties, payment service providers, systems and software providers as well as the vast amount of companies looking to enter this market with key insights into user adoption of this technology.

1.3. Research Question

This thesis aims to answer the research question:

- *What are the driving factors influencing users' behavioral intention to adopt m-P2P payment technologies?*

How are the relationships between the factors and the intention to adopt these technologies moderated?

1.4. Delimitations

The research field of user adoption of m-P2P payment technologies is in its infancy stage; therefore, an analysis of all relevant elements would be inexhaustible to be addressed in a research paper of this scope.

First, while there are many m-P2P payment applications worldwide, this study will focus on *Swish*. Therefore, this thesis is delimited due to its sample which consists of individuals in Sweden who use this specific application. This focus might limit the results to that of a Swedish context in regards to cultural background, values and technology knowledge. Additionally, this study will not go deep into the technical aspects that may also affect user adoption of m-P2P payment technologies (e.g. interface, speed) or other potential factors outside the technology model (e.g. competitors in the market). Finally, since the model is quite extensive, some factors must be omitted to account for the restricted time frame and scope of this study.

1.5. Research Outline

This study will be conducted through quantitative approach using a survey directed at Swish users in Sweden. A deductive approach is utilized to generate hypotheses derived from existing theories and models in the fields of technology adoption. Following the analysis of the survey, the results of each hypothesis testing will be presented. These results will further be discussed and theoretical contributions and practical implications derived. Finally, the study's main findings are connected to the overall aim of the thesis and the general conclusions are presented. The thesis is divided into the following chapters: (1) Introduction, (2) Theory, (3) Methodology, (4) Results & Analysis, (5) Discussion, and (6) Conclusions.

2. Theory

The theory chapter is mainly divided into two sections: (1) Literature Review and (2) Theoretical Framework and hypotheses generation. The literature review will present existing research on mobile payment and technology adoption in general. The research gap, based on the literature review, represents theoretical and empirical gaps in research. To fill this gap, a theoretical framework is created which is based on research related to the field of study. Derived from this framework, hypotheses will be created.

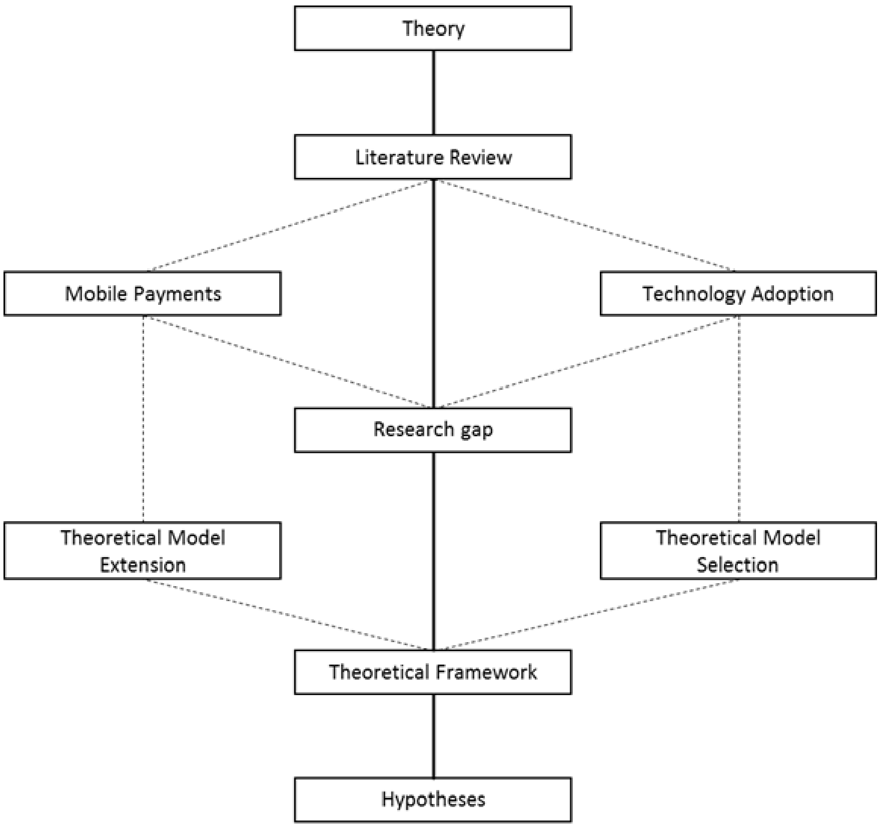

Figure 1. Visualization of Structure of Theory Chapter

2.1. Literature Review

2.1.1. Mobile Payments

Mobile payments (m-payments) are defined as any payment that utilizes a mobile device to make a financial transaction in return for goods and services (Au & Kauffman, 2007). Mobile devices, in turn, consist of mobile phones, wireless tablets and any other device that are connected to the mobile telecommunication network and have the possibility to make financial transactions (Karnouskos et al., 2004). M-payments can be split up into three main categories, (1) Near Field Communication (NFC), (2) m-commerce and (3) m-P2P (Kim et al., 2007).

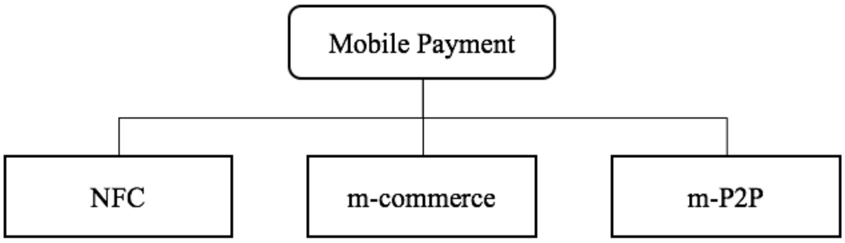

Figure 2. Categories of Mobile Payment

NFC utilizes a contactless smartcard (RFID), which allows mobile devices to perform close proximity payments when close to the RFID tag (Carr, 2007). NFC is mostly used when performing physical payments in stores and the more established applications are mobile wallets such as Apple Pay and Google Wallet. *M-commerce* refers to when customers purchase products through the internet using a mobile device (Carr, 2007). Payment information is stored on the mobile device and by entering a PIN-code the customer can complete their transactions. Both NFC and m-commerce technologies are used by the consumer-to-business payment segment in which counterparties are a consumer (the sender) and a company (the receiver). These payment networks are commonly known as a client-server networks (Hanson, 2000), in which the sender of the transaction is the client and the receiving end is the server, providing a product or service (Hanson, 2000).

The third type of mobile payment is *mobile peer-to-peer* (m-P2P). M-P2P payments are financial transactions made from one mobile device to another mobile device through an intermediary, which is referred to as the m-P2P application (Windh, 2011). This payment method differs substantially from NFC and m-commerce in both the *nature of the transaction* and the *network architecture*. In the context of m-P2P, the counterparties within the person-to-person network are most often consumers (C2C) (Windh, 2011). Therefore, the purposes of the transactions between these individuals are mainly of private nature, i.e. splitting of a bill or resale of a concert ticket. Only recently have small businesses (e.g. barbers) started to take advantage of this new payment method, accepting m-P2P payments. However, they still make up a small fraction in most m-P2P payment networks.

Finally, while there are different ways of how P2P networks are set up, they all share one key characteristic: networks are closed, each counterparty needs to have the same specific application (Bradford & Keeton, 2012). With NFC consumers can use their RFID tags to pay at various terminal while these terminals also accept different RFID tags. However, in the context of m-P2P a PayPal user is unable to transfer funds to a CashEdge user and vice versa.

2.1.1.1. Swish

Sweden is a country at the forefront of m-payment development, leading the migration toward a cashless society with over 80% of consumer transactions today occurring digitally (Sweden, 2016). According to the Swedish central bank, Riksbank (2016), cash transactions made up barely 2 % of all payments in 2016.

One of the main reasons for this trend is Sweden's m-P2P payment service provider *Getswish AB*, commonly referred to as 'Swish', a joint venture between Sweden's largest banks; Danske Bank, Handelsbanken, Länsförsäkringar, Nordea, SEB, Swedbank and Sparbankerna, Skandia, ICA Banken, Sparbanken Syd and Sparbanken Øresund. Through the joint venture, Swish can reach approximately 98 % of all bank customers in Sweden (Getswish AB, 2017). Swish allows users in the network to instantly transfer funds between accounts in all participating banks, in real-time, without any transaction fee. To be able to "swish", users need to be a customer of one of the participating banks, have a registered *Mobile BankID* and the application Swish installed on a mobile device. *Mobile BankID* is a secure user identification which relies on a smartphone app and is used for various financial services (i.e. logging into bank sites). To get a detailed overview of how Swish works, please refer to Appendix 1.

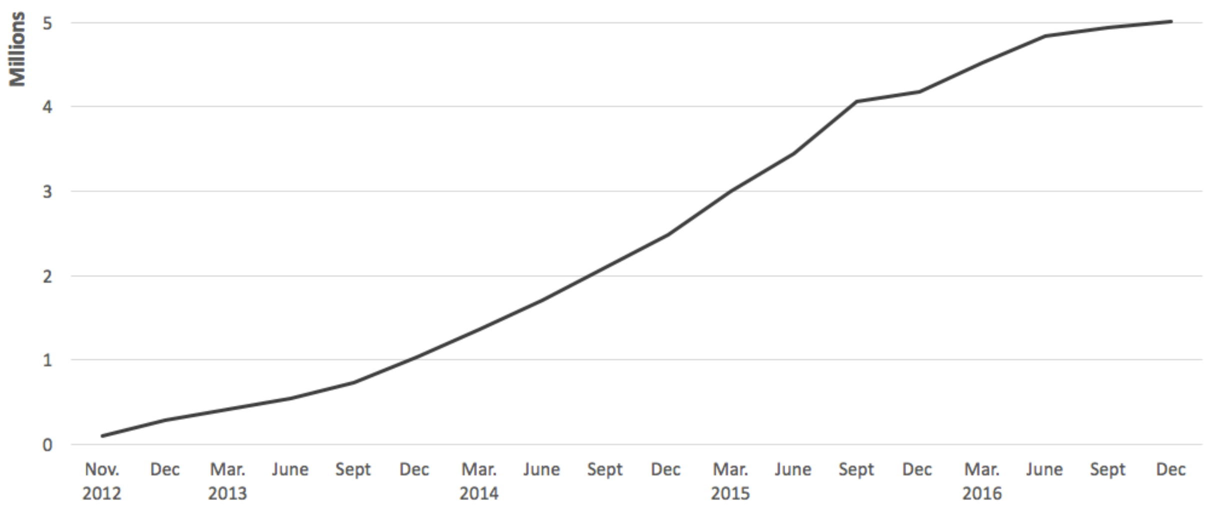

Figure 3. Swish Unique Private Users

The adoption of Swish has been rapid, with currently over five million registered users, a number that grew by roughly 100,000 each month during 2016 (Edlund, 2016). 59% of Swedes who have a smartphone are registered Swish users and sent over 5 million payments through Swish in January 2017 (Statista, 2017). Consequently, Swish is one of the most successful m-P2P payment technologies worldwide as of 2017. One can argue that Sweden and Swish set the stage for future developments in the world of cash free and m-P2P payments.

2.1.2. Technology Adoption

The success of Swish and its rapid adoption leads to the question how the company managed to reach so many users and make them adopt its technology. The following section is therefore dedicated to explaining the origin and development of technology adoption research.

Reviewing existing literature shows the interchangeable use of the terms *technology adoption* and *technology diffusion* even though research has revealed a clear difference between these two terms. Technology adoption generally refers to "the stage in which a technology is selected for use by an individual or an organization" (Carr, 1999) while technology diffusion describes “the stage in which the technology spreads to general use and application" (Rogers, 2003). Therefore, diffusion refers to adoption by the *masses*, while adoption is used at an *individual* level. While adoption generally leads to diffusion, this thesis analyzes the technology selection of individuals and will therefore only consider the evolution of research on *technology adoption*.

Technology adoption implies a two-step process where one first chooses a technology and then, after initial usage, mentally accepts or rejects that technology. Therefore, technology adoption is predicted by the “behavioral intention to use a technology in the future” (Venkatesh et al., 2003). How to ensure user adoption is a major challenge in the field of management (Schwarz & Chin, 2007). This is because interactions between users and technology are moderated by various factors, e.g. psychological aspects (Taiwo & Downe, 2013). However, due to the importance of identifying the driving factors behind the adoption of technologies, research on technology adoption and diffusion has been active for several decades and is among the most mature fields of exploration (Venkatesh et al., 2003). Since Roger’s *Diffusion of Innovation Theory* (1962) research on technology adoption and diffusion has evolved by conceptualizing new factors that can better explain the phenomena of technology adoption. This process of theory evolution has been primarily driven by rapidly changing technologies and has led to new factors which are derived from theories from other fields of research (Sharma & Mieshra, 2014).

The beginning of technology adoption models marks a model called *Theory of Reasoned Action* (TRA) (Fishbein & Ajzen, 1975). According to the model, an individual’s actual behavior is determined by his or her behavioral intentions. Behavioral intentions, in turn, are influenced by the individual’s attitude towards a certain situation as well as so-called subjective norms. Subjective norms are determined by influencers in the user’s social environment who suggest or not suggest to adopt a technology (Fishbein & Ajzen, 1975). Therefore, the model connects individual attitudes and subjective norms with behavioral intentions, thereby enabling the prediction of actual behavior.

Fred Davis (1989) built on the TRA and developed the *Technology Acceptance Model* (TAM) as an extension to the more general TRA. The TAM aims to predict technology usage by determining constructs that influence user's acceptance or rejection of a certain technology (Davis, 1989). While the TAM in contrast to the TRA incorporates technological aspects, it omits subjective norms from the model. Researchers have criticized this since the model is quite simplistic and does not consider other factors that could influence individual's decision to adopt a technology (e.g. Taylor & Todd, 1995; Bagozzi, 2007). However, the literature in general regards the TAM as a highly predictive model which can be applied to various contexts (e.g. Adams, 1992; King & He, 2006). Theorists largely agree that TAM offers an important theoretical contribution toward understanding the usage and acceptance behavior in the field of technology (Malhotra & Galletta, 1999). As a result, TAM is the most widely utilized theory in adoption research with 28 of the 56 quantitative studies within the m-commerce, m-banking and m-payment context studied using the theory (King & He, 2006).

Since its conceptualization in 1989, the TAM has been extended on by Venkatesh & Davis (2000) to include additional key determinants of TAM's perceived usefulness and usage intention construction. The so-called TAM2 incorporates *social influence processes* such as TRA's subjective norms as well as *cognitive instrumental processes* such as perceived ease of use (Venkatesh & Davis, 2000). Furthermore, the authors added the two moderating variables experience and voluntariness.

In contrast to the TAM and TRA which regard relationships between variables as one-sided, the *Social Cognitive Theory (SCT)* conceptualized by Albert Bandura (1989) in the same year as the TAM assumes that there are mutual interferences between factors related to the individual's surrounding, personality, and behavior. A central construct in the SCT is the concept of the Self-Efficacy Theory (SET) which is defined as "the judgment of one's ability to use a technology to accomplish a particular job or task" (Compeau & Higgins, 1995). According to the SET, individuals' actions, social behaviors and cognitive processes are influenced by expectations of outcome related to personal and performance-related gains as well as by actions that individuals have observed in their social environment (Bandura, 1989).

Ajzen (1991) extended the TRA and conceptualized the *Theory of Planned Behavior* (TPB). He set out to improve the previous models by incorporating the construct of *Perceived Behavior Control* (PBC), which describes the "perceived ease of use" (Ajzen, 1991) of an individual with regards to performing a specific behavior. The PBC was originally derived from the SET construct which is also a central element in the SCT. Furthermore, Ajzen's (1991) model was developed to analyze mandatory situations in which individuals adopt technologies, while the TRA is mainly used to analyze voluntary situations. Researchers largely agree that the TPB is superior compared to the TRA in predicting behavior (e.g. Guo et al., 2006).

Thompson et al.'s (1991) *Model of PC Utilization* is based on the *Theory of Human Behavior* (THB) by Trandis (1977) which constitutes an alternative model to the TPB and TRA. The authors differentiate between cognitive and affective factors which influence individual's attitudes. According to the Thompson et al. (1991), adoption behavior is influenced "by what people would like to do (attitudes), what they think they should do (social norms), what they have usually done (habits), and by the expected consequences of their behavior". As indicated by its name, this model mainly focuses on worker's utilization of computers in a voluntary context.

Davis et al. (1992) developed the *Motivation Model* to analyze technology adoption and use. The main premise of the model is that intrinsic as well as extrinsic motivation influence behavior. *Extrinsic motivation* is present when an individual performs a certain activity because of external rewards such as a promotion or an increase in salary. The authors defined perceived ease of use, subjective norm and perceived usefulness as the constructs determining extrinsic motivation (Davis et al., 1992). *Intrinsic motivation* refers to behavior that is driven by internal rewards such as pleasure or satisfaction. In this context, individuals perform an action just for the purpose of performing it, without trying to gain something from it, e.g. enjoyment from using a technology.

The sheer amount of varying models in the research field of user adoption of technology has been enriching, but also confusing to researchers since it requires them to make a decision for one of the models or to choose constructs from competing models (Williams et al., 2015). As a response to this confusion, Venkatesh et al. (2003) conceptualized the *Unified Theory of Acceptance and Use of Technology (UTAUT).* The UTAUT was developed by systematically reviewing the constructs from all above mentioned individual models as well as the *Combined TAM and TPB* (C-TAM-TPB) (Taylor & Todd, 1995) and the *Innovation Diffusion Theory* (IDT) (Moore & Benbasat, 1991) and incorporating consistent factors into a unified model. In the process of developing this unification of models, the authors compiled and tested all constructs and determinants that were used in previous models and theories. According to Venkatesh et al. (2003), only four constructs (*performance expectancy*, *effort expectancy*, *social influence*, and *facilitating conditions*) out of the seven formerly used in earlier models passed the test and can be considered significant determinants of technology adoption. According to the authors, the remaining three determinants (*attitude*, *self-efficacy*, and *anxiety*) are not significant determinants due to them being mediating by *ease of use*, a factor that is already reflected in *effort expectancy* (Venkatesh et al., 2003). Furthermore, the authors incorporated the moderator *experience, age, gender*, and *voluntariness of use* which influence the relationship between the independent variables and the dependent variable *behavioral intention* (Venkatesh et al., 2003).

Empirically, UTAUT has proven to outperform the theories previously presented as it statistically explains more of the variance explained in usage intention by the other theories (Venkatesh et al., 2003). Consequently, the UTAUT has been extensively applied in technology adoption and diffusion research to analyze user intention and behavior (Venkatesh et al., 2012). A number of applications and reproductions have further underlined the model's generalizability (e.g., Neufeld et al., 2007). There have been examinations of UTAUT in new contexts such as mobile internet (Wang & Wang, 2010), new cultural settings (India) (Gupta et al., 2008) and new user populations (healthcare) (Yi et al. 2006). Furthermore, other constructs have been included in the model and others were omitted to account for specific contexts (e.g. Sun et al. 2012). With regards to payment technologies, the UTAUT has been extended and applied to the contexts of mobile payment (Slade et al., 2013; Yu, 2012), mobile banking (Zhou, 2011) and internet banking (Chen & Chen., 2009).

The UTAUT model, as well as the theories and models it unifies, were developed to predict adoption of the use of technology in an *organizational context*. Since consumer behavior differs greatly to employee behavior, Venkatesh et al. (2012) realized the need for an official extension to include factors in relation to consumer adoption processes and developed *UTAUT2*, the latest development in the research field of technology adoption.

The UTAUT2 is based on the main constructs from the UTAUT. The authors further added four new constructs (*hedonic motivation*, *price value*, and *habit*) to account for the consumer context and to improve the applicability of the model (Venkatesh et al., 2012). Furthermore, *voluntariness of use* was removed as a moderating variable since consumer behavior is voluntary in the first place (Venkatesh et al., 2012).

2.1.3. Research Gap

The literature review of existing research within the field of technology adoption and the specific nature of m-P2P payment technologies lead to two research gaps.

The main research gap is derived from a lack of existing research within the *context of m-P2P payment technology adoption*. To the best knowledge of the authors, no previous scientific empirical studies have been conducted in this context. While there have been studies on the adoption of mobile payment technologies (e.g. Mallat, 2007; Kim et al., 2007), this research field is still in its infancy (Linck et al., 2006). Researchers have therefore called for more empirical research in this field (Dahlberg et al., 2008). Schierz et al. (2010) go so far as to say that "it is obvious that there is a research gap in regards to a lack of hypothesis-testing studies on mobile payment acceptance". Furthermore, existing research on m-payment is only to some extent applicable for m-P2P technologies. As pointed out earlier, m-P2P payment technologies differ vastly from other m-payment technologies. One can argue that the different network architecture and counterparties involved significantly influence the context in which such a technology is used and thereby the driving factors behind the user intention to adopt it. However, no research has been conducted to prove this argumentation.

Secondly, most research has focused on the organizational context of employee adoption of technologies. Researchers largely agree that there is a need to expand the theoretical knowledge in the research field of technology adoption to other contexts (e.g. Bagozzi 2007; Venkatesh et al. 2012). Specifically, researchers generally agree that the study of adoption determinants in the *consumer* context is incomplete and limited and therefore represents an opportunity to make an important theoretical contribution (e.g. Venkatesh et al. 2012; Kishore & Sequeira, 2016). Due to the variance between the organizational and consumer context with regards to the individual's behavioral intention towards adopting a technology, factors that influence this intention in one context might become redundant in the other while other factors could play a more significant role.

In conclusion, existing research lacks empirical studies in the field of consumer technology adoption and more specifically does not offer a satisfactory framework explaining the driving factors behind the user adoption of m-P2P payment technologies. When considering the development of m-P2P payment technologies mentioned in the introduction these limitations hamper the further understanding and development of a multi-billion-dollar industry.

2.1.4. Theoretical Model Selection

Taking into considerations above-examined models on user adoption of technologies, the TAM and UTAUT2 provide the best theoretical foundation for analyzing the adoption of m-P2P payment systems (Shin, 2009). TAM and UTAUT2 go beyond the technology aspect and focus on individual and social factors that influence consumer decisions, while other frameworks focus on different levels of analysis and thus show a relatively limited scope for analysis and discussion (Koenig-Lewis et al., 2015).

The TAM has been the most widely used model for the analysis of user adoption of mobile payments (Slade et al., 2013). However, even though the TAM has been proven as a valid and reliable model for analyzing user technology adoption, it has been criticised for being very generalistic on individuals' opinions of novel technologies (which is the case for m-P2P payment technologies), for not considering users' individual characteristics enough, and for presuming that usage is volitional without constraints (Slade et al., 2013). Chuttur (2009) criticized that TAM has a limited explanatory power, a weak predictive power and lacks practical value. According to Benbasat & Barki (2007), the focus is now shifting away from TAM to UTAUT, which is due to TAM's rather static structure and its limitations in the fast-changing technology environment. Thus, the TAM is quite inaccurate to predict behavioral intention with regards to novel technologies.

On the other hand, the UTAUT constitutes a suitable substitute model for TAM since it neutralizes TAM's inaccurate side, i.e. the lacking future prediction. Venkatesh et al. (2003) compared the UTAUT to the models it unifies and concluded that the UTAUT is superior as it can explain 44 % of the variance while the other models were only able to explain 30-40 % variance in behavior intention (Venkatesh et al. 2003). However, as Bagozzi (2007) criticized, the model has an extensive number of independent variables, making it bloated and overly complex. Despite this deficit, empirical studies consistently show that the UTAUT is more reliable than other technology adoption models in analyzing the determinants of behavioral intention and technology adoption (Venkatesh et al. 2003; Park et al. 2007; Nysveen & Pedersen 2014).

The UTAUT2 extension proved to be even more precise in its analysis compared to the original model, consistently explaining more than 50 % of the variance in technology adoption (Venkatesh et al., 2012). Consequently, researchers in the field of m-payment regard the UTAUT2 as the best theoretical framework for analysis (Alalwan et al., 2017).

Due to its proven superiority over competing models and its focus on the consumer context, the UTAUT2 is the most suitable theoretical foundation for this study. Furthermore, while some models within the technology adoption context have reached a certain level of maturity, this is not the case for the just recently conceptualized UTAUT2. This calls for further generalizability studies as well as validations of the model's explanatory power.

2.1.5. Theoretical Model Extension

While UTAUT2 covers most variables needed to provide an understanding of behavioral intention, results of its application have shown that the relative importance of its constructs are not consistent since they are very much depended on the context. This makes it important for researchers to only pick the constructs that are valid for the context to which the model is applied to (Venkatesh et al., 2012; Attuquayefio & Add, 2014). Several constructs used within the context of m-P2P payment technologies can be related to UTAUT2's constructs, other critical factors in consumer adoption of m-P2P payment technologies are not represented in the UTAUT2. Consequently, in the following, the UTAUT2 model will be adjusted to the specific context of m-P2P payment technologies by selecting and incorporating new, relevant constructs into the model.

2.1.5.1. Network Externalities

Economists created the network externality theory (NET) to explain telecommunication adoption in the 1970's (Rohlfs, 1974), since then it has been used by economists to model many organizational technology adoption decisions (Economides, 1996). According to NET, *Network Externalities* (NE) are present when the perceived value of a service or product increases as the number of people using it increases (Economides, 1996). The causal process describes the effect; once more users adopt a technology, its value increases exponentially which in turn encourages other users to adopt it. This creates a circle which causes a fast adoption process; potentially leading to a market in which one company or product dominates (Song & Walden, 2003). Research on NE has focused on two types of externalities - direct and indirect. *Direct externalities* are present if the number of users of a service or product is positively correlated with the value of that product (e.g. telephone network) (Henkel & Block, 2008). If the value of the product is influenced by the diffusion of complementary products or services, *indirect network externalities* occur (e.g. Apple and the apps of its App Store) (Katz & Shapiro, 1992). In the context of m-P2P payments, one can argue that small businesses accepting this payment method act as complementary services since they increase the transaction possibilities with C2B offerings, but are not actively taking part in the network by making transactions to the customer.

To the best knowledge of the authors, the NET has not been tested in the context of m-P2P payment technologies. However, previous research indicates that it might play a significant role. NET has been widely used to explain technology adoption (e.g. Parthasarathy & Bhattacherjee, 1998) and adoption of mobile payment in general (Dahlberg & Mallat, 2002; Mallat, 2007) and P2P technologies in particular (e.g. Asvanund et al., 2004).

According to Song & Walden (2007), NE are proportionally more important for P2P technologies than other technologies since the number of users is the central means of usefulness in a P2P network, and thus it is expected to be impacting the intention to adopt. If a P2P technology shows great performance but does not have users in its network, prospective customers should be quite reluctant to adopt the technology. Therefore, while network effects can help a network gain momentum once it reaches a certain critical mass of users, they can make it difficult to attract early adopters when only a few users are on it. This is particularly the case for payment technologies, which exhibit indirect network externalities (Van Hove, 1999). The failure to reach critical mass had an impact on the continuance of previous payment systems (Szmigin & Bourne, 1999; Van Hove, 1999). Furthermore, Wang et al. (2008) state that it is widely agreed that mobile services, in general, are subject to network externality effects.

Consequently, NE has been included as another external factor in the UTAUT2 extension.

2.1.5.2. Trust

According to Mayer et al. (1995), who integrated the shared characteristics of *Trust* across different disciplines, "trust reflects a willingness to be in vulnerability based on the positive expectation toward another party's future behavior". Therefore, *Trust* can be operationalized as the accumulation of user beliefs of integrity, benevolence, and ability that enhances user willingness to use a technology for a financial transaction (Gefen et al., 2003). In the specific context of m-P2P payment, *Trust* is a combination of trust in the service provider, the technology itself and the counterparty. Since m-P2P payment is financial technology and users are vulnerable to monetary loss (Lu et al., 2011), *Trust* in the service provider that guarantees the value of money is essential to the acceptance of a P2P technology.

Furthermore, the importance of *Trust* is highlighted in m-P2P payments because of the potential temporal and spatial separation between the sender and the receiver which requires receivers to share personal information (e.g. mobile phone number) to the senders (Grabner-Kräuter &

Kaluscha, 2003). In combination with the circumstance that transactions are conducted electronically (Zhou, 2011), *Trust* plays an important role due to the high degree of risk and uncertainties involved. Research showed that users' concerns about the security and privacy of mobile payments are mainly related to confidentiality and authentication issues as well as unauthorized access to user data (Dewan & Chen, 2005).

While no study has been conducted on m-P2P payments, *Trust* has been extensively examined and proven to be a major determinant in predicting users' behavioral intention toward m-commerce transactions (Gefen et al., 2003; Xu & Gutierrez, 2006), mobile banking (Luo et al., 2010; Zhou, 2011; Alalwan et al., 2014), and mobile payment (Zhou, 2011; Lu et al., 2011). In total, the construct *Trust* has been found to be a significant predictor in seventeen studies in the m-commerce, m-banking and m-payment context (Slade et al., 2013). In some of these studies, *Trust* even turned out to be the strongest predictor (e.g. Zhou, 2011; Shin, 2012). Furthermore, research indicates that *Trust* not only influences users' intention to adopt m-P2P payment technologies but also their use continuity (Slade et al., 2014) and their customer loyalty and satisfaction (Lin & Wang, 2006).

Concluding, *Trust* seems to be an important determinant in predicting of technology adoption (Gefen, 1997; Yang et al. 2012), a major factor in the adoption of financial services (Arvidsson, 2014) as well as essential in the field of m-P2P payment as it creates a positive usefulness perception in users' mind towards m-P2P payment technologies (Zhou, 2011). Considering this, *Trust* has been included as an external factor to the UTAUT2 in the same conceptual model as recommended by Venkatesh et al. (2012).

2.1.5.3. Omitted Factors

Facilitating Conditions (FC) refer to "users' perceptions of the resources and support available to perform a behavior" (Venkatesh et al., 2003). When a user has access to FC that are favorable for him, this, in turn, will most likely have a positive influence on his intention to adopt a technology (Venkatesh et al., 2012). In the context of m-P2P payment technologies, users have different resources accessible that could facilitate usage, e.g. support by a bank. Furthermore, depending on smartphone, operating system and internet speed, these facilitating conditions could be influenced. However, as Venkatesh et al. (2003) point out, when both EE and PE constructs are present, FC becomes non-significant in predicting intention. When both EE and PE are favorable for the user, FC is most likely favorable for him or her and vice versa. Dass & Pal (2011) and Peng et al. (2011) come to the same conclusion that FC is insignificant when analyzing mobile payment acceptance. Consequently, FC was excluded from the model.

Price Value (PV) is defined as "consumers' cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them" (Dodds et al. 1991). PV of a technology impacts intention positively if the benefits of using it are perceived to be outweighing the costs related to it (Venkatesh et al., 2012). However, this construct is less applicable in the context of m-P2P payment technologies which usually cause no or very little financial costs to users. This is especially the case for Swish which does not charge a fee for using its service, which is why the construct was excluded from the model.

The moderator *Experience* "reflects an opportunity to use a target technology and is typically operationalized as the passage of time from the initial use of a technology by an individual" (Venkatesh et al., 2012). In other words, experience increases with the time that has passed since the first usage of a technology. Venkatesh et al. (2003) defined levels based on how much time has passed: initial use of technology, one month later; and three months later. Experience is related to the construct *Habit* in the UTAUT2 since experience is a "necessary, but not sufficient condition for the formation of *Habit"* (Venkatesh et al., 2012). Furthermore, experience can form different levels of *Habit* depending on the degree of interaction that the user developed with the technology in terms of use frequency, usage time, etc. However, use behavior is not integrated into the moderator *Experience* which only reflects time passed since initial use. This led Limayem et al. (2007) to include *Prior Use* as a predictor for *Habit*. Therefore, prior experience is already reflected in the construct *Habit*, but with a focus on behavioral intention and not time since initial use, which is far more applicable in the context of this study. Many researchers have followed this train of thought and disregarded the moderator *Experience* from their extensions of UTAUT2 (Huang & Kao, 2015; Alalwan et al., 2017). Following this reasoning, the authors have decided to exclude this moderator from the model.

Furthermore, previous literature on technology adoption has largely and repetitively proven that *Behavioral Intention* has a strong, significant influence in shaping the actual *Use Behavior* of users (Ajzen, 1991; Venkatesh et al., 2003; Venkatesh et al., 2012). Finally, the psychological aspects of the relationship between BI and UB are not of greater interest due to the managerial scope of this thesis. Consequently, to keep a focus on relevant aspects, *Usage Behavior* was omitted from the model.

2.2. Theoretical Framework & Hypothesis Generation

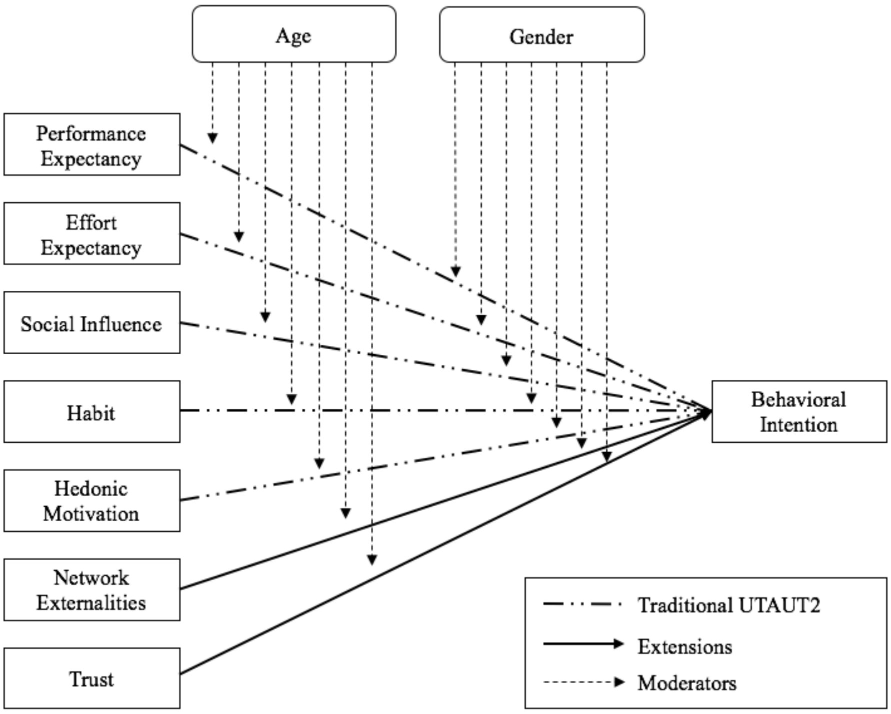

Figure 4. Theoretical Framework

Construct	Definition	Paper
Performance Expectancy	The degree to which using a technology will provide benefits to consumers in performing certain activities.	Venkatesh et al. (2012)
Effort Expectancy	The degree of ease associated with consumers' use of technology.	Venkatesh & Brown (2001) as cited in Venkatesh et al. (2011)
Social Influence	The extent to which an individual perceives that important others believe he or she should use a new system.	Fishbein and Ajzen (1975)
Habit	The extent to which people tend to perform behaviors automatically because of learning.	Limayem et al. (2007)
Hedonic Motivation	The fun or pleasure derived from using a technology.	Venkatesh & Brown (2005)
Behavioral Intention	The degree to which an user has formulated conscious plans to perform or not perform some specified future behavior.	Verplanken & Knippenberg (1998) as cited in Venkatesh et al. (2012)
Network Externalities	The concept that a product's value to a consumer changes as the number of users of the product changes.	Economides (1996)
Trust	The accumulation of user beliefs of integrity, benevolence and ability that enhances user willingness to use a technology for a financial transaction.	Zmijewska et al. (2004)

Table 1. Constructs of Theoretical Framework and Sources

2.2.1. Performance Expectancy and Behavioral Intention

Performance Expectancy (PE) can be defined as "the degree to which using a technology will provide benefits to consumers in performing certain activities" (Venkatesh et al., 2012). Five constructs that are derived from different technology adoption models make up the PE construct; perceived usefulness (TAM & C-TAM-TPB), extrinsic motivation (MM), relative advantage (IDT), job-fit (MPCU), and outcome expectations (SCT). *Behavioral Intention* (BI) on the other side is defined as an individual's perceived likelihood of performing a given action.

Adapting PE to a m-P2P payment context implies that users think a m-P2P payment technology is beneficial because it enables them to accomplish payments faster and with more flexibility. Researchers in the field of m-payment adoption largely agree that if users perceive using mobile payment as beneficial, they will have a stronger tendency to adopt the m-payment technology, making the relationship between PE and BI a significant one (Luo et al., 2010; Wang & Yi, 2012; Yu, 2012).

It is expected that users compare the expected advantage of using m-P2P payment technologies to current payment methods when deciding to adopt such a technology. m-P2P technologies have some distinct competitive advantages when it comes to aspects related to its functional utilities and possible improvements for the performance of users. Compared to mobile bank transfers, transfers through m-P2P payments occur in real time and the funds are directly accessible by the counterparty. Furthermore, both the payer and payee receive an immediate confirmation of the transfer. In comparison with traditional cash payments, m-P2P payments allow for spatial distance to the counterparty, thereby increasing convenience significantly. Additionally, the risk of loss and theft is reduced since cyber theft occurs less often than physical theft (Linck et al., 2006).

Furthermore, a survey conducted by Swish in Sweden revealed that 79 % use the technology since "it is fast", indicating that using the m-P2P payment technology provides a benefit in transferring money (Edlund, 2016). Therefore, this study articulates the following hypothesis:

Hypothesis 1a: Performance Expectancy will have a positive effect on Behavioral Intention to adopt m-P2P payment.

In previous studies, age and gender have been theorized and proven to be moderating the relationship between PE and BI (Venkatesh & Morris, 2000; Venkatesh et al., 2003). Results of studies on gender differences indicate that men are more task-oriented and since PE is related to how well tasks are performed, it is likely to be a stronger predictor for men (Venkatesh et al., 2003; Wang & Wang, 2010; Slade et al., 2013). Like gender, age is commonly theorized to have a moderating effect on PE (Venkatesh & Morris, 2000; Venkatesh et al., 2003; Venkatesh et al., 2012). According to Venkatesh et al. (2003), younger users have a higher interest in a performance increase compared to older users. Thus, this study assumes the following hypotheses:

Hypothesis 1b: The influence of Performance Expectancy on Behavioral Intention to adopt m-P2P payment will be moderated by gender, such that the effect will be stronger for male users.

Hypothesis 1c: The influence of Performance Expectancy on Behavioral Intention to adopt m-P2P payment will be moderated by age, such that the effect will be stronger for younger users.

2.2.2. Effort Expectancy and Behavioral Intention

Effort Expectancy (EE) is defined as "the degree of ease associated with consumers' use of technology" (Venkatesh et al., 2012). EE captures three constructs from previous models: perceived ease of use (TAM), ease of use (IT), and complexity (MPCU) (Venkatesh et al., 2003). Due to the particular nature of m-P2P payments, which requires a certain level of knowledge and skill, it is thought that users' adoption of m-P2P payment technologies will depend on whether or not the usage of it is easy and effortless. Therefore, users' intention to accept a new m-P2P technology is not only predicted by the value of such a technology, but also by how easy it is to use.

Similar to PE, it is expected that users compare the perceived advantages of using m-P2P payments with alternative payment methods like cash or mobile bank transfers when adopting such a technology. In terms of cash, users must ensure the availability when having to make a personal transfer to a counterparty. Furthermore, if the counterparty is unable to give change, the payer must provide the right amount of cash, further complicating the situation.

Additionally, the process of a mobile bank transfer involves far more process steps compared to m-P2P payments. The payer first needs to log into the mobile bank account and then enter the payee's full name, bank account number (or IBAN), amount and reference. Furthermore, since mobile bank accounts offer various services, they most often suffer in terms of their interfaces. M-P2P payment technologies such as Swish, however, offer only one service, making the interface well-arranged, user-friendly and thereby easy to use.

Several studies in related fields such as online banking (e.g. Alalwan et al., 2014) or mobile banking (Luarn & Lin, 2005; Riquelme & Rios, 2010) have validated the impact of EE on users' behavioral intention. Furthermore, the survey conducted by Swish in Sweden revealed that 80 % use the technology since "it is easy to use", indicating that the user's associated ease of use with the m-P2P technology (Edlund, 2016). Thus, this study assumes the following hypothesis:

Hypothesis 2a: Effort Expectancy will have a positive effect on Behavioral Intention to adopt m-P2P payment.

Venkatesh & Morris (2000), citing research from Bem & Allen (1974) and Bozionelos (1996), theorized that EE is more salient for women compared to men with regards to technology adoption. According to some researchers, this could be connected to gender roles (Wong et al., 1985; Lynott & McCandless, 2000). Other studies from Venkatesh et al. (2012) and Wang & Wang (2010) further proved this moderating effect of gender. Like gender, age is commonly theorized to have a moderating effect on EE (Venkatesh et al., 2003; Venkatesh et al., 2012). In the context of the influence of EE on BI, a previous study found the effect to be stronger for older users (Venkatesh et al., 2003). Thus, the authors propose following hypotheses:

Hypothesis 2b: The influence of Effort Expectancy on Behavioral Intention will be moderated by gender, such that the effect will be stronger for female users.

Hypothesis 2c: The influence of Effort Expectancy on Behavioral Intention will be moderated by age, such that the effect will be stronger for older users.

2.2.3. Social Influence and Behavioral Intention

Social Influence (SI) is defined as "the extent to which an individual perceives that important others believe he or she should use a new system" (Venkatesh et al., 2003). The SI construct incorporates subjective norm (TRA, TAM2, TPB and C-TAM-TPB), image (IDT) and social factors (MPCU) (Venkatesh et al., 2003). As for m-P2P payment technologies, SI can be conceptualized as the influence of the surrounding social environment on users' intention to adopt such a technology. Influencers in this context could be reference groups, opinionated leaders, family, friends, and colleagues (Zhou, 2011).

The selection of SI as a key construct of BI in this study is built on prior studies on mobile payment (Püschel et al., 2010; Riquelme & Rios, 2010; Yang et al., 2012; Yu, 2012) which found SI to be a significant determinant of BI, indicating a similar scenario for m-P2P payment technologies. Furthermore, m-P2P payment technologies are generally used in a social or public context in which users can observe others' behavior, increasing the chances of them being influenced by their social environment (Nysveen et al., 2005).

Consequently, the authors assume that SI plays a significant role in contributing to the user's awareness and intention toward the m-P2P technology. Therefore, the following hypothesis was proposed:

Hypothesis 3a: Social Influence will have a positive effect on Behavioral Intention to adopt m-P2P payment.

Furthermore, it has been theorized that females are more sensitive to the others' opinion (Venkatesh et al., 2003). Therefore, SI will be more salient for women to form a behavioral intention toward adopting a technology (Venkatesh et al., 2000; Venkatesh et al., 2003). This effect could again be explained through social gender roles as in the case of PE and EE (Lubinski et al., 1983). Additionally, needs for social affiliation increase with age, indicating that older users place a higher value in the opinions of their social environment (Rhodes, 1983; Venkatesh & Morris, 2000). Therefore, the following hypotheses were included:

Hypothesis 3b: The influence of Social Influence on Behavioral Intention will be moderated by gender, such that the effect will be stronger for female users.

Hypothesis 3c: The influence of Social Influence on Behavioral Intention will be moderated by age, such that the effect will be stronger for older users.

2.2.4. Habit and Behavioral Intention

Venkatesh et al. (2012) refer to Limayem et al. (2007) when they define *Habit* (H) as "the extent to which people tend to perform behaviors automatically because of learning". The H construct has been tested in various research fields, such as consumers' purchase behavior, psychology, and management (Huang & Kao, 2015). It consists of three determinants: *past behavior*, *reflex behavior*, and *individual experience*. *Past behavior* describes users' prior behavior. *Reflex behavior* refers to behavior sequences which are frequent parts of users' daily life. *Individual experience* relates to the sum of experiences, norms, and routines that users collect when using a technology frequently, thereby decreasing the need for rational decision-making in future usages (Limayem et al., 2007).

According to Venkatesh et al. (2012), H can have an effect on BI which has been proven by researchers in the past (Kim et al., 2007; Sheeran & Luszczynska, 2009; Wang & Wang, 2010). According to Ajzen & Fishbein (2000), repeated performance of a behavior can lead to established behavioral intentions. Once triggered by certain stimulus cues, these intentions can turn into behavior without the user making a conscious decision (Fazio, 1990). Translating this to the context of m-P2P payments, the repeated performance of splitting the bill with friends using m-P2P could lead to the development of such intentions. Intentions could then be triggered in similar contexts, e.g. paying friends for a concert ticket.

Concluding, it is hypothesized that stronger habits will lead to stored behavioral intentions (Venkatesh et al., 2012):

Hypothesis 4a: Habit will have a positive effect on Behavioral Intention to adopt m-P2P payment.

Previous research has theorized that gender and age have an impact on the way users process information which in turn could influence to what extent habit guides their behavior (Venkatesh et al., 2012). Studies conducted in this context show that older users rely to a higher extent on automatic information processing (Jennings & Jacoby, 1993), resulting in habits that can suppress the motivation to use something novel (Lustig et al., 2004). Furthermore, once these habits have been established through repeated performance of a behavior, it becomes difficult for individuals to disregard them.

Gender is again hypothesized to moderate the relationship between H and BI (Venkatesh et al., 2012). Studies in this context have shown that women process more detailed information (Gilligan, 1982), while men follow a more schema-based approach (Meyers-Levy & Maheswaran, 1991). It can, therefore, be assumed, that in the context of m-P2P payment technologies, women are more sensitive when making the decision to adopt the technology, thereby weakening the relationship between H and BI. Thus, the following hypotheses were included in the model:

Hypothesis 4b: The influence of Habit on Behavioral Intention will be moderated by gender, such that the effect will be stronger for male users.

Hypothesis 4c: The influence of Habit on Behavioral Intention will be moderated by age, such that the effect will be stronger for older users.

2.2.5. Hedonic Motivation and Behavioral Intention

While the original UTAUT model only consists of rational constructs, studies have found that hedonic motivation can have an impact on technology adoption (e.g., Koufaris, 2002; Zhou & Wang, 2009; Zhou & Lu, 2011). Researchers have suggested that consumers adopt new technologies not just to enhance their performance, but also as sources of fun and enjoyment (van der Heijden, 2004; Thong et al., 2006). As a result, Venkatesh et al. (2012) included intrinsic utilities (i.e. joy, fun, playfulness) under the concept of *Hedonic Motivation* (HM) in their model and defined it as "the fun or pleasure derived from using a technology" (Venkatesh et al., 2012). Studies in related fields such as mobile banking (Püschel et al., 2010; Alalwan et al., 2014) provided evidence supporting the role of hedonic motivation in shaping users' decision to adopt such a technology. Consequently, this study proposes the following hypothesis:

Hypothesis 5a: Hedonic Motivation will have a positive effect on Behavioral Intention to adopt m-P2P payment.

Previous research has revealed that gender and age moderate the relationship between HM and BI. Male and young users have a higher tendency towards seeking new and innovative technologies (Chau & Hui, 1998). This, in turn, influences the relative importance and thereby strength of the HM construct towards BI. Thus, the authors of this thesis propose the following hypotheses.

Hypothesis 5b: The influence of Hedonic Motivation on Behavioral Intention will be moderated by gender, such that the effect will be stronger for male users.

Hypothesis 5c: The influence of Hedonic Motivation on Behavioral Intention will be moderated by age, such that the effect will be stronger for younger users.

2.2.6. Network Externalities and Behavioral Intention

According to Song & Walden (2007), P2P networks are clearly possessed of *Network Externalities (NE)*, with each user adopting the technology increasing the value of the network for other users. However, the aim of this thesis is not to measure the degree of NE in m-P2P payment technologies in itself, but to analyze their impact on technology adoption. According to NET, as the perceived size of the network increases, so do the perceived benefits of that network (Katz et al., 1985).

Therefore, NET should follow the intuitive causal process that the user first subjectively evaluates the characteristics of the P2P technology network and forms a perception of the network size of that technology (Song & Walden, 2007). It is then the user's own insight that benefits increase with a larger number of users. Consequently, as the perceived network externalities increase, it should have a positive effect on user's BI to adopt the m-P2P technology (Song & Walden, 2007). Therefore, if users' mental processes follow the NET, this translates into the following hypothesis:

Hypothesis 6a: A higher level of perceived Network Externalities will have a positive effect on Behavioral Intention to adopt a P2P payment technology.

A study conducted on NE and social networking websites confirmed that the impact NE has on BI to use these websites is moderated by gender (Lin & Lu, 2011). The study found that network size is an important factor to predict BI to use a social network for women, but that it did not effect BI significantly for men (Lin & Lu, 2011). In addition, a study on the role of NE's impact on the use of blogs in organizations also found that NE has a larger impact on women than on men (Wattal et al., 2010).

Furthermore, the same study found that NE had a stronger impact on younger generations and that the relationship between NE and BI is more significant for younger users (Wattal et al., 2010). Wattal et al. (2010) argue that this is because younger users are more connected to certain technologies, as they have more extensive experience using technological tools both professionally and privately. Therefore, the authors propose the following hypotheses:

Hypothesis 6b: The influence of Network Externalities on Behavioral Intention will be moderated by gender, such that the effect will be stronger for female users.

Hypothesis 6c: The influence of Network Externalities on Behavioral Intention will be moderated by age, such that the effect will be stronger for younger users.

2.2.7. Trust and Behavioral Intention

As described earlier, *Trust* (T) is a subjective belief that a party will fulfill its obligations which has been proven to play a significant role in the context of financial transactions (Gefen et al., 2003; Lu et al., 2011). Primarily trust in the service provider that guarantees the value of money is of significance in the acceptance of a m-P2P payment technology. Therefore, the authors propose the following hypothesis:

Hypothesis 7a: Trust will have a positive effect on Behavioral Intention to adopt m-P2P payment.

Studies in the related fields of m-banking and m-payments (Gefen et al., 2003; Awad & Ragowsky, 2008) found that perceptions of trust differed by gender and age. According to Awad & Ragowsky (2008), the effect of T on BI is more significant for women. Furthermore, studies have found that women are more concerned and cautious when using e-commerce and are less likely to trust a web page than their male counterparts (Garbarin & Strahilevitz, 2004).

Furthermore, age is likely to be influencing the relationship between T and BI. As younger people have been less hesitant in their adoption of technology (Ofcom, 2011), it is likely that T has a less significant effect on their BI to adopt m-P2P payment technologies. Furthermore, trust is influenced by the general attitude toward technology, which in turn is influenced by technology experience (Blank & Dutton, 2012). Since younger users are, on average, more connected to technology (Wattal et al., 2010) they are likely to have more experience in technology and therefore T should not be as important in predicting of BI. Therefore, the following hypotheses are included:

Hypothesis 7b: The influence of Trust on Behavioral Intention will be moderated by gender, such that the effect will be stronger for female users.

Hypothesis 7c: The influence of Trust on Behavioral Intention will be moderated by age, such that the effect will be stronger for older users.

2.2.8 Summary

Construct	#	Hypothesis
Performance Expectancy	1a	Performance Expectancy has a positive effect on Behavioral Intention to adopt m-P2P payment.
	1b	The influence of Performance Expectancy on Behavioral Intention will be moderated by gender, such that the effect will be stronger for male users.
	1c	The influence of Performance Expectancy on Behavioral Intention will be moderated by age, such that the effect will be stronger for younger users.
Effort Expectancy	2a	Effort Expectancy has a positive effect on Behavioral Intention to adopt m-P2P payment.
	2b	The influence of Effort Expectancy on Behavioral Intention will be moderated by gender, such that the effect will be stronger for female users.
	2c	The influence of Effort Expectancy on Behavioral Intention will be moderated by age, such that the effect will be stronger for older users.
Social Influence	3a	Social Influence will have a positive effect on Behavioral Intention to adopt m-P2P payment.
	3b	The influence of Social Influence on Behavioral Intention will be moderated by gender, such that the effect will be stronger for female users.
	3c	The influence of Social Influence on Behavioral Intention will be moderated by age, such that the effect will be stronger for older users.
Habit	4a	Habit will have a positive effect on Behavioral Intention to adopt m-P2P payment.
	4b	The influence of Habit on Behavioral Intention will be moderated by gender, such that the effect will be stronger for male users.
	4c	The influence of Habit on Behavioral Intention will be moderated by age, such that the effect will be stronger for older users.
Hedonic Motivation	5a	Hedonic Motivation will have a positive effect on Behavioral Intention to adopt m-P2P payment.
	5b	The influence of Hedonic Motivation on Behavioral Intention will be moderated by gender, such that the effect will be stronger for male users.
	5c	The influence of Hedonic Motivation on Behavioral Intention will be moderated by age, such that the effect will be stronger for younger users.
Network Externalities	6a	A higher level of perceived Network Externalities will have a positive effect on the Behavioral Intention to adopt m-P2P payment.
	6b	The influence of Network Externalities on Behavioral Intention will be moderated by gender, such that the effect will be stronger for female users.
	6c	The influence of Network Externalities on Behavioral Intention will be moderated by age, such that the effect will be stronger for younger users.
Trust	7a	Trust will have a positive effect on Behavioral Intention to adopt m-P2P payment.
	7b	The influence of Trust on Behavioral Intention will be moderated by gender, such that the effect will be stronger for female users.
	7c	The influence of Trust on Behavioral Intention will be moderated by age, such that the effect will be stronger for older users.

Table 2. Hypothesis Summary

3. Methodology

In the following chapter, the methodological approach of the study is explained. It increases the study's reliability, as well as provides a clear guidebook for how to replicate the study. The chapter starts with the research design, where the scientific approach is discussed. Secondly, the preparatory methodological work is explained before presenting the main study. The chapter is concluded with an overview of data quality.

3.1. Research Design

3.1.1. Scientific Research Approach

This study aims to discover and explain patterns between different constructs and their effects on users' behavioral intention to adopt m-P2P payment technologies, with gender and age moderating the relationships. The study is considered *epistemological positivistic* and *ontological naturalistic* as distinctions between *value-laden statements* and *pure factual statements* are made as the observations are tested empirically per the *falsification principle* and a *correspondence theory of truth* (Bryman & Bell, 2011; Moses & Knutsen, 2012).

Operationally, the study takes a *deductive* approach. From extant theoretical considerations and research, a theoretical framework is developed from which hypotheses are generated (Bryman & Bell, 2011). The study utilizes a quantitative research strategy that tests the theoretical framework and indicates as well as measures the effects the constructs have, with the moderating effects of gender and age, on the adoption of m-P2P payment technologies through a study on the Swedish m-P2P payment application Swish.

There are several reasons why Swish is chosen for this study. First, Swish matches the criteria of a m-P2P payment technology. Second, Swish is by far the most dominant m-P2P payment application in Sweden with a user-base that represents over 50% of the Swedish population. Subsequently, this indicates that it will be easier to get in touch with users of Swish compared to other m-P2P payment solutions and get a representative sample.

A quantitative research strategy is deemed optimal as the extant studies in the domain have taken quantitative approaches (e.g. Venkatesh et al, 2003; Venkatesh et al, 2012), which allows this study to build on earlier findings and carry the research forward. An alternative approach would be to pursue a qualitative research strategy. This was deemed as an inferior approach as qualitative studies tend to develop through an inductive, explorative nature, which in turn can lead to difficulties in replicating the study and generalizing the findings (Bryman & Bell, 2011). A qualitative study would be better suited if the study was aimed at identifying *what* constructs affect behavioral intention, but a quantitative is superior for understanding *how* they affect behavioral intention.

The study is carried out through an online-based self-completion survey. Online-based surveys have a reach advantage by using Internet as an access-point to groups and demographics which would be difficult and costly to reach through other channels (Wright, 2005). The self-completion questionnaire opens for a larger sample size to be studied as the absence of an interviewer allows for a more effective method to collect larger data sets (Bryman & Bell, 2011). Furthermore, a self-completion questionnaire is preferable when collecting data that is difficult to observe, which is the case with *behavioral intention* (Bhattacherjee, 2012). The drawbacks of the time and cost effective online survey is the lack of control and difficulties with sample bias (Evans & Mathur, 2005). However, it can be argued that the benefits listed above outweigh this drawback and that mitigating actions can be taken to minimize the weaknesses of online surveys (Evans & Mathur, 2005).

3.2. Preparatory Methodological Work

To, (1) prevent sampling errors, (2) increase probability of reaching a larger and more representative sample size and (3) improve survey quality and thereby response rates, preparatory methodological work is conducted. As the study's contribution depends on reaching a representative sample of the user-base of Swish, research to develop strategies and identify potential channels and access points is done. To ensure that the survey is understandable and fulfils its purpose a survey pre-test is conducted.

3.2.1. Identifying and Accessing the Representative Sample

To create findings which can be generalized, the study must identify and access a representative sample. To do so the sample must take considerations in terms of user age, gender, ethnicity, socio-economic background, geographical presence etc. Since Swish has over 5 million users, it is fair to assume that the user-base is heterogeneous, which makes it difficult to access a truly representative sample. Therefore, it is imperative that a clear strategy is laid out for how to best identify and access a representative sample. Ideas for how to achieve this were taken from previous studies when researching large populations in technology adoption (Viehland & Leong, 2007; Mbobo, 2010).

3.2.2. Survey Pre-test

There are two main reasons to why a survey pilot test is administered. It acts as an indicator of how the survey will operate and ensures that the research instrument functions as intended (Bryman & Bell, 2011). The pilot group was chosen as a small representation of the population which the real survey then targets. The pilot group consists of five two-man groups with one male and female. The groups were differentiated by the age brackets 10-20, 20-35, 35-50, 50-65 and 65+. Survey respondents were ordered to measure the time needed to finish the survey as well as note any confusion on eventual questions. The group members, individually, left verbal feedback on survey experience that was taken into consideration before initializing the main study.

3.3. Main Study

The main study consists of sampling, survey design, data collection and data analysis.

3.3.1. Sample Selection

To generalize the study's findings, it is imperative to reach and study a representative sample (Bryman & Bell, 2011). To achieve this the study gathers inspirations from the sample selection process of two previous studies within technology adoption, Mbobo's (2010) study on the population of Kenya and Viehland & Leong (2007) on the population of New Zealand. Both studies find attractive access points to a representative sample by accessing heterogeneous channels, such as school forums and business centers. To further increase the reach this study is performed with the help of ten volunteers that represent the demographical groups studied, i.e. one volunteer per gender and age group, and included students and working professionals from all of Sweden. The research team then distributes the survey through anonymous online links to their surrounding settings, i.e. e-mail, social networks and school or work. This sample selection process can be defined as a convenience-sampling in combination with stratosphere-sampling (Bryman & Bell, 2011). Furthermore, to increase the sample size and increase the probability of successfully representing Swish's user-base in the form of age and gender, the survey was distributed through the social media channels of Swish, SEB, Danske Bank, Nordea, Swedbank, Handelsbanken, and ICA-Banken.

3.3.2. Survey Design

The main study's survey embodies the conceptual model of the theoretical framework presented in the theory chapter. The survey consists of blocks that match the variables on behavioral intention, that is *Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Habit, Network Externalities,* and *Trust* as well as *Behavioral Intention.* To increase validity, the survey questions are replicated from previous studies and consist of three questions per criteria (Katz & Shapiro, 1992; Gefen et al., 2003; Zmijewska et al. 2004; Yu & Tao, 2007; Venkatesh et al., 2012). The scales for PE, EE, SI, HM, H and BI are based on Venkatesh (2012) study on UTAUT2. NE was taken from Song & Walden's (2007) study on NE and P2P technologies and T scales were taken from Zmijewska et al.'s (2004) study on mobile payments. Therefore, as seen in Appendix 2, all measurements and scales are drawn from extant research. All items are measured using a seven-point Likert scale, an appropriate scale to use when one measures attitude (Bryman & Bell, 2011). The extremes of the scales are "strongly disagree" and "strongly agree". Gender was measured nominally ("female", "male", and "others"), while age was measured in years.

To stay true to the format of previous studies, the survey is conducted in English. Although English is not the native language in Sweden, Swedes are very proficient in English and ranked as the third best-speaking country in the world by Education First (EF, 2016). This in combination with the relatively easy language of the survey indicates that the potential language barrier for respondents will be minimal.

Finally, to promote honest self-reporting amongst respondents the survey clarified respondent anonymity in both the invitation to participate as well as in the survey instruction.

3.3.3. Data Collection

The data collection was carried out using a survey constructed in Qualtrics, a sophisticated survey tool. The collection process occurred between the 22/03/2017 until the 05/04/2017. Respondents would access the survey through a link sent to them by e-mail as well as through board posts on Facebook pages of the groups mentioned previously.

Online surveys are deemed very effective in circumstances when one wants to reach a wide audience quickly as they give the survey a long reach and a capacity to generate more responses than physical surveying-methods (Evans & Mathur, 2005). Criticism towards online surveys such as skewed attributes of internet population, i.e. the internet user being a male of higher socio-economic standard (Greenspan, 2004) as cited by Evans & Mathur, (2005) does not apply as over 94% of Sweden's population has access to the internet (World Bank, 2013). The same statistics also debunks the criticism toward convenience sampling not producing generalizing findings due to lack of representative sampling.

Since self-completion surveys tend to have lower response rates and the tracking of response rates are difficult for online surveys, the following steps have been used to increase the likelihood of response (Cook et al., 2000):

1. Initiate contact with a cover letter as to why the study is important and that the questionnaire will be treated with utmost confidentiality.
2. Follow-up posts, e-mails and reminders to non-respondents. First three days after initial posting, then one week after and finally ten days after initial posting of the survey.

3.3.4. Data Analysis

From the survey software Qualtrics, the dataset is imported into the statistical analysis software IBM SPSS which will be used for the further process and analysis of the data. Due to the direct link between Qualtrics and SPSS, the transfer of the data does not suffer from any factors related to human error. In order analyze the collected data, structural equation modeling (SEM) will be applied. SEM is a multivariate statistical analysis technique which is used throughout research fields to analyze structural relationships. Researchers have recognized the advantages of SEM in distinguishing structural models and their measurement as well as taking measurement error into consideration (Henseler et al., 2009). The SEM approach follows two stages: *measurement model* and *structural mode*l.

First, the *measurement model* is examined by evaluating the constructs normality, reliability, and validity as well as the model fitness with a confirmatory factor analysis (CFA). If the measurement model results are satisfactory, the constructs can be used to test the structural model. The structural model then consists of a multiple linear regression (MLR) that is conducted to assess if the independent variables (PE, EE, SI, H, HM, NE, T) significantly predict the dependent variable (BI).

4. Results & Analysis

In this chapter, the empirical findings from the study will be presented and analyzed. First, a (1) Descriptive Analysis will be conducted to give an overview of the reached sample. Further, the (2) Measurement Model will be tested to ensure the data and measurement quality. Finally, the (3) Structural Model and thereby the hypotheses will be tested and summarized.

4.1. Descriptive Analysis

In the beginning of the analysis, incomplete data points were identified and excluded from the dataset. After descriptive statistics were conducted to examine the sample, incompatible responses were identified and excluded from the sample. Incompatibilities existed due to discrepancies in age (i.e. 125, 2 and 4) and were identified through an initial multiple regression test. Three data points were excluded from further analysis, resulting in a final sample size of *545 responses*. This amount of responses counters potential sample bias as well as greatly increase the generalization of the survey findings (Bryman & Bell, 2011). Table 3 summarizes the demographic characteristics of the sample in terms of gender, while Table 4 describes the age groups.

Gender	Frequency	Sample in %	Swish User Base in %*
Female	328	60.2	49.8
Male	217	39.8	50.2

Table 3. Respondents Gender Distribution

Age	Frequency	Sample in %	Swish User Base in %*
<20	15	2.75	7.2
20 - 29	291	52.40	29.5
30 - 39	92	16.88	20.4
40 - 49	64	11.74	17.6
50 - 59	52	9.54	13.2
=>60	31	6.69	12.1

Table 4. Respondents Age Distribution

**Swish data derived from confidential Swish PowerPoint presentation, January 2017*

As can be seen in the two tables above, the sample represents more female than male Swish users compared to the actual Swish user base as of January 2017. Furthermore, the age group of Swish users between 20 and 29 is overrepresented. However, the relative distribution of age and gender groups in comparison to the actual Swish user base still provides a sufficient representation of the Swish user base. Therefore, the sample is satisfactory in terms of size and distribution of gender and age, enabling a detailed and representative analysis.

4.2. Measurement Model: Data Quality

Before performing the SEM and testing the hypotheses, an inspection of the basis for assuming such variables was needed. Therefore, one must first deal with the issues of *normality*, *validity*, *reliability*, and *model fitness*.

Construct		Descriptive		Normality		Reliability / Validity			
Variable	Item	Mean	Std. Dev	Skewness	Kurtosis	Factor Loading	Cronbach's Alpha	CR	AVE
Performance Expectancy	PE1	6.26	1.239	-1.497	2.765	0.819	0.795	0.88	0.71
	PE2	4.87	1.417	-0.582	0.442	0.809			
	PE3	5.95	1.336	-0.964	1.27	0.897			
Effort Expectancy	EE1	6.54	0.835	-1.348	2.138	0.852	0.846	0.908	0.767
	EE2	6.42	0.879	-0.874	0.644	0.909			
	EE3	6.23	1.082	-0.771	0.408	0.865			
Social Influence	SI1	5.12	1.293	-0.278	-0.165	0.784	0.724	0.851	0.656
	SI2	5.57	1.45	-1.28	1.43	0.789			
	SI3	5.76	1.092	-0.787	0.02	0.855			
Habit	H1	5.43	1.529	-1.209	1.146	0.911	0.909	0.944	0.848
	H2	5.46	1.475	-1.231	1.368	0.947			
	H3	5.79	1.317	-1.557	1.721	0.904			
Hedonic Motivation	HM1	4.55	1.365	-0.065	0.071	0.914	0.88	0.927	0.809
	HM2	4.59	1.313	-0.068	0.147	0.92			
	HM3	3.84	1.408	0.04	0.381	0.863			
Trust	T1	5.78	1.104	-1.343	1.861	0.841	0.854	0.912	0.775
	T2	5.43	1.245	-0.969	0.894	0.89			
	T3	5.39	1.236	-0.829	0.584	0.908			
Network Externalities	NE1	5.45	1.394	-0.914	0.468	0.851	0.766	0.865	0.682
	NE2	5.34	5.62	-0.367	-0.354	0.785			
	NE3	5.62	1.224	-1.022	1.361	0.84			
Behavioral Intention	BI1	6.29	0.985	-0.858	1.44	0.916	0.915	0.946	0.855
	BI2	6.2	1.015	-0.615	0.706	0.943			
	BI3	6.09	1.078	-0.56	0.735	0.914			

Table 5. Descriptive and Measurement Model

4.2.1. Normality

A skewness-kurtosis approach was conducted to test the univariate normality for each variable (Kline, 2005). Researchers largely agree that the values of skewness and kurtosis need to be within the range of -2 and +2 for the data to be normally distributed (e.g. Gravetter & Wallnau, 2014). As can be seen in Table 5, values given for all items except for PE1 and EE1 passed the normality test since skewness and kurtosis of each item are within the acceptable ranges.

For PE1 (K = 2.765) and EE1 (K = 2.138), the test showed that data distribution was different from a normal distribution. However, the sample size was still deemed appropriate since it satisfied the central limit theorem which states that the sum of items of a construct will tend to follow a normal distribution even if the initial items are not distributed normally (Rice, 1995). This is underlined by the fact that the other items of the respective constructs are well within the skewness and kurtosis ranges. Furthermore, all statistical tests which were about to follow consider the distribution of the data, thereby not affecting the hypothesis testing.

4.2.2. Reliability

A test of the reliability of the survey was needed to determine the extent to which the data set is consistent and repeatable (Hernon & Swartz, 2009). Reliability relates to the repeatability of the study, that is, if the measurements that are devised produces similar results under consistent conditions (Bryman & Bell, 2011). Therefore, all constructs were tested to ensure an adequate level of *construct reliability* and *indicator reliability*.

Construct reliability was tested using *Cronbach's a*, *Composite Reliability (CR)*, and *Average Variance Extracted (AVE)*. According to Hair et al., (2010), the Cronbach's *a* values must be more than 0.7 to ensure *construct reliability*. Table 5 shows that Cronbach's *a* values for all constructs are above the threshold of 0.7, ranging between 0.724 for SI and 0.915 for BI. Furthermore, CR for all constructs existed within the respective level of 0.7 which was defined by Hair et al., (2010) to be the minimum significance level. Table 5 shows that H has the highest value of CR (0.944), while SI has the lowest CR value (0.851).

Moreover, Average Variance Extracted (AVE) was calculated to determine the explanatory power of each item. AVE is an indicator of the adequacy of convergence which means that the variance due to the construct itself is greater than the variance due to error. As seen in Table 5, the AVE values of the constructs ranged from 0.656 to 0.855, being all above the cut-off value of 0.5 as recommended by Hair et al. (2010).

In order to ensure indicator reliability, *factor loadings* of constructs should be higher than 0.7 and factor loadings below 0.4 should be eliminated from the model (Henseler et al., 2009). As displayed in Table 5, all items have a factor loadings as low as 0.784, thereby surpassing the threshold of 0.7.

Consequently, it can be concluded that the constructs of the survey show high reliability, ensuring the repeatability of this study.

4.2.3. Validity

Validity mainly checks for extreme values of correlations between any of the independent variables as this will affect both the magnitude and direction of the betas in the regression analysis later on (Bryman & Bell, 2011). If independent variables overlap significantly, it will be difficult to correctly analyze their individual impact on the dependent variable BI. To measure the validity of the constructs, both *discriminant* and *convergent validities* were inspected.

Convergent validity tests if factors correlate well with each other within their parent factor, analyzing if the construct is well explained by its observed variables (Hair et al., 2010). To test for convergent validity, a Confirmatory Factor Analysis (CFA) was conducted in which all factors estimated are recommended to have CR or AVE above 0.5 (Bagozzi & Yi, 1988), so that the construct explains at least half of the variance of its indicators (Henseler et al., 2009; Hair et al., 2010). The statistical findings in Table 5 show that all items supported such required threshold.

Discriminant validity indicates that factors used to measure constructs correlate more with each other than they do with other factors outside their parent construct. If this is not the case, the independent variables are insignificant predictors of the dependent variable and the classic problem of multicollinearity arises (Grapentine, 1997). To establish discriminant validity, the square root of AVE of the potential variables needs to be greater than the correlation coefficients of other dimensions (Hair et al., 2010). In this context, Pearson's Correlation Matrix was employed on the data set to evaluate these correlations. The matrix in Table 6 indicates that all constructs correlate significantly with BI (with $p<0.01$). Further, the table shows that the square root values of AVE were all higher than the correlation coefficients. Additionally, the highest value of correlation coefficient being 0.65 was lower than the maximum level of 0.85 as suggested by Kline (2005), leading to the conclusion that discriminant validity was established.

Construct	Mean	Std. D	PE	EE	SI	H	HM	T	NE	BI
Performance Expectancy (PE)	5.48	1.18	**0.84**							
Effort Expectancy (EE)	6.07	1.02	0.60	**0.82**						
Social Influence (SI)	5.49	1.03	0.54	0.40	**0.81**					
Habit (H)	5.56	1.33	0.61	0.50	0.61	**0.92**				
Hedonic Motivation (HM)	4.33	1.23	0.37	0.27	0.41	0.44	**0.90**			
Trust (T)	5.53	1.05	0.44	0.44	0.42	0.48	0.34	**0.88**		
Network Externalities (NE)	5.47	1.06	0.47	0.40	0.51	0.52	0.41	0.46	**0.83**	
Behavioral Intention (BI)	5.77	1.12	0.63	0.65	0.54	0.64	0.41	0.52	0.57	**0.93**

Table 6: Discriminant Validity

* *All correlations are significant at p < 0.01 (2-tailed)*

** *Diagonal values (in bold) are squared roots of AVE; off-diagonal values are correlations between the constructs.*

4.2.4. Model Fitness

Furthermore, the *model fitness* needed to be evaluated. The fitness of the model refers to how well the proposed model accounts for correlations between variables in the survey dataset (Hair et al., 2010). In this context the values of chi square (χ2), goodness of fit index (GFI), adjusted goodness of fit index (AGFI), normed fit index (NFI), comparative fit index (CFI) and the root mean square error of approximation (RMSEA) were examined. To do this, the data set was imported into the program AMOS 20 and the research model tested. Table 7 includes the values of the mentioned indices as well as their acceptable thresholds as defined by Hair et al. (2010).

Index	Value	Threshold values
Chi-square (χ2)	579.45, p < 0.001 df = 319	Significant
GFI	0.978	>0.9 (Bagozzi & Yi, 1988)
AGFI	0.912	>0.8 (Etezadi-Amoli & Farhoomand, 1996)
NFI	0.913	>0.90 (Hu & Bentler, 1999)
CFI	0.955	>0.90 (Hu & Bentler, 1999)
RMSEA	0.068	>0.06 (Joreskog & Sorbom, 1996)

Table 7: Model Fitness

The results indicate that the fitness of the structural model was sufficient with all values within their acceptable limits.

4.3. Structural Model: Hypothesis Testing

The statistical results presented in the previous chapter demonstrated constructs with high *normality*, *reliability*, *validity*, and *model fitness*. Therefore, all criteria related to measurement model were successfully achieved, providing the foundation for an adequate test of each hypothesis. Subsequently, the structural model was specified by analyzing the structural paths between the independent variables and the dependent variable. For this purpose, a Multiple Regression Analysis (MLR) was conducted.

4.3.1. Main Hypotheses

The results of the MLR are shown in Table 8, Table 9, and Table 10. As can be seen in Table 8, 62.8 % of the variation in the dependent variable can be explained by all independent variables, indicating a good level of prediction. A further examination of the structural model was conducted without the extensions *Trust* and *Network Externalities*. As can be seen in the same table, the inclusion of these constructs increased the power of the model in predicting BI from 59.6 % to 62.8 %.

Model	**R**	**R^2**	**Adjusted R^2**	**Std. Error of Estimate**
1	0.793	0.628	0.623	0.6889
2 (w/o T & NE)	0.772	0.596	0.592	0.71758

Table 8. Model Summary

Additionally, an *Analysis of Variance* (ANOVA) test was conducted to test whether the overall regression is a good fit for the data. As shown in Table 9, the independent variables significantly predict the dependent variable with $F(7,537) = 129.578$, $p < 0.005$.

Model	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Regression	431.722	7	61.675	129.578	0
Residual	255.594	537	0.476		
Total	687.316	544			

Table 9. Analysis of Variance (ANOVA)

Pertaining to the path coefficient analyses, Table 10 shows that most of the causal paths proposed over the conceptual model are supported. For coefficients to be statistically significantly, the p-value (Sig.) must be below 0.05. Consequently, *Behavioral Intention* was found to be significantly predicted by the factors *Performance Expectancy* ($\beta = 0.131$, $p < 0.001$), *Effort Expectancy* ($\beta = 0.321$, $p < 0.0001$), *Habit* ($\beta = 0.193$, $p < 0.0001$), *Trust* ($\beta = 0.093$, $p < 0.004$), and *Network Externalities* ($\beta = 0.185$, $p < 0.0001$). All significant independent variables have a positive influence on the dependent variables, with *Effort Expectancy* and *Habit* being the strongest predictors. The UTAUT2 extensions *Trust* and *Network Externalities* both proved to have a significant positive influence on BI with *Network Externalities* being the third strongest predictor.

On the other hand, both *Social Influence* ($\beta = 0.70$, $p > 0.05$) and *Hedonic Motivation* ($\beta = 0.53$, $p > 0.08$) proved to have a non-significant influence on BI since their p-values were above the limit of 0.05. However, since the p-value of *Social Influence* ($p = 0.053$) is very close to the threshold of 0.05, this constructs most likely accounts for some variation in the dependent variable. Therefore, a *tendency* can be noted (Cohen et al., 2013).

Criteria	**Unstandardized Coefficients Beta**	**Standardized Coefficients Beta**	**Coefficients Std. Error**	**t**	**Sig.**
Constant	-0.238		0.219	-1.087	0.278
Performance Expectancy (PE)	0.125	0.131	0.036	3.434	0.001
Effort Expectancy (EE)	0.355	0.321	0.038	9.353	0
Social Influence (SI)	0.076	0.07	0.039	1.939	0.053
Habit (H)	0.164	0.193	0.033	4.978	0
Hedonic Motivation (HM)	0.049	0.053	0.028	1.732	0.084
Trust (T)	0.099	0.093	0.035	2.866	0.004
Network Externalities (NE)	0.196	0.185	0.036	5.469	0

Table 10. Coefficients

4.3.2. Age and Gender as Moderators

To analyze the moderator effects of age and gender on BI, a moderation analysis was done by using the split sample approach (Serenko et al, 2006). For this purpose, responses were divided into two groups for each moderator. *Gender* naturally emerges from the study and forms two moderator levels which cannot be modified by researchers (since "Other" was not selected as a gender type in the survey).

To determine the moderator effects of age, the sample was again divided into two groups, each representing users from a specific generation. Following Serenko et al.'s (2006) approach, 40 years of age was chosen as the cut-off point.

The moderating effects of user variables were tested by comparing the path coefficients produced for each moderator in each of the groups. To determine the significance of differences between the constructs for each of the groups, p-values need to be $p < 0.05$ and the differences between the coefficients' paths need to be > 0.1 or < -0.1 (Jaccard & Turrisi, 2003). If they are significant, they can be interpreted as having moderating effects.

Paths	**Gender**			**Age**		
	Male	**Female**	**Difference**	**<40**	**=>40**	**Difference**
PE → BI	0.619	0.624	-0.005	0.614	0.643	-0.029
EE → BI	0.623	0.665	-0.042	0.618	0.726	-0.108
H → BI	0.623	0.640	-0.017	0.674	0.461	0.213
T → BI	0.563	0.482	0.081	0.514	0.548	-0.034
NE → BI	0.485	0.611	-0.126	0.562	0.516	0.046

Table 11. Moderator Analysis
** N = 545, p < 0.001 for all results*

The results show that no conclusions can be drawn in terms of the effect of both gender and age on the influence of *Performance Expectancy* on *BI* since both gender and age groups report equally high betas. Consequently, both Hypothesis 1b and Hypothesis 1c are *not supported*.

While gender does not significantly influence the relationship between *Effort Expectancy* and *BI*, the influence of EE on BI is moderated by age with the effect being stronger for older users ($\beta = 0.726$) compared to younger users ($\beta = 0.618$). Therefore, Hypothesis 2b is *not supported* while Hypothesis 2c is *supported.*

The analysis reveals that while gender does not moderate the relationship between *Habit* and *BI*, age significantly influences this relationship such that the moderation is stronger for younger users ($\beta = 0.674$) compared to older users ($\beta = 0.461$). However, this contradicts the assumptions made in the theoretical framework. Therefore, Hypothesis 4b and Hypothesis 4c both are *not supported.*

The results of the analysis further indicate that no conclusions can be drawn in terms of the effect of both gender and age on the relationship between *Trust* and *BI*. Consequently, Hypothesis 7b and Hypothesis 7C are *not supported*.

Regarding the moderation of the relationship between *Network Externalities* and *BI*, gender has a significant effect in a way that the effect is stronger for female users ($\beta = 0.611$) compared to male users ($\beta = 0.485$). Age on the other side does not effect this relationship significantly. Accordingly, Hypothesis 6b is *supported* while Hypothesis 6c is *not supported*.

Given that both *Social Influence* and *Hedonic Motivation* proved to have a non-significant influence on *BI*, no tests were deemed appropriate to determine whether there was a statistically significant difference between the groups. Due to the lack of statistical significance ($p > 0.05$) in the testing of Hypothesis 3a and 5a, Hypotheses 3b, 3c, 5b, and 5c were *not tested*.

4.3.3. Summary

Relationship	Hypothesis	Result
PE → BI	H1a: Performance Expectancy will a positive effect on Behavioral Intention to adopt m-P2P payment.	Supported
EE → BI	H2a: Effort Expectancy will a positive effect on Behavioral Intention to adopt m-P2P payment.	Supported
SI → BI	H3a: Social Influence will have a positive effect on Behavioral Intention to adopt m-P2P payment.	*Not Supported**
H → BI	H4a: Habit will have a positive effect on Behavioral Intention to adopt m-P2P payment.	Supported
HM → BI	H5a: Hedonic Motivation will have a positive effect on Behavioral Intention to adopt m-P2P payment.	*Not Supported**
NE → BI	H6a: A higher level of perceived direct Network Externalities will have a positive effect on Behavioral Intention to adopt a P2P payment technology.	Supported
T → BI	H7a: Trust will have a positive effect on Behavioral Intention to adopt m-P2P payment.	Supported
Gender: PE → BI	H1b: The influence of Performance Expectancy on Behavioral Intention will be moderated by gender, such that the effect will be stronger for male users.	*Not Supported***
Gender: EE → BI	H2b: The influence of Effort Expectancy on Behavioral Intention will be moderated by gender, such that the effect will be stronger for female users.	*Not Supported***
Gender: SI → BI	H3b: The influence of Social Influence on Behavioral Intention will be moderated by gender, such that the effect will be stronger for female users.	*Not Applicable*
Gender: H → BI	H4b: The influence of Habit on Behavioral Intention will be moderated by gender, such that the effect will be stronger for male users.	*Not Supported***
Gender: HM → BI	H5b: The influence of Hedonic Motivation on Behavioral Intention will be moderated by gender, such that the effect will be stronger for male users.	*Not Applicable*
Gender: NE → BI	H6b: The influence of Network Externalities on Behavioral Intention will be moderated by gender, such that the effect will be stronger for female users.	Supported
Gender: T → BI	H7b: The influence of Trust on Behavioral Intention will be moderated by gender, such that the effect will be stronger for female users.	*Not Supported***
Age: PE → BI	H1c: The influence of Performance Expectancy on Behavioral Intention will be moderated by age, such that the effect will be stronger for younger users.	*Not Supported***
Age: EE → BI	H2c: The influence of Effort Expectancy on Behavioral Intention will be moderated by age, such that the effect will be stronger for older users.	Supported
Age: SI → BI	H3c: The influence of Social Influence on Behavioral Intention will be moderated by age, such that the effect will be stronger for older users.	*Not Applicable*
Age: H → BI	H4c: The influence of Habit on Behavioral Intention will be moderated by age, such that the effect will be stronger for older users.	*Not Supported***
Age: HM → BI	H5c: The influence of Hedonic Motivation on Behavioral Intention will be moderated by age, such that the effect will be stronger for younger users.	*Not Applicable*
Age: NE → BI	H6c: The influence of Network Externalities on Behavioral Intention will be moderated by age, such that the effect will be stronger for younger users.	*Not Supported***
Age: T → BI	H7c: The influence of Trust on Behavioral Intention will be moderated by age, such that the effect will be stronger for older users.	*Not Supported***

** statistically insignificant results* *** statistically significant results, but not supporting the hypothesis*

5. Discussion

This section will focus on a discussion of the results presented in the previous section. The section begins by discussing theoretical contributions with elaborations on the traditional UTAUT2 constructs, the UTAUT2 extensions suggested by the authors and the moderator effects. Furthermore, implications for practitioners, limitations of the study as well as suggestions for further research will be presented.

5.1. Theoretical Contribution

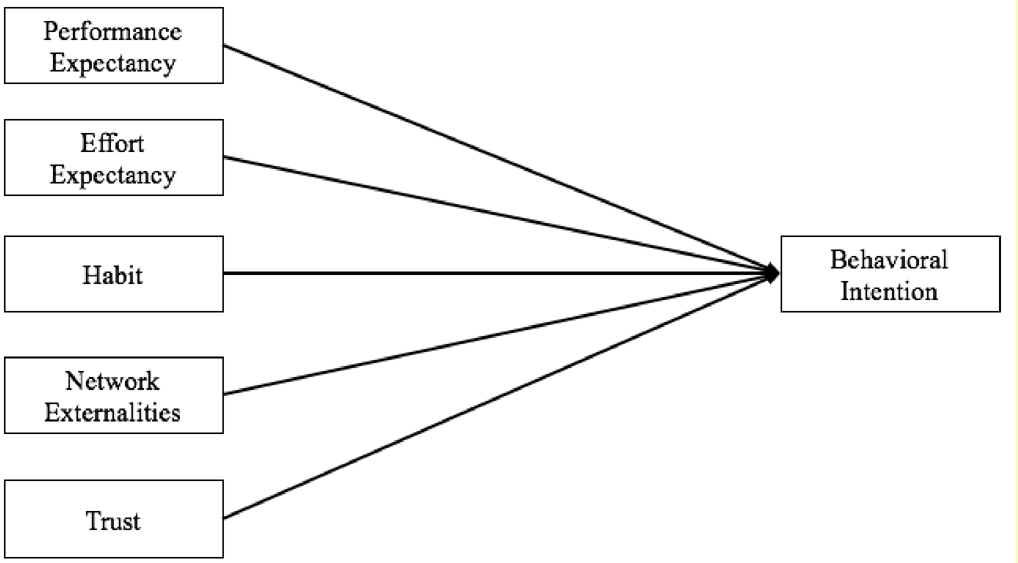

Figure 5. Revised Conceptual Framework

The basic theoretical contribution of this thesis is the identification of a research gap in the existing literature and the filling of this gap. While research on user adoption of technology is a mature field, no previous scientific empirical studies have been conducted in the context of m-P2P payment technologies. Furthermore, most research has focused on the organizational context of employee adoption and extensions of theories to the consumer context have been made just recently. Therefore, this thesis answered the call of many researchers (Bagozzi 2007; Benbasat & Barki, 2007; Venkatesh et al. 2012) to make a theoretical contribution and expand the space of technology adoption theories by applying the UTAUT2 model to a new context. Following Attuquayefio & Add's (2014) suggestion, the model was further re-evaluated and adjusted to account for the specific context of m-P2P payment technologies. The constructs *Network Externalities* and *Trust* were identified as potential relevant constructs and added to the conceptual framework. The constructs *Facilitating Conditions* and *Price Value* as well as the moderator *Experience* were regarded as irrelevant and consequently omitted from the model. Furthermore, *Usage Behavior* was excluded from the model as there exists consensus among researchers that the relationship between BI and UB is significant and positive.

The results reveal that the conceptualized theoretical framework has good explanatory power in predicting user intention to adopt m-P2P payment technologies as the added constructs increase the variance explained in *Behavioral Intention* from 59.6% to 62.8%.

5.1.1. UTAUT 2 Constructs

In relation to the path coefficient analyses, *Effort Expectancy* was found to be the strongest factor predicting users' intention to adopt m-P2P payment with a coefficient value of $\beta = 0.321$. This shows that users' intention to adopt this technology is not only influenced by the value of such a technology, but also by the extent of difficulty and simplicity in using the technology. These findings come to no surprise as they are in line with most studies on related fields (Riquelme & Rios, 2010; Alalwan et al., 2014), further validating the importance of EE on users' behavioral intention. However, an interesting result is that while Performance Expectancy has been proven to be the strongest predictor in most technology adoption studies (Venkatesh et al., 2012), EE seems to be more important in the context of m-P2P payment technologies.

Habit turned out to be the second strongest predictor of BI with a coefficient value of $\beta = 0.193$. This implies that the repeated performance of behavior (using Swish as a payment method) has produced habituation for most users (Venkatesh et al., 2012). These findings are in line with other studies in the fields of financial technology adoption (Kim et al., 2007; Sheeran & Luszczynska, 2009; Wang & Wang, 2010). It can be argued that in the context of P2P financial transactions which occur on a frequent basis, users repeat a certain performance (paying someone) more often and are also surrounded by more stimulus cues (having to pay someone) compared to other consumer technologies. In the context of P2P financial transactions, it can be assumed that users do not want to put much thought into the process of it, thereby being more open for habituation. This habituation is further strengthened by the fact that in the case of Swish the user base is steadily growing while more and more businesses accept it as a payment method, enabling the usage of Swish in increasing number of situations.

Statistical results also provide strong proofs confirming the causal paths between *Performance Expectancy* and BI with a coefficient value of $\beta = 0.131$. This implies that the extent to which m-P2P payment provides benefits in performing payment tasks is significant to the adoption of such technologies. These results further validate the findings of other researchers (Luarn & Lin, 2005; Zhou, 2011; Riquelme & Rios, 2010; Alalwan et al., 2014). Concluding, m-P2P payment technologies increase the performance of users by accomplishing payments faster and with more flexibility than alternative payment methods.

Although *Social Influence* did correlate significantly with BI (see Table 6), the relationship with BI was not significantly with $p > 0.05$. However, as reasoned earlier, this construct is still able to account for some statistical variance in BI with a lower confidence level and simply loses its significance when competing with other constructs. As a result, users' willingness to adopt m-P2P payment applications is only influenced by the opinions of other individuals in their social environment to some extent. Users seem to be less interested in recommendations and attitudes of their reference groups (i.e. friends) when formulating behavioral intentions to adopt a m-P2P payment technology.

The results contradict some previous studies in related fields which stated that users are highly influenced by the opinions in their social environment (Püschel et al., 2010; Riquelme & Rios, 2010; Zhou, 2011; Yang et al., 2012; Yu, 2012). However, there are other studies in relevant areas that have disapproved the impact of SI or similar factors (e.g. image, subjective norm, social desirability, and reference groups) (Riffai et al, 2012). Nonetheless, these findings come as a surprise to the authors of this thesis. It was expected that, since m-P2P payment technologies involve connectivity among peers as well as network externalities, SI should play an even more significant role compared to other consumer technologies (Dickinger et al., 2008). As elaborated on in the context of network externalities, the value of a network good like m-P2P payment applications increases with the amount users using it. Therefore, those who have already adopted the m-P2P payment technology should have a strong incentive to persuade others to then also adopt the technology since their own utility depends strongly on their peers being in the network (Henkel & Block, 2008).

Reasons for the insignificance of the SI construct could be of diverse nature and are hypothetical. From a psychological point of view, it could be argued that the way SI is perceived by users potentially differs to the actual extent of SI exercised on them. In a modern society like Sweden's, people tend to regard themselves as strong and independent individuals who are not significantly influenced by their surrounding (Bihagen & Katz-Gerro, 2000). Even though SI and peer pressure undeniably still play a factor in today's world (Henkel & Block, 2008), users could subjectively disregard the effects on them. Even though this reasoning is hypothetical, it is supported by the survey conducted by GetSwish AB in which 77 % of users have “urged others to get Swish” and 37 % say that they are ”bothered if someone of their friends or at work does not have Swish” (Edlund, 2016). These results imply that users do try to exercise influence on people in their social environment to adopt Swish. Therefore, it can by hypothesized that participants of the survey might have been unable to observe SI. However, this reasoning stands against aforementioned studies in which SI actually did play a significant role and needs further investigations and validations.

Hedonic Motivation was empirically evidenced to be a non-significant factor in predicting users’ intention to adopt Swish with $p > 0.05$. These findings imply that users do not adopt m-P2P payment technologies as sources of intrinsic utilities such as fun, pleasure or enjoyment. This contradicts studies in related fields that provided evidence supporting the role of HM in shaping users’ intention to adopt a technology (Zhou & Wang, 2009; Püschel et al., 2010; Zhou & Lu, 2011; Alalwan et al., 2014). However, a further analysis of these studies revealed that they share two common characteristics: most of them were conducted in developing countries or at a time when the technology being analyzed had just recently been made accessible. It can be assumed that these factors have an influence on the users in terms of novelty seeking and perception of the novelty of target technology, two key drivers of hedonic motivation (Venkatesh et al, 2012).
First, in developing countries, adopting a novel technology represents an added value in terms of modernism and novelty for the people there (Alalwan et al., 2017). Novelty seeking and desire for modernity could, in turn, lead to perceived enjoyment of using such a technology and thereby HM (Venkatesh et al., 2012). However, since Sweden is a technologically far developed country, Swish users’ most likely are familiar with similar applications. Therefore, it can be assumed that in the context of developed countries a m-P2P payment application does not compromise novelty or uniqueness in its technology for the user, thereby not adding to intrinsic motivation to use such a technology for enjoyment.

Second, HM of using a technology might decrease over time to an extent where this construct becomes non-significant. In the beginning of using a technology, users most likely are more interested in its features (e.g., the interface of the application) and may simply use it because of its novelty (Holbrook & Hirschman, 1982). Once experience in using the technology increases, aspects related to its novelty could become less relevant, thereby diminishing the influence of HM on technology adoption. Users could start to use the technology with more pragmatic intentions that relate to other constructs of the model, such as PE (Venkatesh et al., 2012). Since its launch in 2012 and this study, almost five years have passed in which most users have used Swish on average several times a week. Arguably, HM as a construct could have played a more significant role if the survey would have been conducted a few years earlier. Since this reasoning is hypothetical and needs further evaluations, readers are advised to treat it accordingly. However, with the beta coefficient being the lowest ($\beta = 0.49$), even if the construct would be of significant nature, it would most likely still not be a strong predictor of BI.

5.1.2. UTAUT 2 Extensions

To account for the specific context of m-P2P payment technologies, this study added the external factors *Trust* and *Network Externalities* to the model. The results show that both constructs have high explanatory power in predicting behavioral intention. The statistical results have revealed that including these two constructs along with traditional UTAUT 2 constructs increased the R^2 value extracted from 59.6 % to 62.8 %. Given these results, it is highly recommended to include both constructs in future research in this field. Especially *Network Externalities*, the third strongest predictor in this study, which is not included in any of the common technology acceptance models (e.g. UTAUT, UTAUT2, TAM, TRA), should be emphasized as an important predictor in the study's context.

5.1.2.1. Network Externalities

With regards to *Network Externalities,* statistical results empirically approve its considerable influence on adoption of m-P2P payment technologies, being the third strongest predictor of BI ($\beta = 0.185$, $p < 0.001$). Thereby, the results validate findings of previous studies that emphasize the influence of NE in the adoption of mobile payment (Dahlberg & Mallat, 2002; Mallat, 2007).
The analysis revealed that both direct externalities ($\beta = 0.156$, $p < 0.001$) as well as indirect externalities ($\beta = 0.148$, $p < 0.001$) are present.

Regarding *direct network externalities*, results indicate it is the users' own insight that the number of users is of utmost importance for them due to the closed network of these technologies. As hypothesized, direct network externalities are important for m-P2P technologies since the number of users is the central means of usefulness in a P2P network. A m-P2P payment technology, even though it performs well and effortless, would be of no use to the user if he would be the only one in the network.

It is interesting to note that NE still plays an important role for Swish users, even though the network has long surpassed the point of critical mass with almost 60 % of Swedes using the application. It can be argued that the construct NE would have been an even stronger predictor of BI to adopt Swish in its early stage in which the number of users was small. This is because the value of each user joining the network is exponentially decreasing, i.e. the second user joining the network increases the value of the network by the highest margin since he doubles the network size. The insight of users that an increase in the number of users is still beneficial for them at this late stage of technology diffusion further emphasizes the importance of this construct.

In terms of *indirect network externalities*, the number of businesses accepting m-P2P as a payment method also positively influences users' choice of adoption of the application since it increases the opportunities for users to use the service. Swish has been quite active over the years in encouraging businesses to accept Swish, i.e. retail businesses and SME's. Results indicate that users acknowledge and value the growing possibilities to use Swish as a payment method in different contexts.

NE was likely one of the major drivers behind the collaboration of banks in the first place. One can argue that each bank, individually, could not have produced a large enough network to reach critical mass, making a collaboration a necessity. This also lowered development and running costs significantly for the individual banks, allowing Getswish AB to offer the service free of charge. The compatibility with each bank's individual bank accounts enabled GetSwish AB to establish Swish as the standard in the market and increase the barriers of entry for potential competitors. At this point, it will be difficult for a competitor to establish its service in the market, as "swishing" someone has already become a common phrase amongst Swedes.

5.1.2.2. Trust

The second added construct, *Trust,* also turned out to be a significant predictor for BI with a beta coefficient of $\beta = 0.093$ ($p < 0.05$). These results validate findings in other studies on mobile payment that have included Trust as a construct (Lu et al., 2011; Zhou, 2011). The findings indicate that for technologies that involve sensitive and personal data, the security capability to secure data transfers is highly relevant and a direct determinant of the users' intention to adopt such a technology.

First, in terms of the security of the Swish technology, a driving factor behind users' trust is most likely Swish being the result of a collaboration between six of Sweden's largest banks. This, in turn, can have a positive impact on the perceived security standard of the technology due to the banks' experiences and resources. Furthermore, as research showed, users are mainly concerned about confidentiality and authentication issues (Dewan & Chen, 2005). Swish successfully collaborates with *mobile BankID*, the leading electronic identification in Sweden with 7.5 million people using it on a regular basis for online and mobile banking, e-trade, tax declaration, and others (BankID, 2017). This application has been proven to be a secure authentication method prior to the launch of Swish and most users were most likely familiar with it prior to their adoption of Swish.

Second, trust in the service provider that guarantees the value of money is essential. In the case of Swish which is a bank-centric P2P payment method, the participating banks guarantee the value of money and not Swish as an institution. Even though the financial crisis had a negative impact on the trust of bank customers towards these institutions (Roth & Gros, 2010), a recent study from EY revealed that 93 % of all participants still trust banks to keep their money safe (EY, 2016). This could give bank-centric m-P2P payment network an advantage over nonbank-centric solutions in which nonbank intermediaries handle the transactions.

Concluding, due to the sensitive nature of financial transactions that are conducted electronically, trust in the service and its provider plays a significant role in adoption m-P2P technologies.

5.1.3. Moderating Effects

The moderating effects *gender* and *age* were utilized to provide further insight into user adoption and to better understand how constructs are influenced by demographic factors. The moderating effects failed to show significance in all but three cases (gender effect on NE and age effect on EE and H). In hindsight, it seems, with regards to the results, that the moderator hypotheses are less relevant in the context of m-P2P payment technologies in Sweden and that other moderating effects should be explored.

5.1.3.1. Gender

Several studies in the stream of literature examining user acceptance of technology have proven gender to have a moderating effect, such that certain relationships are stronger for men than for women, and the other way around. However, the results from this study show that except for *Network Externalities*, there is no significant difference with regards to the beta coefficients of the two gender groups. Explanations for this outcome can be diverse and are hypothetical.

One of the underlying assumptions that the UTAUT2 model bases its hypotheses in terms of gender as a moderator on is related to gender roles in the society (Wong et al., 1985; Lynott &

McCandless, 2000). Venkatesh et al. (2012) conducted the study for their extension of the original UTAUT model in Hong Kong, a country in which the role of men is traditionally dominant and where women still face gender inequalities (Blundy, R. 2016). The study of this thesis was conducted in Sweden, a country which is known for having a strong focus on gender equality. According to the Swedish government, "Sweden has the world's first feminist government" (Regner, Å., Wallström, M., 2016), with gender equality policies at the top of their political agenda. These policies have a significant influence on the two gender groups in terms of division of power and influence, economic well-being, education, and distribution of unpaid housework and provision of care. This, in turn, affects the individual traits that exhibit gender differences in the adoption of technology, i.e. income, tech savviness, education and facilitating conditions. Therefore, the above-average gender equality standard in Sweden could be related to the insignificance of gender as a moderator in this study.

Furthermore, since gender roles are not only changing in Sweden but in other parts of the world as well, some of the research which theorists base these moderating effects on (i.e. Wong et al., 1985) could be outdated and would need to be re-evaluated. Kolsaker's study on gender and trust in technology points to this trend since differences between genders were negligible (Kolsaker, 2002). Kolsaker contributes this change to developments in consumer behavior: while traditionally early adopters used to be young, male users, women have become more competent and interested in technologies in general (Kolsaker, 2002). Concluding, the results of this study suggest that differences between genders are marginal or possibly even diminishing, calling for further research.

5.1.3.2. Age

When analyzing the influence of age on the relationship between independent variables and the dependent variable, two constructs turned out to be moderated by age: *Effort Expectancy* and *Habit*. In terms of *Effort Expectancy*, the hypothesis was supported that older users put a higher emphasis on how easy the application is to use.

With regards to *Habit*, the moderating effect of age proves to be significant, but it contradicts the hypothesis of this study. In fact, the results indicate that younger users tend to form habits more easily than older users. One could argue that since older participants of the study are internet users and have adopted Swish, they are more connected to technology compared to the average of that age group. They could be generally more inclined to try new technologies and could rely less on habits.

Younger users, on the other hand, have been developing more habits towards technology recently, e.g. ‘millenials’ and Social Media (Lenhart et al., 2010). In fact, recent studies have found that teenagers and young adults develop habits much faster than seniors (Tanner, 2009). Again, current trends might call for a re-evaluation of underlying assumptions that the moderator hypothesis in the context of H is based on.

With regards to *Performance Expectancy*, *Trust*, and *Network Externalities*, age does not play a significant factor in moderating the relationships to BI. The hypotheses concerning the moderating effects of age are mainly based on underlying assumptions that younger users are more tech savvy, more interested in high performing technologies, or less hesitant to adopt new technologies. However, while seniors have historically been late adopters to the world of technology compared to younger users, this trend has been changing in recent years. Older users are more and more connected to the world of digital tools and services, both physically and psychologically (Smith, 2014). In fact, when it comes to the user base of Swish, both age groups (with the threshold age of 40) are equally represented (~2.5 million).

Furthermore, since this study used an online survey which was distributed through electronic channels, the requirement to be able to answer it was a connection to the internet. Research shows us that once seniors join the online world, digital technologies often become an integral part of their daily lives (Smith, 2014). Therefore, participants in the study are most likely digitally proficient individuals which can have an impact on the results of age moderator analyses.

5.2. Implications for Practitioners

As mentioned in the beginning of this thesis, consumer acceptance is regarded as the greatest barrier to mobile payment diffusion (Edgar Dunn & Company, 2007). Players in the financial market are fiercely competing to gain and retain users (Hassouna et al. 2015). Therefore, understanding users’ intention to adopt a technology should be the focus of attention of players in the market or players planning to enter the market in their endeavour to motivate users to adopt m-P2P payment technologies.

The results of this research have revealed several implications which are valuable for practitioners in the financial ecosystem, giving suggestions on how to optimize product development or marketing efforts to increase the likelihood of adoption.

Naturally, since users put a great emphasis on both *Performance Expectancy, Effort Expectancy* and *Habit* product developers should consider this when designing and marketing a m-P2P payment application. The focus should be to develop a high-quality technology with a simple interface design to add value with regards to uniqueness and innovativeness (Dwivedi et al., 2013; Simintiras et al., 2014). A way to communicate the usefulness and the degree of ease using of m-P2P payment technologies could be promotional campaigns that emphasize these benefits, e.g. faster transactions, improved performance, productivity gains. Contemporary Social Media channels like YouTube or Facebook are very cost-effective channels in this context and proven to be successful (Dwivedi et al., 2013). Furthermore, the application should be developed in a way that enables habit forming, i.e. by producing cues, routines, and rewards for the user.

The results of this thesis also provide insights into the importance of *Trust*. The intention of users to adopt a technology is also tied to their ability to trust the application and the service provider behind it. If the users feel insecure about the technology, an adoption of it becomes very unlikely. Therefore, a trustworthy brand and corporate image need to be used when marketing the actual offering, e.g. by being officially certified by governmental control institutions. Once the trustworthy brand is established, the service provider should ensure that the payment application and its technological infrastructure can conduct financial transaction efficiently and safely, ensuring a secure environment.

To communicate high-security standards and build trust amongst potential users, service providers should address user concerns through direct marketing and effective advertising. However, the *Trust* construct is not only important for marketers, but also for product developers since trust must also be built into the product, e.g. its system features or interface. According to Alexander et al. (2010), system transparency plays an important role in this context. The terms of agreement should be made very transparent, the user should be able to distinguish between content and advertisements and potential financial transactions costs should be labelled clearly.

As the results show, *Network Externalities* play a special role influencing the adoption of m-P2P payment technologies. As elaborated on before, while network effects can help a network good gain momentum once it reaches a certain critical mass of users, they can make it difficult to attract early adopters when only a few users are on it. Therefore, the creation of the critical mass of users is crucial for the adoption of such a technology. With a network good like m-P2P payment technologies, practitioners will be faced with the classic 'chicken and egg' problem (Caillaud &

Jullien, 2003). Consumers and merchants alike will be reluctant to adopt such a technology if the user base is not big enough. However, once critical mass is reached and users decide for a service provider because of that, this circle can cause rapid adoption, leading to a market where a single provider dominates, as it is the case with GetSwish AB in Sweden.

The practitioners, therefore, need to focus on attaining *critical mass*. This can be done in multiple ways, e.g. a collaboration with competitors like in the case with Swish, which lowers costs, enables access to more resources and also ensures a high level of compatibility, enabling the setting of a standard in the market. Furthermore, the service provider could incentivize users through not charging a transaction fee or by offering a bonus for those users who successfully attract new users. Once the critical mass is reached, the user base should be communicated as the main value proposition.

5.3. Limitations

While this thesis offers insights in the user adoption of m-P2P payment technologies, it is restricted by the number of limitations mentioned in the following.

Due to the scope of this thesis, the authors were not able to collect data from the entire recommended population sample, therefore the study is limited by the number of participants. Furthermore, the study was conducted in Sweden and the findings might not be generalizable to other populations. The impact that the culture could have on Swedish users' behavioral intention was not examined in the current study. More specifically, analyzing factors related to the national culture (e.g. individualism vs. collectivism) could be of interest since they could potentially weaken or strengthen constructs, e.g. *Social Influence*, or moderators, e.g. *gender* (Alalwan et al., 2017).

Other limitations concern the technology being analyzed, Swish. As described earlier, Swish follows a bank-centric model, with each Swish account being connected to a bank account. Results could potentially differ for other, non-bank-centric models. Furthermore, since Swish does not charge a fee for transactions, the authors were unable to include *Price Value* as a parameter in the UTAUT2 model even though chances are high that it could play a significant role in determining behavioral intention to adopt this technology.

Finally, even though the authors utilized validated items and questions from previous studies, the way constructs were measured could also be disputed by other researchers.

5.4. Suggestions for Further Research

This thesis extended the applicability of UTAUT2 in the consumer context, providing a starting point for future research on the field of m-P2P payment technologies and further refinements in different contexts. The discussion and preceding limitations give cause to suggestions for further research.

First, this study is based on cross-sectional data. Therefore, a longitudinal study would provide a more detailed understanding of behavioral intentions. Since m-P2P payment technologies are still in an early stage, this kind of study could be more appropriate to gain a deeper insight. It would be interesting to analyze if the relationships of the independent variables and BI are stable or change over time.

Second, since this study only collected data in Sweden and since the development of m-P2P payment technologies varies from country to country with regards to its maturity and the actual usage, future studies should expand to other countries. Future studies could also integrate demographic factors into their model, e.g. income or cultural differences, since this probably has an influence on user adoption in the context of financial transactions.

Furthermore, it would be beneficial to analyze links between the different constructs and how they influence each other. An example in this context is *Habit* and how it influences other constructs over time. If *Habit* becomes strong enough, do factors like *Performance Expectancy* or *Effort Expectancy* lose their significance? Furthermore, one can argue that the two constructs *Network Externalities* and *Performance Expectancy* are positively correlated. Subsequently, if a technology is influenced by NE then the PE construct, i.e. benefit of using it, is directly linked to the size of the network.

Additionally, a question that calls for further research is how users form their perception of the network size of a m-P2P payment application. If indeed most people form their perception based on their social environment, a link between social influence and network externalities needs to be examined. Furthermore, it would be interesting to compare the perception of size to the actual size of a network.

Finally, since the study's moderating hypotheses were largely unsupported, the authors suggest that new moderating effects should be tested. An interesting moderator would be *general experience with technology*, as recent research points to that this moderator and not gender or age is more likely to influence behavioral intention (Kolsaker, 2002). It may be that gender and age previously determined general experience with technology as it was mainly young males driving technology adoption, a scenario that is not in line with today's society (Kolsaker, 2002).

6. Conclusions

Concluding, in the following, the thesis is shortly summarized with regards to the research gap. Furthermore, the final conclusions and remarks are presented.

Mobile peer-to-peer payment technologies are receiving growing attention on a global scale, from consumers, banks, other players in the financial sector, and large tech companies to startups, as an alternative to using cash, credit cards or other payment methods. They are one of the factors driving the cashless transformation with a potential global market value of approximately €900 billion (Heggestuen, 2015). Researchers claim that this new way of transferring money has the potential of being a trigger for a rearrangement of major players in the eco-system of financial services (Koenig-Lewis et al., 2015).

Despite this, the literature review of this thesis revealed that previous research does not offer a satisfactory framework that explains the driving factors behind the user adoption of m-P2P payment technologies. Therefore, the aim of this thesis was to answer the research question:

- *What are the driving factors influencing users' behavioral intention to adopt m-P2P payment technologies?*

In the search for an answer to the research question, there was a need to select a theoretical foundation which can capture the most important aspects associated with the user adoption of such technologies. Thus, after comparing existing models on user adoption of technology, the UTAUT2 (Venkatesh et al., 2012), widely regarded as the best theoretical framework for adoption of technologies (Alalwan et al., 2017), was selected as the most appropriate conceptual model for this study. The model was further extended with the two constructs *Network Externalities* and *Trust.* The results of the conducted study revealed that the proposed model has high explanatory power, accounting for 62.8 % of the variance in users' behavioral intention to adopt m-P2P payment technologies, the extended constructs increased the predictive power by 3.2 %. *Performance Expectancy*, *Effort Expectancy*, *Habit* all proved to be significant predictors of *Behavioral Intention* as well as the extended constructs *Network Externalities* and *Trust*. The authors, therefore, suggest researchers to include the extended constructs when conducting further research in this field. With these findings, this study fills in the proposed research gap and contributes to the theoretical fields of research with regards to user adoption of technology. Finally, this thesis contributed to practical contexts by indicating potential key insights for managers and other practitioners.

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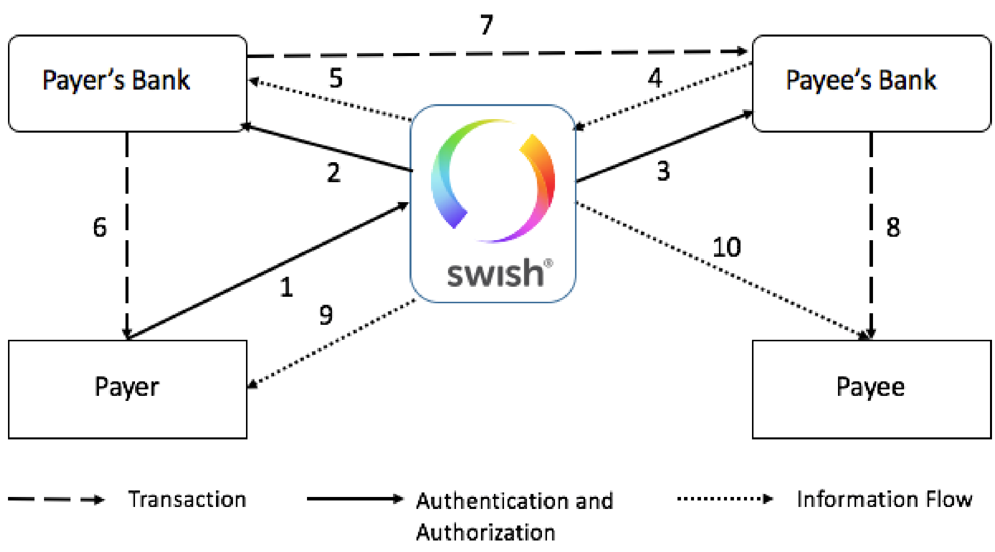
8. Appendix

Appendix 1

In order to "swish", (1) the payer needs to log on to *Swish*, the front-end of the technology, indicate that (s)he wants to pay a certain amount to the payee and provide the payee's mobile number or specific Swish number (assigned upon request), transfer amount and text to payee. The payee's number is registered with the actual bank account in the bank of the receiving party. (2) Swish verifies that both payee and payer are connected to Swish and have correctly activated accounts. (3) Swish then authorizes the transaction via mobile bank ID. (4) After the authorization has been approved, Swish sends a debit request to the payer's bank. (5) The payer`s bank then debits the amount and transmits debit confirmation to Swish. (6) Thereupon, Swish sends a credit request to payee's bank. (7) When the credit request has been approved, the back-end transfer system developed by Bankgirot transfers the money from payer's bank to payee's bank in real-time. (8) In the next step, the payee's bank posts credit to payee's bank account and sends a confirmation to Swish. (9) This confirmation is then received by the payer. (10) As the last action, Swish pushes a message to payee's Swish app to inform him / her of the received payment.



Appendix 2

Survey

Construct	Criteria	Question	Sources
Performance Expectancy	PE1: Perceived Usefulness	*I find Swish useful in my daily life.*	Venkatesh et al. (2012)
	PE2: Extrinsic Motivation	*Using Swish increases my chances of achieving things that are important to me.*	Venkatesh et al. (2012)
	PE3: Relative Advantage	*Using Swish helps me accomplish things more quickly.*	Venkatesh et al. (2012)
Effort Expectancy	EE1: Perceived Ease of Use	*I find Swish easy to use.*	Venkatesh et al. (2012)
	EE2: Ease of Use	*My interaction with Swish procedures is generally clear and understandable.*	Venkatesh et al. (2012)
	EE3: Complexity	*It is easy for me to become skillful at using Swish.*	Venkatesh et al. (2012)
Social Influence	SI1: Subjective Norm	*People whose opinions that I value prefer that I use Swish.*	Venkatesh et al. (2012)
	SI2: Social Factor	*I use Swish because because a lot people in my social environment use it as well.*	Venkatesh et al. (2012)
	SI3: Image	*Using Swish is well-regarded by others.*	Venkatesh et al. (2012)
Habit	H1: Past Behavior	*The use of Swish has become a habit for me.*	Venkatesh et al. (2012)
	H2: Reflex Behavior	*Swishing someone has become automatic to me.*	Venkatesh et al. (2012)
	H3: Individual Experience	*Using Swish is natural to me.*	Venkatesh et al. (2012)
Hedonic Motivation	HM1: Fun	*Using Swish is fun.*	Venkatesh et al. (2012)
	HM2: Enjoyment	*Using Swish is enjoyable.*	Venkatesh et al. (2012)
	HM3: Entertainment	*Using Swish is entertaining.*	Venkatesh et al. (2012)
Trust	T1: Trustworthiness	*Swish is trustworthy .*	Zmijewska et al. (2004)
	T2: Security	*I believe that data sent is confidential .*	Zmijewska et al. (2004)

	T3: Security 2	*I feel assured that legal and technological structures adequately protect me from problems at Swish.*	Gefen et al. (2003)
Network Externalities	NE1: Direct Network Effect	*If more and more users join Swish, the benefit I get from using Swish will increase.*	Katz & Shapiro (1992); Yu & Tao (2007)
	NE2: Direct Network Effect 2	*I believe that Swish will be dominant among m-P2P payment applications because of its network size.*	Katz & Shapiro (1992); Yu & Tao (2007)
	NE3: Indirect Network Effect	*The more businesses accept Swish, the higher the benefit that I get from using the application.*	Katz & Shapiro (1992); Yu & Tao (2007)
Behavioral Intention	BI1: Reuse Intention Short Term	*I intend to continue using Swish in the near future.*	Venkatesh et al. (2012)
	BI2: Reuse Intention Long Term	*I expect my use of Swish to continue in the next years.*	Venkatesh et al. (2012)
	BI3: Reuse frequency	*I plan to continue to use Swish frequently.*	Venkatesh et al. (2012)