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Factors Influencing Behavioural Intention Towards Usage Likelihood of Fintech Services Among Bank Users: Evidence from Norway

Master's thesis in International Business amd Marketing
Supervisor: Ahmad Amine Loutfi & Ghulam Mustafa
December 2020

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Dedication

I would like to dedicate this thesis to my loving wife, Nusrat Jarin, for always being my side and supported throughout this hectic and stressful period.

A B M Ahsan

Ålesund, December 10, 2020

ABSTRACT

The financial industry is going through a remarkable transformation for the last few years. As modern technology is enhancing, the financial industry is utilizing this new technology to spread the services. Fintech formed because of the utilization of contemporary technology in financial services, and it is growing rapidly throughout the world, and Norway is not exceptional to that. Regular consumers' point of view is changing these days because of their familiarity with the technological world. They are using several services from alternative sources other than their traditional banks. As Norway is one of the leading countries having well-developed digital infrastructures and the country is moving towards a cashless society, the consumers are taking advantage to use many of these digital services like mobile wallets, insurtech, financial advice, and so on. Moreover, recent PSD2 integration in the Norwegian banking and financial industry made it even more competitive by creating a level playing field for all the players. Although there is a vast growth in the Fintech industry, the influential factors that are driving the domestic consumers towards Fintech usage seem a little bit understudied academically. Thus, this project comes into light and study the factors that are affecting Norwegian consumers choosing Fintech over their banks.

In order to investigate the adoption intention of Fintech services by Norwegian consumers, the behavioural factors and environmental factors were studied. The Unified Theory of Acceptance and Use of Technology model 2 developed by Venkatesh, Thong, and Xu (2012) was used to conduct this study by some modifications. Image was added as Brand Image in the conceptual model from extended TAM, and few predictors were dropped in the context of Norway. Additionally, types of service are used as moderators, and age group, country, and gender were used as control variables in the model. Data collected through an online survey and then analysed on SPSS.

The findings indicate that the model explains about 49.3% (R^2) of the variation in the dependent variable Behavioural Intention, whereas 29.2% (R^2) of the variation in the dependent variable Usage Likelihood. Predictor Price Value is the strongest predictor predicting Behavioural Intention following its Effort Expectancy second and Hedonic Motivation third strong predictor. Rest was found insignificant. 'Payment' as service has a strong moderating effect, where high category users were found most likely to adopt Fintech services. Furthermore, age group 30-39 has a positive impact towards in adoption and under 24 was found negative impact in adoption. Rest age groups were found insignificant.

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ABBREVIATIONS

BI_1	Brand Image
BI_2	Behavioural Intention
EE	Effort Expectancy
Fintech	Financial Technology
GLM	General Linear Model
HM	Hedonic Motivation
IDT	Innovation Diffusion Theory
IS	Information System
IT	Information Technology
MLR	Multiple Linear Regression
MPCU	Model of PC Utilization
OR	Ordinal Regression
PR	Perceived Risk
PSD1	The Payment Services Directive
PSD2	The Revised Payment Services Directive
PV	Price Value
Sci-Tech	Science & Technology
SCT	Social Cognitive Theory
SDT	Self-Determination Theory
SI	Social Influence
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology 2

1. INTRODUCTION

The financial services industry is at the core of modern economies. Today, it is going through a profound digital transformation due to advances in revolutionary technologies and the advent of the open banking directive, which unleashes a wealth of innovative alternative solutions. Moreover, we have witnessed an escalating number of successful service providers who use innovative technologies to disrupt traditional financial services. Fintech startups are encroaching upon established markets, leading with customer-friendly solutions developed from the ground up and unencumbered by legacy systems (PWC Global, 2019). These financial technology players (Fintech) build and execute specific parts of the banking value chain better, cheaper, and faster than what banks currently offer (Innopay, 2015). Although to date, the financial industry as a whole comprises traditional financial players like big banks; however, the existence and the movement of Fintech services certainly influenced this sector lately.

To conduct this research, the author has chosen Norway as the country which has been ranked as one of the leading countries; having a leading digital infrastructure where internet and smartphone penetration is close to 100%. Consumers are early adopters of digital services in the country, and society is characterized by high levels of trust (Hernaes, 2018). The market is also continuously evolving where incumbent banks are no longer the only ones on the financial market, and the recent implementation of PSD2 has made it even easier for other players to make space for themselves. However, the common scenario says most Fintech firms have limited customers, but some Fintech firms like Klarna have established themselves on the market as a challenger to traditional banks. Although there are few existing research papers on Fintech in Norway however, those only provide the data on how the Fintech industry is affecting the conventional banking industry and how they are collaborating with each other to attain the maximum outputs, but it looks at banking customers' behavioral intention behind overall Fintech usage still understudied. As this field seems understudied, therefore, it will be interesting to conduct this study in the Norwegian market.

Based on the above analysis, it is understandable the significance of finding out the reasons why banks are facing competition from Fintech services, and it also needs to figure out, are users actually feeling the demand of finding alternatives beyond their banks?

1.2 Problem Statement

Once Bill Gates said in 1994, “Banking is necessary, banks are not” (Herneas, 2017). Many people opposed his opinion at that time, but today we see radical changes in the banking sector because of the growing numbers of Fintech firms. Despite the fact that banks are still holding their strong position in the financial market; however, they are facing tremendous competition from these companies. The purpose of using Fintech for banking is to improve user experience and banking efficiency. Most existing research works we have, are on Fintech strategy and risk for banking from the supply-side more than the demand side. Zavolokina et al. researched about “peer-to-peer” partnership model between Indonesian banks and Fintech companies (Zavolokina et al., 2016). Furthermore, Chang et al. explored how Indonesian banks changed their process in the perspective of Fintech and competed. According to Moody, the parents of and grandparents of millennials are mainly dominant customers of the banks, whereas millennials are primarily users of Fintech firms (Chang et al., 2016). Today, the situation is consumers are more aware of their demands and about their rights than before. Hence, the author feels the necessity for more research about the customers’ adoption of Fintech based on their demand side.

The Norwegian banking industry is highly regulated since the end of the Second World War, though the market had seen three major crises so far (Berg and Eitrheim, 2009). The first crisis was in 1899, which affected mostly banks in Oslo but shaken the whole country because of the crash in real estate. The second crisis happened in 1920, which persisted throughout that decade, and the last crisis happened in 1988 when many small banks faced high losses (Gerdrup, 2003). Since the last major crisis, the industry has not witnessed any serious catastrophe, and it achieved the trust of the Norwegian population. Norwegian society has a high level of trust, and the banking sector has scored the highest 61 among various sectors in terms of having trusts by Norwegians (Hernaes, 2018). It will be interesting to study why these consumers are shifting towards Fintech now, who have a high level of trust in their banks. Or it is the banks who are unable to provide the service as per consumers’ expectations, or it is an individual choice. This research will help us to understand the facts that are influencing these consumers to shift towards Fintech services.

Similar research has been conducted in countries like Malaysia and Indonesia earlier, but in Norway, the field seems a bit understudied, which I have mentioned earlier, and the context of Norway is different from those two countries in terms of social values, banking governance, and access to bank accounts. According to Bank Negara Malaysia, 92 percent adult population of Malaysia have access to bank accounts (Luna-Martinez, 2017), and in Indonesia, it is only 38.4 percent (SNKI, 2018). Therefore, it is understandable in Malaysia and Indonesia, a significant percentage of the population do not have bank accounts; hence, they adopted alternative Fintech services. Whereas, Norway is a country where almost everybody has access to bank accounts; as of 2017, the average proportion of the population who had access to the bank account was 99.87 percent (The Global Economy, 2017). The interesting part is, having after almost 100 percent population who have bank accounts, the Norwegian population is using various services offered by several Fintech firms. This would be exciting research to conduct to find out the answer, what are the reasons; a country which has nearly 100 percent population with access to bank accounts and who trust the banking sector more than any other sectors started adopting similar alternative services offered by various non-traditional financial companies or in other words from Fintech firms.

From a static point of view, studying the factors that influencing banking users to adopt Fintech services will give a proper insight into why customers are shifting their preferences, and it will help banks to comprehend the deficient they have in their services so that they can come with better services which will strengthen the contact between banks and the customers (Priem et al., 2011); (Davis, 1986) (Priem and Swink, 2012). From a dynamic point of view, millennials in the current scenario are less financially solvent compared to their parents and grandparents, but as time goes, they will be financially capable in the future and will be the core customers for banks. Hence, it is very important banks can hold these customers for their businesses in the future. As per a report, 63% of the millennials say innovation in service is a much-needed factor in getting them as customers, which gives them the ultimate users' experience (Medallia, 2015). Moreover, it is also mentionable that bank customers favour tailored pricing, products, and digital authentication (KPMG, 2017).

Therefore, this study will eventually help the banks to understand what factors are influencing banking customers to adopt Fintech services and how they can meet the demand of the current and future customers.

1.3 Research Purpose and Research Questions

Based on the discussion above, the preliminary purpose of this thesis paper is to ascertain and validate the factors that will, directly and indirectly, influence a bank user's intention to use a Fintech service. In order to understand bank users' perspectives to use alternative Fintech services, the research will be based on The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model by Venkatesh and others. The model was created to understand the consumer context to use a technology (Venkatesh et al., 2012).

Furthermore, it is assumed in this paper that users' acceptance of Fintech services is characterized by few other variables besides those originally described in the model. Therefore, few variables have been eliminated, and few have been added to the proposed model. Among three moderators from the original model, 'Experience' has been removed from the conceptual model because FinTech services are offered to achieve the same experience for everyone. Besides, Norway has a society that is highly influenced by egalitarian values (Teigen and Wängnerud, 2009). Even Norwegians have been found more supportive of implementing government intervention to increase gender equality (Jakobsson and Kotsadam, 2010). Regardless of consumers' gender, they are freely involved in the use of technology in Norway. Therefore, gender has been kept to use as one of the control variables to determine whether it has any impact on the user's actual likelihood to use the service. Another moderator age has been used as second control variable in the conceptual model. Age or age group has been found as one of the key component in technology adoption (Morris and Venkatesh, 2000). Therefore, it is believed that it will play a key factor in the adoption of Fintech services. In addition, respondents' nationality or country of birth has been used as another control variable to check if there is any impact of the nationality to adopt Fintech services in Norway in comparison to the respondents who are Norwegian by birth. There is also one moderator in the model which is based on the different types of Fintech services used by Norwegian consumers. This has been done to find out the answer of second research question wheather their preference in type of services influence their intention to adopt the services eventually or not.

In order to address the problem, the study will find out the answers to the following research questions.

1. What factors influence behavioural intention towards usage likelihood of fintech services among Norwegian bank users?
2. Does behavioural intention influence actual behaviour after controlling for the effects of different financial service types?

1.4 Scope of the Study

The scope of the study is to evaluate the factors which affect banking customers' intention to accept Fintech services in the Norwegian financial market. This study is a quantitative study where the survey questions are close-ended with a 7-Likert scale to collect the responses from the customers of different banks in Norway. The survey questions have been developed by validating scales used in earlier research works.

1.5 Structure of the Study

Chapter 1: Provides the introduction of the study with its background information, and it also includes research purpose and questions with the scope of the study.

Chapter 2: This chapter provides an overview of relevant earlier research works that have been done, and it also illustrates the concepts used in the formulation of the conceptual framework along with hypothesises and the developed conceptual model.

Chapter 3: This chapter includes information about the methodologies used in the study to collect data, relevant methods, and statistical techniques that were used in this study.

Chapter 4: Analysis of the collected data, and it also presents the results.

Chapter 5: The final chapter discusses the findings of the study, limitations, further research, and conclusion.

2. LITERATURE REVIEW & THEORETICAL FRAMING

This chapter provides a description of a brief discussion about the literature review and theoretical approach that has been used in the research to answer the formulated research questions. The chapter assesses earlier research and literature that has been done in the past, and a theoretical framing has been proposed on which the research has been conducted.

Based on the discussion in the previous chapter and formulated research questions, the thesis paper will try to find out the influential factors and the relationship of the adoption behavior of banking customers and will conduct in-depth quantitative research from the perspective of Unified Theory of Acceptance and Use of Technology 2 (UTAUT2).

2.1 Fintech

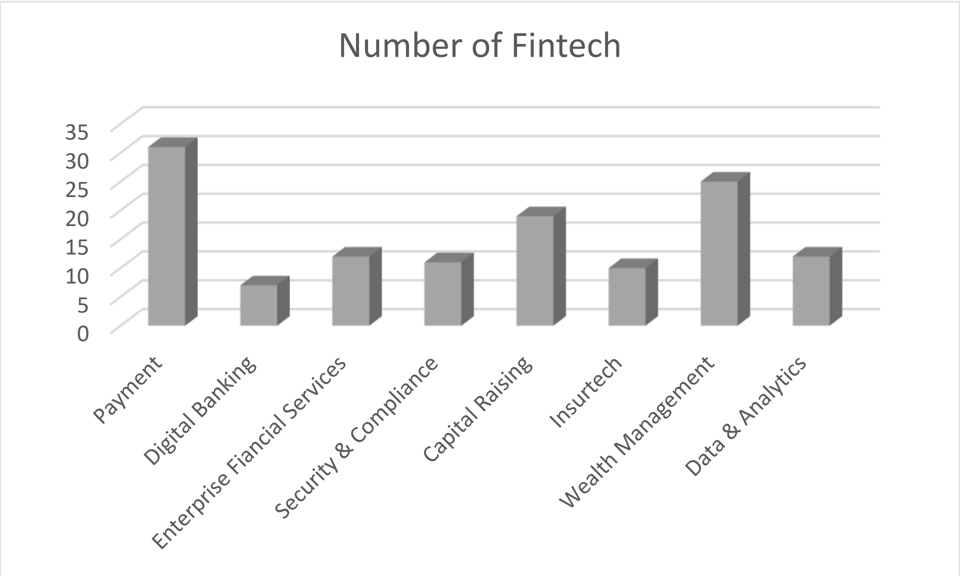
The relationship between technological progress and financial innovation has always been studied highly from different angles by several researchers. Since the proposal of 'Financial Deepening' in 1973 by McKinnon and Shaw, there are many Sci-tech finances were established in large numbers (Hermes and Lensink, 2008). Distinct from the notion of offering financial services to large enterprises, Fintech can be described as new types of tools that use modern technologies, for instance, big data, the Internet of Things, and cloud computing, to spread financial services (Nakashima, 2018). Fintech as financial technology unit in one company improves service quality and management efficacy by using new technology (Gai et al., 2018). Thus, it might develop the efficiency and scale of financial services using technology in the banking area (Hu et al., 2019). Major concerns of security and privacy of Fintech are divided into four components; they are data-oriented, facility and equipment, applications, and service models (Du et al., 2019). The main distinction between Fintech and traditional financial services is, Fintech is not a simple mixture of financial services and IT, rather it is an expanded capacity of traditional services by the application of modern technology (Arner et al., 2015).

2.1.1 The Global Market of Fintech

In recent years, the Fintech industry is observing remarkable growth; therefore, this industry has become a leading sector to study, and this market is growing rapidly. As per Accenture, a USA-based consulting firm, they say Fintech investment was $12.20 billion in 2010, whereas; in 2016, it increased to $153.10 billion, which was around 12.5 times higher than in 2010. Moreover, only in 2016, the Fintech investment reached to $23.20 billion, which 21.5% more than the previous year 2015, and the number of the firms used to increase 800 approximately before April 2015; whereas, by December 2016, it increased more than 2000 (Gabor and Brooks, 2017). If we think from a competitor perspective, the banks basically provide their customers three key financial services, which are deposit, payment, and lending, but Fintech firms are more into providing a better user experience for their niche market. However, now banks realize the importance of providing users experience, and they are trying to improve their core competencies and market shares by acquiring or cooperating with Fintech firms, for example, Goldman Sachs acquisition of Financelt, a Fintech firm that is specialized in providing a cloud-based platform that helps to provide an easy route to offer financing options for financial firms to their customers from any device (CBINSIGHTS, 2018). Banks are seeing this sector as prospective, the reason why they are taking the steps to either collaboration or acquisition. As per a report of Ernest & Young's global Fintech adoption index 2019, the adoption of Fintech services has shifted progressively upward from 16% in 2015 to 33% in 2017 to 64% in 2019, which indicates that the Fintech industry is steadily becoming the competitor of the traditional finance industry. The report also claims that Fintech awareness among non-adopters is very high nowadays; 96% of consumers know about at least one alternative Fintech service available for them to transfer money or make payments (Ernst & Young, 2019).

2.1.2 The Domestic Market of Fintech

Soon after Norwegian bank DNB introduced its first true Fintech concept Vipps it became a well-known household app among Norwegian consumers, later, Nordea launched their own Fintech accelerator program in Stockholm, partnering with Nestholma (TheFactory, 2019). From 2015 till 2019, the country witnessed immense growth, increased from 30 Fintech startups in 2016 to 127 firms in 2019 (TheFactory, 2019). The payment solution Vipps has become an important player in the industry from a simple app by merging with Bank-ID and Bankaxept. In the B2C area, Vipps has over 2.9 million users to date, and they dominate in the field of payment over other Fintech firms (TheFactory, 2019). Due to the PSD2 directive, the banks have to share information with third parties moreover;, these third parties can make payments on behalf of the account holders. Therefore, banks are responding by opening up their API for developers in the expectation for in solutions, resulting in digital banks like Sbanken (TheFactory, 2019). Initially, banks considered Fintech firms as challengers; however, the situation is now changing, and they are now partnering up with several Fintech services.



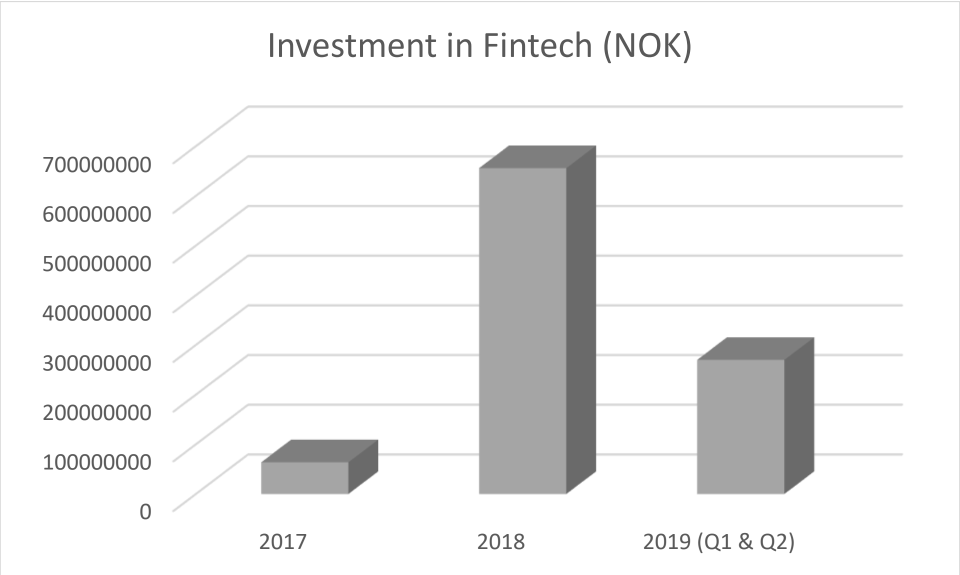


Figure 1: Fintech Scenario in Norway (TheFactory, 2019)

2.2 The Revised Services of Directive (PSD2)

The European Union initiated a new directive on payment services, which is known as PSD2, to enhance earlier service directive PSD1; in the EU, it was enforced on 13th January 2018 and in Norway on 14th September 2019 (Moen and Helgøy, 2018). PSD1 and PSD2, which are known as directives, are EU legitimate acts that are obligatory for EU countries to achieve a certain result; however, countries are free to decide how to do so (European Commission, 2018). The PSD1 and PSD2 both were implemented into the EEA agreement; therefore, Norway integrated these directives into the domestic law as an EEA country, which gave an edge to grow a lot of Fintech firms within the country from 2015 to 2019. PSD2 updated and complemented the earlier EU PSD1, which sets stricter rules in terms of consumers' protection (Moen and Helgøy, 2018). With this updated directive, the European Commission has strengthened payment services within the EU and EEA by:

- Aiding to make a more integrated European payment market.
- Making equal level playing field for the payment service providers, comprising new firms which were outside the extent of PSD1.
- Encouraging innovation and competition in the financial market.
- Providing a safe and secure payment environment.
- Improving consumer protection (European Commission, 2018).

From the discussion above, we understand why in Norway, Fintech firms have grown so rapidly. As PSD2 gave a lawful right to form these Fintech firms, hence; Norwegian customers are putting their trust in these types of firms and shifting a lot of their financial services to these firms. Therefore, it is needed to study in more detail about this switching, and the reasons for this switch might make this thesis very exciting.

2.3 Theoretical Frameworks of Technology Adoption

Many researchers have been trying to explain correctly the factors that work behind the technology adoption for a long period of time, and in recent times, various theoretical models have been developed to identify the factors that influence the adoption and use of technology. For example, we can include:

1. The Technology Acceptance Model (TAM)
2. The Theory of Reasoned Action (TRA)
3. The Theory of Planned Behaviour (TPB)
4. Innovation Diffusion Theory (IDT)
5. The Model of PC Utilization (MPCU)
6. Social Cognitive Theory (SCT), and
7. The Unified Theory of Acceptance and Use of Technology (UTAUT) etc.

In 2003 UTAUT was proposed by Venkatesh, Thong and Xu by reviewing and comparing eight competing models, these models are Theory of Reasoned Action (TRA, Fishbein & Ajzen, 1975), Technology Acceptance Model (TAM, Davis, 1989), Motivational Model (MM, Davis et al., 1992), Theory of Planned Behaviour (TPB, Ajzen, 1991), Combined TAM and TPB (C-TAM-TPB, Taylor and Todd, 1995), Model of PC Utilization (MPCU, Thompson et al. 1991), Innovation Diffusion Theory (IDT, Rogers, 1962), and Social Cognitive Theory (SCT, (Compeau and Higgins, 1995) (Venkatesh et al., 2003). These eight theories are considered as one of the leading theories in predicting users' behaviour in technology adoption. Below a brief discussion about the above theories is given along with the justification of why UTAUT2 has been chosen in terms of this study rather than other technology acceptance models.

2.3.1 Theory of Reasoned Action (TRA)

Theory of Reasoned Action (TRA) has derived from social psychology and one of the most influential theories of human behaviours (Venkatesh et al., 2003). The theory was created first in 1967 by Fishbein. Later it was revised and extended by Fishbein and Azjen in 1975 (Fishbein and Ajzen, 1977). The theory focuses on a person's intent to behave in a particular manner. The intention is a plan or objective that a person will act in a specific way that is expected, although he or she does it or does not do it. TRA was applied in technology acceptance and found that the variance explained was largely consistent that was applied in TRA in the context of other behaviours (Davis et al., 1989). The purpose of the theory is to rationalize volitional behaviour (Hale et al., 2002). Since its development, TRA has been used in several IS and technology research works by modification for a better explanation to use a specific technology or service. TBP and TAM are both derived from TRA.

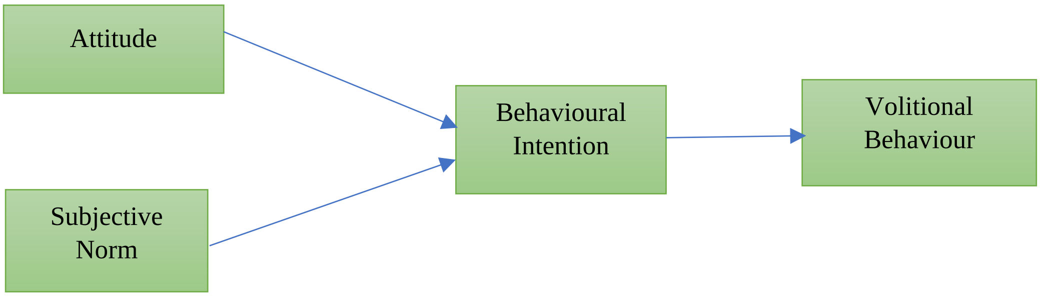


Figure 2: Theory of Reasoned Action (Fishbein and Ajzen, 1977)

2.3.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was developed to predict users' technology acceptance and use by Davis in 1989. TAM was constructed in the context of the Information System (IS). This is a widely used and applied theoretical model in technology and IS research. It was created to predict about acceptance of information technology and usage on the job (Venkatesh et al., 2003). Later TAM was extended to TAM2 by including few other variables as a predictor of intention in mandatory settings (Venkatesh and Davis, 2000). Compared to other prominent models, TAM is considered a more frugal, predictive, and strong theory in terms of technology acceptance (Venkatesh and Davis, 2000). The model is based on social psychology and derived from TRA in particular (Ma and Liu, 2005). Although TAM is a broadly popular model, however, it has been criticized on few grounds. TAM is more appropriate to predict individuals' technology acceptance; however, it is not very accurate in predicting institutional or corporate usage of information technology (Ajibade, 2018). Despite that, TAM is considered one of the most popular models to date for its simplicity, and many researchers have been cited and used it in their papers (Ajibade, 2018).

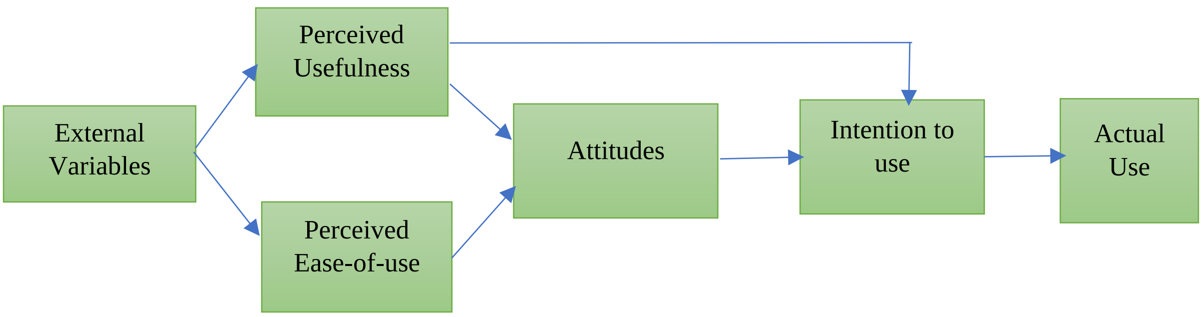


Figure 3: Technology Acceptance Model (Davis et al., 1989)

2.3.3 Motivational Model (MM)

Since the 1940's several theories have been developed from motivation research, and one of the famous motivations theories is Self-Determination Theory (SDT) created by Deci and Ryan (Momani and Jamous, 2017). SDT suggested that self-determination is a human characteristic that consists of the experience of choice, having the choice, and making a choice (Deci and Ryan, 1985). The motivational Model (MM) is a significant theory in psychology that supports general motivation theory to explain people's behavior, and many studies have used this theory and tailored it for a particular context (Venkatesh et al., 2003). In technology acceptance motivation was recognized as a substantial factor (Huang, 2017). This theory was applied to understand new technology adoption and use (Davis et al., 1992). The theory basically supports the explanation for human behaviour to use something.

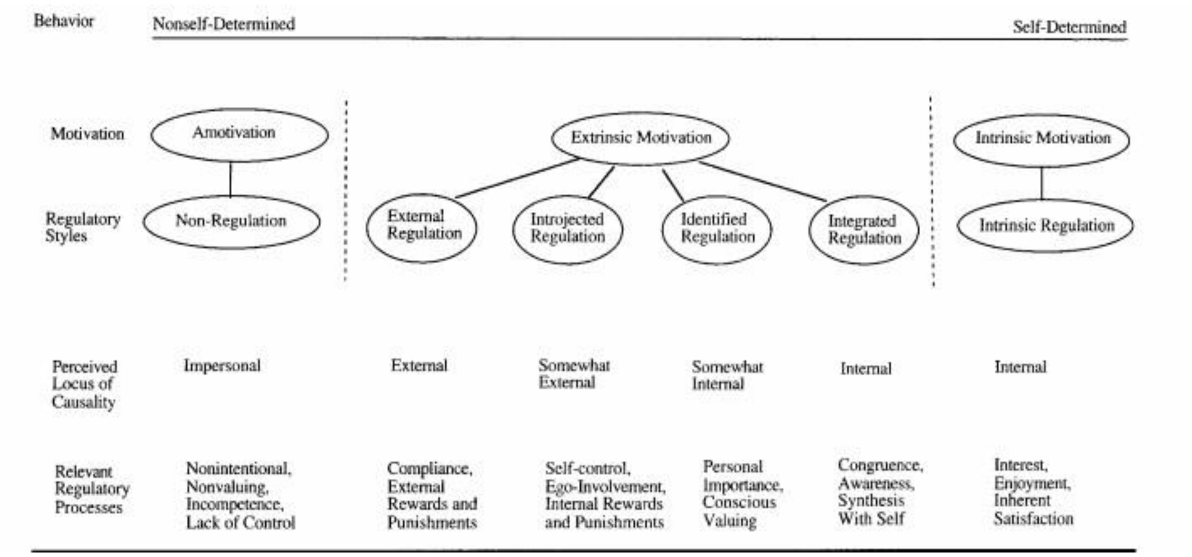


Figure 4: Motivational Model-SDT (Ryan and Deci, 2000)

2.3.4 Theory of Planned Behaviour (TPB)

TPB is an extension to TRA where the construct perceived behaviour control was added, and this extension was done by Ajzen (Ajzen, 1985). The predictor was added to theorized to be an added determinant of intension and behaviour (Venkatesh et al., 2003). TPB has been used in various papers to understand the use of different technologies. The theory is moderated by three constructs; they are attitude toward behaviour, subjective norm (adopted from TRA), and perceived behavioural control (Momani and Jamous, 2017).

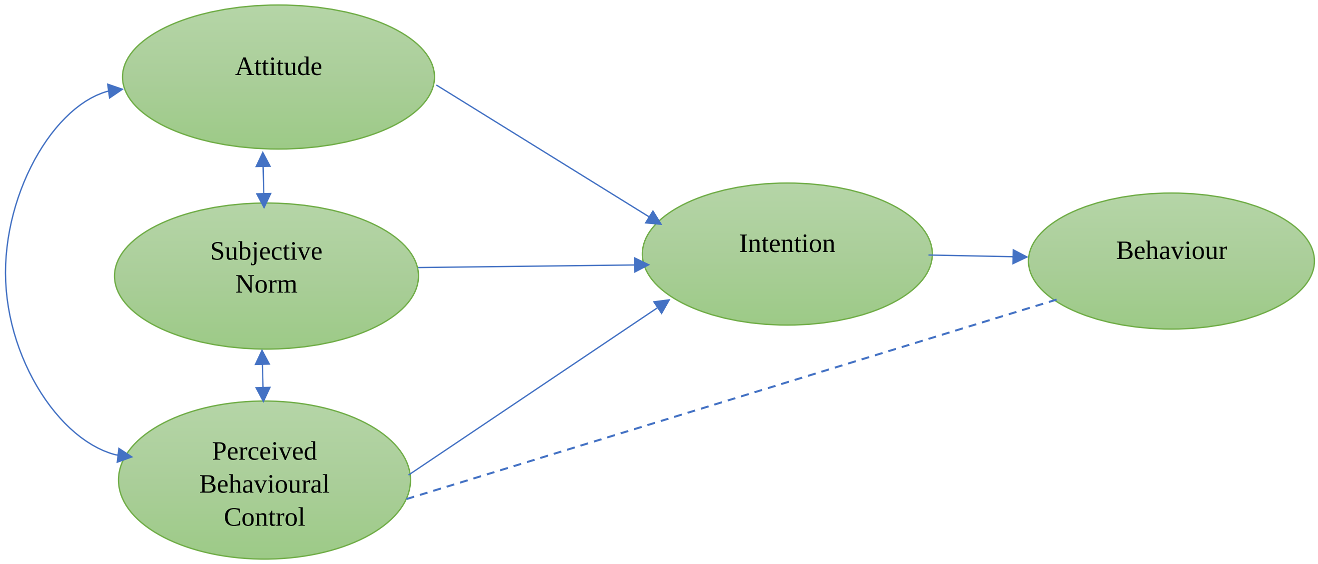


Figure 5: Theory of Planned Behaviour (Ajzen, 1985)

2.3.5 Combined TAM and TPB

Combine TAM and TPB is a hybrid model that added the perceived usefulness construct from TAM into TPB (Venkatesh et al., 2003). Taylor and Todd established this model by blending TPB from social psychology, and TAM from IT fields to get a more accurate prediction of users' behaviour in technology adoption (Momani and Jamous, 2017). The model assumes behaviour is determined by the users 'or consumers' plan to execute or perform a behaviour. At the same time, attitude towards behaviour determines the intention. This model has been used in research like internet banking adoption.

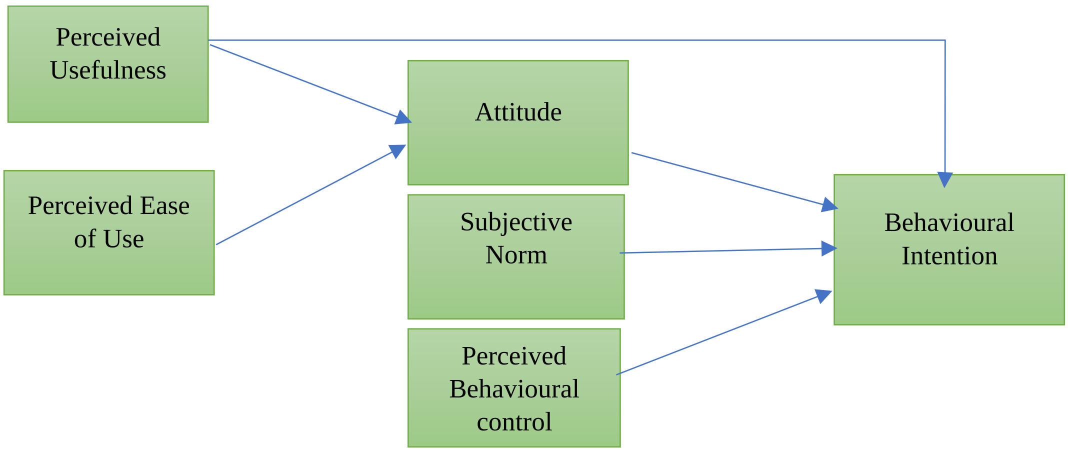


Figure 6: Combine TAM and TPB (Taylor and Todd, 1995)

2.3.6 Model of PC Utilization (MPCU)

MPCU is massively influenced by the theory of human behaviour by Triandis' (1977), which represents a competing perspective that was proposed by TRA and TPB (Venkatesh et al., 2003). This theory was a modification of Triandis' model in the context of IS to understand and predict PC utilization (Thompson et al., 1991). However, this model is very suitable to predict individual acceptance and use of different technologies. In this model, it is assumed behaviour has a purpose consequences which are construed by individuals (Triandis, 1979).

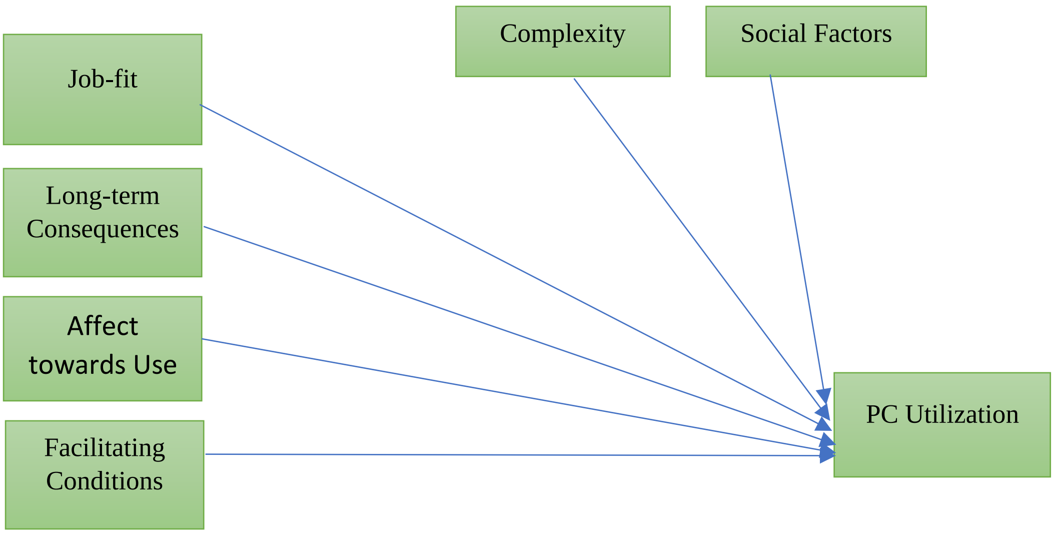


Figure 7: Model of PC Utilization (Triandis, 1977)

2.3.7 Innovation Diffusion Theory (IDT)

IDT has been grounded in sociology, which has been used since the 1960s to study various innovations like agricultural tools and organizational innovation (Tornatzky and Klein, 1982). The model is one of the oldest models in social science developed by Rogers in 1962 to study innovation (Tornatzky and Klein, 1982). Later the theory was modified and adapted to the characteristics of innovations presented in the original theory that could be implemented to study technology acceptance (Moore and Benbasat, 1996).

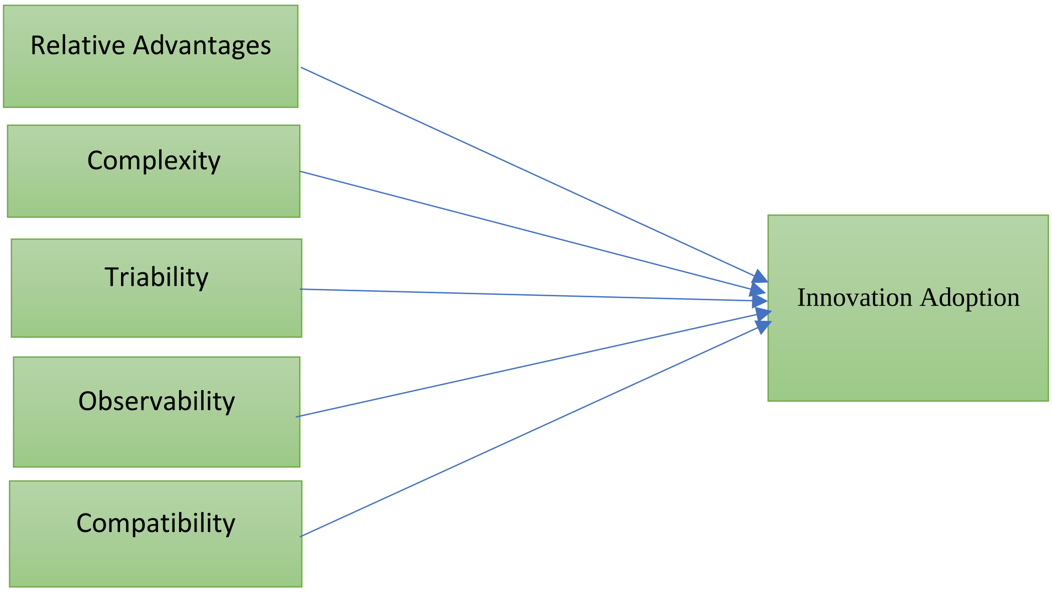


Figure 8: Innovation Diffusion Theory, (Rogers, 1983)

2.3.8 Social Cognitive Theory (SCT)

The idea of SCT was initiated in 1941 by Miller and Dollard with the Social Learning Theory (SLT) for modelling purpose in the principal of learning (Momani and Jamous, 2017). SCT is one of the most compelling theories to predict human behaviour (Bandura, 1986), which has been applied successfully in the context of computer utilization (Compeau et al., 1999). The theory was originally used to study computer use, however, the nature of the model and fundamentals of this theory allows it to use in the context of the adoption of IS in general (Venkatesh et al., 2003).

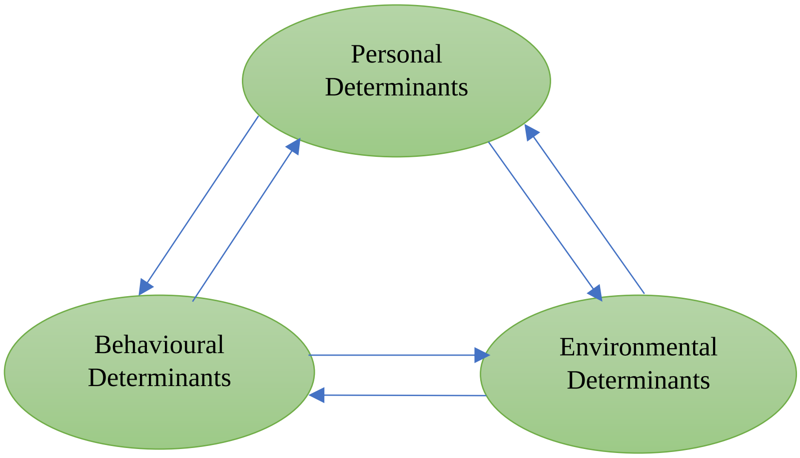


Figure 9: Social Cognitive Theory, (Bandura, 1986)

2.4 The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

It has been mentioned earlier that UTAUT has been derived after comparing and examining the eight above mentioned prominent models. The UTAUT has four main constructs, which are: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) with four more moderator variables, which are: gender, age, experience, and voluntariness. Later in 20012, they added three more constructs, which are: price value (PV), hedonic motivation (HM), and habit (HB), by modifying earlier UTAUT, which was created mainly to explain the technology acceptance in the context of organizational use. The newly added variables enhanced the original UTAUT model's explanatory power in terms of consumers' context, and they named the model as UTAUT2 besides the above-mentioned major theories in technology adoption, IT, and IS research. After the addition of new constructs into UTAUT2, Venkatesh tested it on 1,512 of mobile internet technology, and it has produced a significant improvement in the variance explained in behaviour intention (56 percent to 74 percent) and technology use (40 percent to 52 percent) (Venkatesh et al., 2012). Moreover, UTAUT2 has been used in many technology acceptance research works by several researchers in their papers due to its simplicity, frugality, and strength. Therefore, this study utilizes the model to determine the adoption intention of Fintech by banking customers in Norway. As it has been mentioned in the earlier chapter for this study, few variables, including one moderator, have been eliminated from the model, and a new variable has been added in the proposed model to determine the actual consumers' behaviour in terms of accepting Fintech services over their regular banking services in the context of Norwegian financial market. In the proposed model, the newly added independent variable is the brand image (BI_1). It is assumed that the newly added predictor in the original UTAUT2 will increase the chance to explain more precisely the users' actual behavioural intention to adopt Fintech services, as the society has a high level of trust. Earlier research has found the relationship between brand image and trust is significant in today's economy (Zatwarnicka-Madura et al., 2016). Therefore, it is believed that brand image will play a crucial role in determining consumers' behavioural intention to use Fintech services.

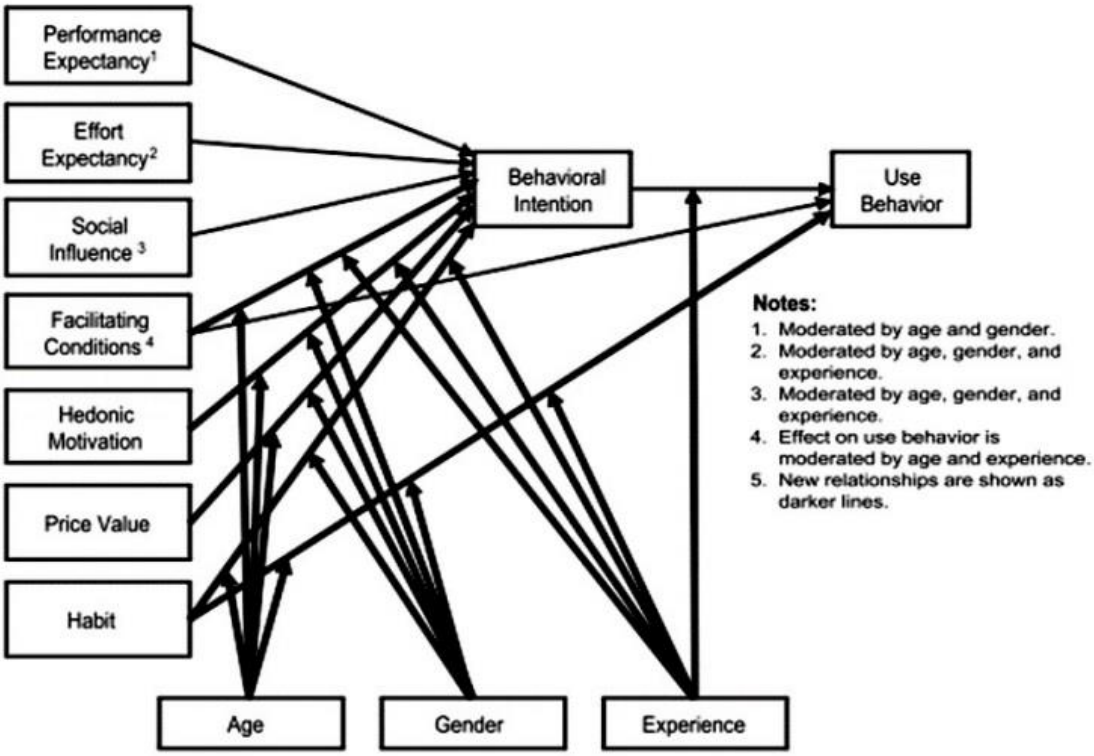


Figure 10: UTAUT2 Framework (Venkatesh et al., 2012)

There is a brief description presented below about the factors that are mentioned in the UTAUT2 framework, along with additional factors that have been included in the proposed research model.

2.4.1 Effort Expectancy (EE)

Effort expectancy is "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450). It is like perceived ease of use in TAM/TAM 2, complexity in MPCU and ease of use in IDT. Effort expectancy is also theorized as a direct determining factor of behavioural intention. Davis found that an application or a service is preferred by users that is simpler to use is more likely to be acceptable (Davis, 1989). Users have higher expectations toward getting desired performance from a service or technology when they find it easier to use (Venkatesh et al., 2003). Other previous researches also proved that effort expectancy had a higher impact on a user's intention to use technology and it comes from a user's experience of how easy a technology to use (Venkatesh et al., 2012); (Abrahão et al., 2016).

From the above discussion, we can see performance expectancy is a significant predictor within the UTAUT2 model to apply to understand consumers' intention to accept Fintech services, and based on it; the following hypothesis has been developed.

H_1: Effort Expectancy (EE) has a significant effect on Behavioural Intention (BI) to use Fintech services.

2.4.2 Social Influence (SI)

Social influence has been defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p. 451). In other words, it can be said social influence is a social pressure that comes from an outside environment where an individual's behaviours and perceptions get influenced in a certain action (Venkatesh et al., 2003). Social influence is a direct determining factor of users' behavioural intention to use technology. It is similar to the subjective norm in TRA, TAM2, and TPB/DTPB, and C-TAM-TPB; social factors in MPCU, and image in IDT (Venkatesh et al., 2003).

The direct impact of social influence over behavioural intention is justified by the fact that people may be influenced by the view or opinion of others that their involvement in particular behaviour gets changed even though they do not want to change. However, the effect of social influence arises only in a mandatory environment but remains lower in a voluntary environment (Venkatesh and Davis, 2000).

Previous research works have provided inconclusive findings If social influence has a significant effect on behavioural intention. Some studies found that social influence has a large impact in forming an individual's intent to use technology (Blaise et al., 2018) whereas other researchers found differing results (Lancelot Miltgen et al., 2013); (Morosan and DeFranco, 2016); (Shaw and Sergueeva, 2019).

From the discussion above, we can say Fintech is quite new in our society, and as it is mentioned earlier, it has various services like mobile payments, banking, crowdfunding, money transfer, and so on. In terms of using any of these services, as these are spread across our society, people are greatly influenced by their friends, families, and surroundings. Therefore, social influence is expected to be a big predictor in terms of accepting Fintech services over traditional banks. Based on the discussion, the following hypothesis has been developed.

H_2: Social Influence (SI) has a significant impact on Behavioural Intention (BI) to use Fintech services.

2.4.3 Hedonic Motivation (HM)

Hedonic motivation has been described as "the fun or pleasure derived from using a technology" (Venkatesh et al., 2012). It has been found to play a crucial part in terms of accepting and use technology (Brown and Venkatesh, 2005). It involves an individual's intent to explore a technology where it entails several stages, and the effects vary across various stages of technology adoption (Magni et al., 2010). In the consumer context, the predictor has been found as one of the vital determining factors in technology acceptance and use (Brown and Venkatesh, 2005); (Childers et al., 2001). According to Lee, when a technology produces pleasure and fun when it is in use, and users get enjoyment, it influences users' behavioural intention to engage in the technology (Lee, 2009).

Moreover, it has been found in studies, hedonic motivation as a crucial predictor to influence behavioural intention to accept or adopt technologies like mobile banking (Baptista and Oliveira, 2015). Thus, the following hypothesis has been developed.

H_3: Hedonic Motivation (HM) has a significant impact on Behavioural Intention (BI) to use Fintech services.

2.4.4 Price Value (PV)

The price value is defined as consumers' cognitive trade-off in terms of getting benefits from using a service and the price for using it (Venkatesh et al., 2012). The price value was found to have a positive impact on behavioural intention towards embracing technology in IS research (Arenas Gaitán et al., 2015); (Tarhini et al., 2015). In terms of Fintech acceptance, cost and price structure play an important role because if Fintech companies do not have a lower price than traditional banks, then it is difficult for the users to adapt their services; moreover, there might be additional costs such as mobile data, service cost, device cost, and transaction fees. As Fintech firms provide various services to their customers, and lots of their services are free to use; however, there are many services like cross border payments and premium banking services which customers need to pay for. Hence, price value has been considered as one of the important predictors in this study. Based on the discussion above following hypothesis has been formulated.

H_4: Price Value (PV) has a significant effect on Behavioural Intention (BI) in terms of using Fintech services.

2.4.5 Perceived Risk (PR)

Perceived risk is originated from a lack of trust in something. A lot of scholars believe that perceived risk is the factor that influences users negatively in terms of technology adoption (Kesharwani and Singh Bisht, 2012); (Sikdar and Makkad, 2015). In this study, perceived risk will be referred to as the financial and privacy risks that users might have while choosing Fintech services. Financial risks are involved with the loss of properties caused by various events like return on investment, while privacy risks are associated with the disclosure of private, transactional, and other types of personal data into the wrong hands when users choose any online financial products. (Khedmatgozar and Shahnazi, 2018) found that risk perception is a tremendously crucial factor when it comes to adopting any e-services. It was also found that users are highly concerned about the misuse of personal data during the usage of Fintech services, which might bring more severe consequences (Bansal et al., 2010).

Fintech services are involved with the internet, big data, and cloud computing; therefore, there are some possible risks that are involved with this when getting the service (Zhou et al., 2010). For example, when users are choosing financial services online, they have to provide a lot of personal information before joining or when getting the service; hence, there is always a chance of leaking this information online, and that has a significant impact on users' trust to get the service which ultimately influences users' behavioural intention to choose the Fintech services. (Kim and Prabhakar, 2000) also found in his research that users' trust is greatly affected by perceived risk. Based on the discussion above, the following hypothesis has been formulated.

H$_5$: Perceived Risk (PR) has a significant effect on Behavioural Intention (BI) to use Fintech services.

2.4.6 Brand Image (BI$_1$)

The brand image is considered as an intangible asset for a business firm, which brings economic benefits. A company with a high brand image certainly can create a positive impact on the market for its customers or users. "The brand effect of service providers has an important influence on the provision of reliable services to users, and it plays a positive role in promoting users' achievements of their intended purposes" (Park et al., 2015). Earlier research work on Fintech revealed that brand image has a great impact in terms of users' perceptions or behavioural intentions to use the service (Riyadh et al., 2010).

In the context of Fintech adoption, users' awareness of the brand has been theorized and observed as a prerequisite to attain organizational trust (Chandra et al., 2010). As it has been mentioned earlier, to get Fintech services, users need to provide several personal information which associated with perceived risk; (Semuel and Lianto, 2014) suggested a good brand image can reduce this associated risk by boosting users' trust.

From the above discussion, it can be said brand image plays a crucial role in attaining users' trust in a service, which eventually drives users' behavioural intention to adopt that service, and it can be an important predictor to understand users' actual behavioural intention to use a Fintech service. Thus, the following hypothesis has been developed.

H$_6$: Brand Image (BI$_1$) has a significant impact on Behavioural Intention (BI$_2$) to use Fintech services.

2.4.7 Behavioural Intention (BI$_2$)

The concept behavioural intention has been explored by many scholars, scientists, and psychologists for many years. Behavioural intention has been defined as users' intent to act or not to act some specified future behaviour(s) (Aarts et al., 1998). (Islam and Hasan, 2013) defined behavioural intention as a user's intention to perform a given act, which can foresee his or her corresponding behaviour from their voluntary acts.

In terms of technology acceptance, it can be defined as an individual's keenness or chances that he or she will use the technology system (Venkatesh et al., 2003); (Venkatesh et al., 2012); (Davis, 1989). Several aspects, like users' attitude, subjective norm, perceived behavioural control, etc., might drive users' behavioural intention.

Many scholars reckon that the higher the behavioural intention, the higher the chances that a user will use or adopt new technology. (Mun et al., 2006) said behavioural intention is the subjective possibility of carrying out a behaviour that causes a specific usage behaviour.

From the above discussion, it can be summarized that behaviour intention is the predictor that ultimately determines actual users' likelihood to adopt a technology system or, in other words, the adoption of Fintech services. Thus following hypothesis was formulated.

H_7: Behavioural Intention (BI_2) has a significant influence on Usage Likelihood (UL) to use Fintech services.

2.4.8 Usage Likelihood (UL)

The ultimate goal of UTAUT2 was to measure the influence of behavioural intention on use behaviour, however; it is very difficult to validate the actual usage by the consumers due to a strong tendency for people to overestimate the probability that they will engage in a certain behaviour. The is true when it comes to a complex technology like Fintech. For instance, (Venkatesh et al., 2012) used UTAUT2 model to predict consumer behavioural intention to use mobile internet and found only 33% of the variance in the technology has a direct effect from behavioural intention; which makes us believe that there are several other factors which influence users' intention to adopt or use a specific technology.

Since we cannot measure the actual usage behaviour in this study because of the incapability of gathering accurate data from service providers and the limitations of the survey, therefore; a substitute variable Usage Likelihood (UL) has been introduced. This variable is kind of alike to use behaviour, but it has some major differences. This construct involved with users' perceived likelihood to use a specific technology under a context or their Behavioural Intention to use is moderated by other factors. Moreover, it depends on the decision-making process rather than the adoption process. It means a customer's final choice to use a certain technology over another one depends on other moderators or contexts as well, apart from the predictors used in the conceptual model. For example, the usage of Fintech might vary among different age groups and users' experience from using it. Thus, Age Group has been used in the model as a control variable to determine users' actual behavioural intention to use Fintech services.

2.5 Proposed Conceptual Framework

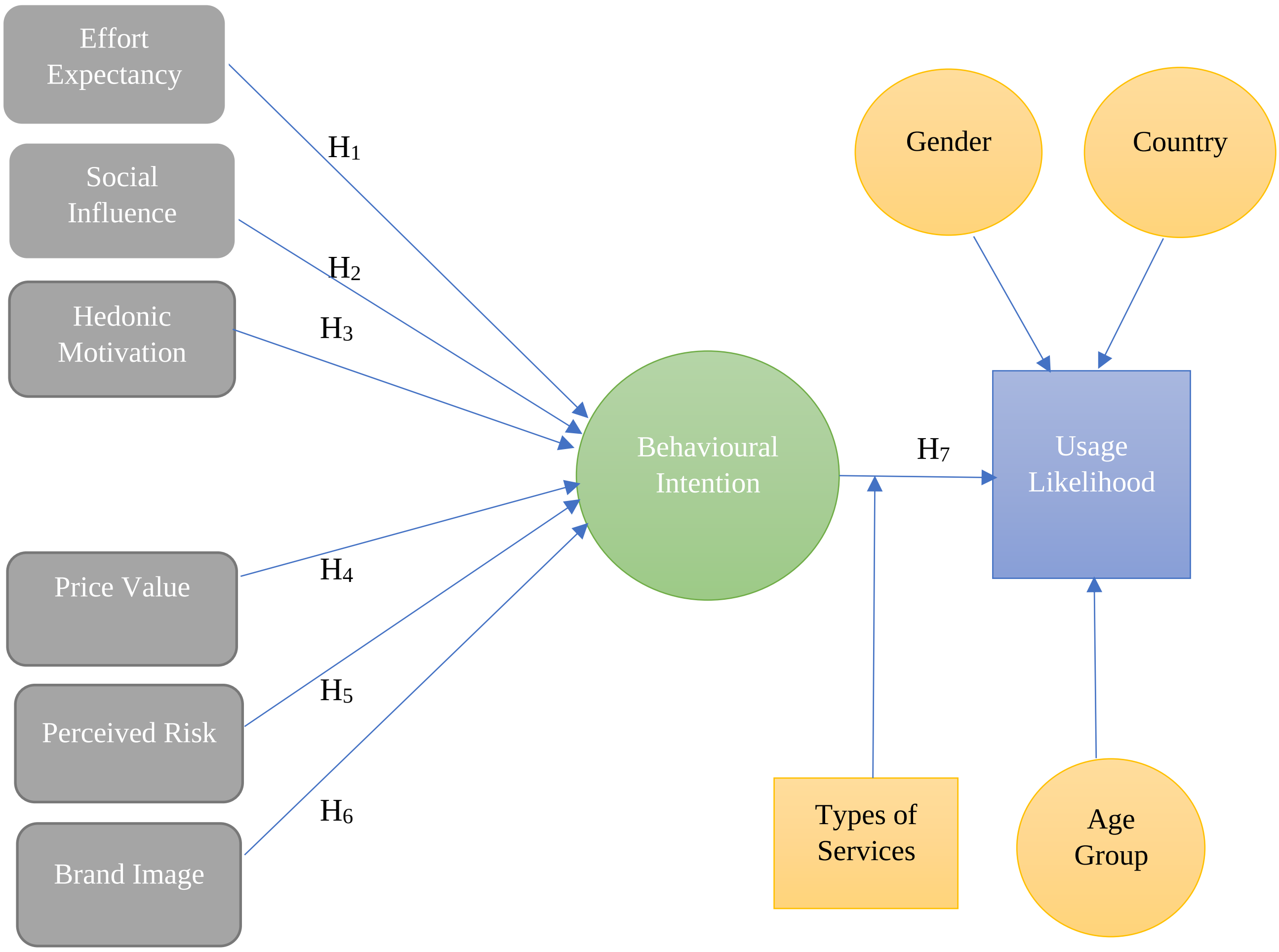


Figure 11: Conceptual Framework

3. METHODOLOGY

This chapter gives a complete description of the research technique that has been used in the study to assess the effects of various factors on Fintech adoption. Precisely it gives an overview of the research methodology, research design, sample of the data, data collection methods, variables, and measurement, along with the techniques to analyse data to test the hypothesis developed earlier.

3.1 Research Methodology

A research methodology is a combination of all kinds of research methods. In other words, research methodology is a way to resolve research problems in a systematic manner. A research methodology is concerned to answer why a research study has been undertaken, how the research problem is labeled, in what way hypothesis has been developed, what data have been collected and what method has been selected, why a particular technique of analysis was used to analyse data, etc. (Kothari, 2004). In this research, the positivism[1] research approach was chosen, and in the positivism, approach the researcher is unbiased from the study, and he has no provisions for human interests within the study. The common rule for positivist studies to choose deductive reasoning rather than inductive reasoning approach (Crowther and Lancaster, 2012). Therefore, the deductive research approach was selected as the common practice of positivism studies. The quantitative data collection strategy was also used in this study. A brief discussion on these approaches and techniques presented below.

3.1.1 Deductive Reasoning

Deductive reasoning or approach starts from a hypothesis or general statement and assesses the possibility to come up with a rational conclusion. In this approach, the researcher moves from theory to reality. The deductive reason is a psychological process rather than an abstract theory, and the psychological study of this approach has largely focused on investigating its algorithmic underpinnings (Schechter, 2013). It has been intensively studied in psychology, philosophy, and cognitive science. This approach is also known as the top-down approach to inspecting the questions, which analyse practical data against the theory by which the durability

[1] Positivism research approach rely on quantifiable observations that drive to statistical analysis.

and accuracy are tested. A practical justification for selecting the deductive approach is it is less time consuming and can be generalized across empirical data collection (Sander, 2020).

3.1.2 Quantitative Approach

Research methods are basically two types, one is quantitative, and another one is qualitative. The quantitative method deals with statistics and numbers while the qualitative with words. As it is mentioned previously, a quantitative research considers a deductive approach towards research (Rovai et al., 2013). The researchers in the quantitative approach reckon the world as being outside of themselves and that there is “an objective reality independent of any observations” (Rovai et al., 2013, p. 12). The researchers subdivide this reality into small pieces for an easily manageable reason so that the reality is understood. The analysis is conducted within these smaller manageable pieces so that the hypothesis test can produce results that show a correlation between the variables. A characteristic of this method of research is that the collection and analysis of data utilize mathematical based techniques (Aliaga and Gunderson).

Since the study is related to collect empirical data, which will be in numerical form and will be studied with great exactness and moreover data are going be quantified to assess the hypotheses; therefore, a quantitative approach in conducting this study will be suitable.

3.2. Research Design

Research designs refer to the way of obtaining the answer to the research question as it is a framework for collecting and analysis of the data (Burns and Burns, 2008); (Lee and Lings, 2008). There are several types of doing research, like exploratory, descriptive, correlational, and experimental studies (Burns and Burns, 2008). To conduct research in an unknown area, we use the exploratory study. A qualitative study is used in exploratory research. On the other hand, descriptive study is concerned with documenting what is occurring, and for this type of study, qualitative or quantitative or mixed research is used. In experimental studies, the researcher changes the predictors and tries to observe if there are any changes in corresponding dependent variable (Burns and Burns, 2008).

For this study, the cross-sectional design has been used as it needs fewer resources in terms of time and cost. This approach allows selecting all the variables at a single point in time, which is crucial because of the limited period (Burns and Burns, 2008). Furthermore, a cross-sectional approach allows gathering data on several variables, which is important as different factors that may affect the dependent variable according to theory. To ensure the validity of the study, items that have been used to measure the outcomes have been adopted with modification of wording from existing literature to fit into the Fintech scenario. A survey has been distributed by following close-ended type of questions created with the help of Google forms. The participants in the survey were entirely voluntary and anonymous without any sort of influence or compensation, and it was distributed among Norwegian banking customers through emails, Facebook messenger, WhatsApp, who are of course, customers of different Norwegian banks. The Survey has been designed to understand users' intention to use a Fintech service over their regular banks. The survey contains two parts: the first part of the survey has some general questions to determine the participants' demographic factors if they use Fintech services and their experience with these types of services. The second part has 3 to 4 questions from each variable based on the proposed model created from UTAUT2 by Venkatesh with some modification with 7-point Likert scale for the questions which refers '1' as "strongly disagree" and '7' as "strongly agree."

3.3 Sample and Data Collection Technique

The study aims to investigate which factors may affect consumers to use Fintech services rather than their regular banks. The respondents who participated in the survey are the customers of various banks in Norway. The survey was made using Google forms, which is an easily reachable tool through an online link. The survey contains 31 questions in total, where 25 questions are based on the variables used in the model, 6 questions are to get the generic information about the respondents, which also used to understand the demography of the sample. The survey was distributed through emails, Facebook messenger, WhatsApp, and other media, and they were asked to forward the survey further to get more respondents. 285 respondents answered the survey in total. In order to understand the demography of the population, their age group has been divided into five generations. The generations are Baby boomers (over 56 years old), Gen X or Baby Bust (40 to 55 years old), Gen Y.1 or Millennials (25 to 29 years old, Gen Y.2 or Xennials (30 to 39 years old), and Gen Z or iGen (less than 24 years old) (KASASA, 2020); (Robinson, 2016).

3.4 Development of the Questionnaire

This section provides a concise explanation of the questionnaire, which has been formulated under corresponding constructs. The survey questions have been adopted from similar research works, which have been done using the UTAUT2 model and extended TAM.

Dependent variable: Behavioural Intention (BI_2)

Independent variables: Effort Expectancy (EE), Social Influence (SI), Hedonic Motivation (HM), Price Value (PV), Perceived Risk (PR), Brand Image (BI_1).

A measurement approach is used to measure the variables in the research. There are eight approaches to measure variables, and they are paired comparison, rank order, constant sum, semantic differential rating, Likert rating, continuous rating, Q-sort, and staple rating (Schmidt and Hollensen, 2006). Among these techniques, a seven-point Likert scale rating has been used in this study.

3.4.1 Dependent Variable

The dependable variable in the study is Behavioural Intention, which means consumers' intention to use fintech services. Following questions have been developed under the dependent variable.

3.4.1.1 Behavioural Intention (BI_2)

In order to measure behavioural intention, a seven-point Likert scale has been used, which ranged from 1 (strongly disagree) to 7 (strongly agree). The questions under behavioural intention are:

1) I shall prefer to pay with Vipps or with other mobile payment systems over my regular bank card.

2) I shall try to use Fintech services for cross-border payments rather than my regular bank.
3) I intend to use Fintech services in the future.

4) I shall recommend others to use Fintech services.

3.4.2 Independent Variables

There are six predictors used in this study. Based on these independent variables, the following scale items have been developed.

3.4.2.1 Effort Expectancy (EE)

Effort expectancy is involved with the ease associated with using a system. Under this construct, the following questions have been developed.

1) I find Fintech services are easy to learn.
2) It is simple and understandable to interact with a Fintech service.
3) The system is flexible to interact with.
4) I do not have any confusion about “what I am doing” while using the service.

3.4.2.2 Social Influence (SI)

It refers to the degree of influence of a person’s surroundings to use something. Based on this predictor, three questions have been developed. The questions are as follows.

1) My friends, family, and surroundings value the use of Fintech services.
2) Many of my friends use Fintech services.
3) Family and friends’ suggestions influence my decision to use Fintech services.
4) I find usage of Fintech trendy.

3.4.2.3 Hedonic Motivation (HM)

The hedonic motivation is involved with the pleasure or fun to use something. Under this construct, three questions have been formulated. They are as follows.

1) To me, using a Fintech app or service is fun.
2) It is something I like doing.
3) I feel the motivation to explore more about Fintech.

3.4.2.4 Price Value (PV)

The price value is the involvement of the price a customer pays to get benefits from service. In this study, based on price value, three questions have been formulated. They are presented below.

1) Price plays a crucial role for me to select a financial service.
2) I find Fintech services are cheaper to use.

3) Fintech services are cheaper than my regular bank considering other associated costs to use it.

3.4.2.5 Perceived Risk (PR)

Perceived risk is associated with the risks of using a system. Four questions have been developed under this predictor. They are mentioned below.

1) I feel unsafe by providing personal information to use the system.
2) I feel unprotected to send confidential data while using the mobile app of the service providers.
3) I feel the chances of happening something wrong with these types of services higher than my regular bank.
4) There is a high risk of breaching my financial data if I lose my phone as Fintech services are mostly based on mobile apps.

3.4.2.6 Brand Image (BI1)

Brand image is an intangible asset that brings monetary benefits for a company. Under this predictor, there are three questions.

1) I feel the brand name is important to choose a financial product.
2) I feel a service provider with a good brand image is more trustworthy to use.
3) I feel safe using a Fintech service if it is from a renowned brand.

3.5 Statistical Technique

There are few statistical techniques used in this study, for instance, factor analysis using principal component analysis, reliability analysis, multiple linear regression, and so on. A brief discussion of major statistical techniques that were used in data analysis is presented below.

3.5.1 Multiple Linear Regression (MLR)

For the first half of the model, the author decided to use multiple linear regression. Multiple linear regression is a statistical technique that predicts the outcome of a dependent variable. This technique considers two or more independent variables to explain one continuous dependent variable. This is the most used statistical technique in behavioural science. In multiple regression, the independent variable can be in quantitative measures or in categorical measures, or in treatment conditions for analysis (Aiken et al., 2012). The common form of MLR is where the dependent variable is continuous; in terms of this study, the dependent variable is continuous, which makes it easier to use multiple linear regression in this analysis.

Moreover, there are six independent variables in this study, which also make this technique an obvious choice.

3.5.2 Ordinal Regression (OR)

In statistics, ordinal regression is used to predict an ordinal dependent variable (the variable's value exists on an arbitrary scale). By carrying out an OR, it is easier to determine which independent variables have a strong effect on the dependent variable (Lærd Statistics, 2020). As this thesis contains an ordinal variable as the dependent variable for the second half of the model, therefore; carrying out an ordinal regression analysis will certainly produce suitable outcomes. However, for this regression analysis, there are four assumptions which are needed to be passed. They are as follows.

i) The dependent variable should be quantified at the ordinal level.

ii) One or more independent variables should be continuous, ordinal or categorical.

iii) There is no multicollinearity exists in the dataset among predictors.

iv) There should be proportional odds, which means each independent variable has and equal effect on the ordinal dependent variable.

In this study, an ordinal variable was created based on the respondent's usage frequency of Fintech services. The category consists of three levels: low usage, medium usage, and high usage. As the dependent variable has been categorized as ordinal, therefore, it will be beneficial to use ordinal regression in this study.

3.5.3 General Linear Model (GLM)

A general linear model is a useful framework to compare the effects of several variables over different continuous variables. "The term 'general' in GLM simply refers to the ability to accommodate variables that represent both quantitative distinctions that represent continuous measures, as in regression analysis, and categorical distinctions that represent experimental conditions, as in ANOVA" (Rutherford, 2001, p. 5). There are four manners in linear modeling, and they are model selection, parameter stigmatisation, model checking, and the prediction of future values (Box et al., 2011); (McCullagh and Nelder, 1989). With GLM, the linear modelling method of estimation so specified that the four linear modelling process become even more recursive (Rutherford, 2001). The prime reason for choosing the GLM approach offers conceptual and practical benefits over the traditional approach (Rutherford, 2001). GLM

divides data into model and error, which means the better the model, the less the error it produces.
In this study, GLM was used to verify the final results, which were calculated using ordinal regression, and it provides similar manner results to OR.

3.6 Ethical Consideration

Ethical issues might arise in different phases in research works; thus, consideration of these types of issues is necessary since they are related to the integrity of the research directly. The correspondence with the respondents must be ethical, no harm to the once studied, and the physical, social, and emotional well-being of research participants is not influenced (Burns and Burns, 2008). Besides, the privacy and anonymity of the respondents must be given, alongside they are well informed about the whole process (Burns and Burns, 2008).

In this research, ethical standards were maintained. The respondents were informed about the whole procedure, and they were asked if they want to take part in the survey. Furthermore, to keep the confidentiality of the respondents, the survey was kept anonymous, and it is not possible to identify any of the respondents individually from the sample. It was completely voluntary to answer the survey, and the participants were given a choice if they want to, they could leave the survey. The privacy of the respondents was well-respected in this study.

3.7 Primary Data Preparation

Prior to the data analysis and testing of the model, I conducted the initial preparation of the dataset in two steps. In total, 285 respondents participated in the survey; among them, dataset was cleaned initially by removing the respondents based on who do not use any Fintech services and who did not complete the survey by answering all the questions. After that, 230 respondents left in the dataset, and then in the second stage, more respondents were removed from the dataset who answered the Likert questions with the same values or the respondents who seemed biased while answering the survey. They could be biased for many reasons, like they did not understand the questions properly or they felt the language barrier perhaps. Therefore, I had to remove more respondents whose answered felt incongruous. The reason for doing so is to make sure the further analysis remains fruitful, which actually represent the actual users' behavioural intention to use and adopt Fintech services. The Final dataset contained 157 respondents whose responses were processed through various evaluation processes in SPSS.

4. DATA ANALYSIS

In this chapter, the results are exhibited for the conceptual model. At first, a descriptive statistic has made based on the categorical and continuous variables. Next, Factor analysis and Reliability analysis results will be discussed. In the next step, outputs from Linear Regression analysis will be discussed for the first half of the model, where there are six independent variables, and the dependent variable is Behavioural Intention. Afterwards outputs for the second part of the model will be shown, which was achieved through Ordinal Regression and in this step Behavioural Intention is the independent variable, and Usage Category (low, medium, and high), which acts as representative of Usage Likelihood, is dependent variable and it is an ordinal variable in the analysis. After that, there will be a brief discussion on the results achieved through Ordinal Regression. In the end, the author conducted an analysis on the General Linear Model, and this was done to verify the results generated in the previous stage for the evaluation.

4.2 Descriptive Statistics

In research works that are involved with human participates, it is worthwhile to gather and present descriptive statistics to define the attributes of the sample and to check if it is authentic and it describes the actual population. The collected data were checked across measured items by testing distribution scores to evaluate normality, linearity, and homoscedasticity. In addition, descriptive statistics can be beneficial to verify the assumptions of the selected statistics technique (Pallant, 2016). To assess these assumptions, I have computed frequency, percent, and cumulative percent of the categorical variables. On the other hand, I have also calculated minimum, maximum, mean, and standard deviation statistics along with their skewness and kurtosis of the continuous variables.

4.2.1 Frequency Analysis

In order to attain descriptive statistics for categorical variables, frequency analysis was run. The sample population of this study is customers of different banks in Norway who use various services offered by Fintech firms.

4.2.1.1 Categorical Variables

For respondents' anonymity, some generic data were collected about the respondents so that they cannot be identified. This data includes the country of birth, gender, and age group. Respondents are from 22 different countries who took part in the survey, 157 left after screening in total as it was mentioned earlier; where highest 90 respondents (57.3%) were born in Norway and rest are from 21 different countries. For further analysis and to use the country as a control variable, it was categorized into two categories. The first category is 'Norway', who are Norwegians by birth, and the second one is 'other.' This was done to check and compare the outcome of adoption intention by Norwegian population and by the expats living in Norway. The next categorical variable is the age group. The respondents are divided into five different age groups according to their generations. These generations are iGen or Gen Z (under 24), Millennials or Y1 (25-29), Xennials or Y2 (30-39), Baby Bust or Gen X (40-55), and Baby Boomers (over 56). For further analysis, generations have been transformed into four groups only where Baby Bust and Baby Boomers have been merged into one group to compare against the rest. Out of 157 respondents, 20 (12.7%) of them are from the age group under 24, 50 (31.8%) are from age group 25 to 29, the highest 56 (35.7%) are from age group 30 to 39, 23 (14.6%) are from age group 40 to 55, and the lowest 8 (5.1%) are from age group over 56. Furthermore, the sample contains 85 respondents (54.1%) are males, and 72 respondents (45.9%) are females.

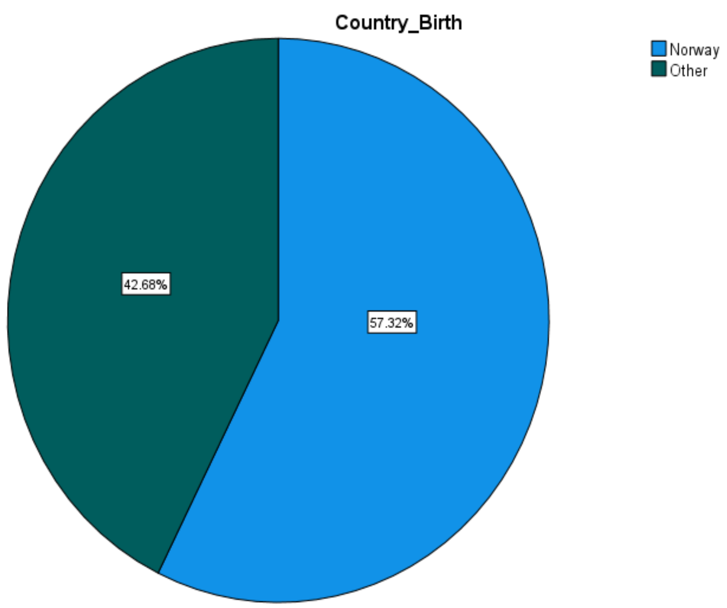
An overview of demographic attributes is presented below through graphs and tables.

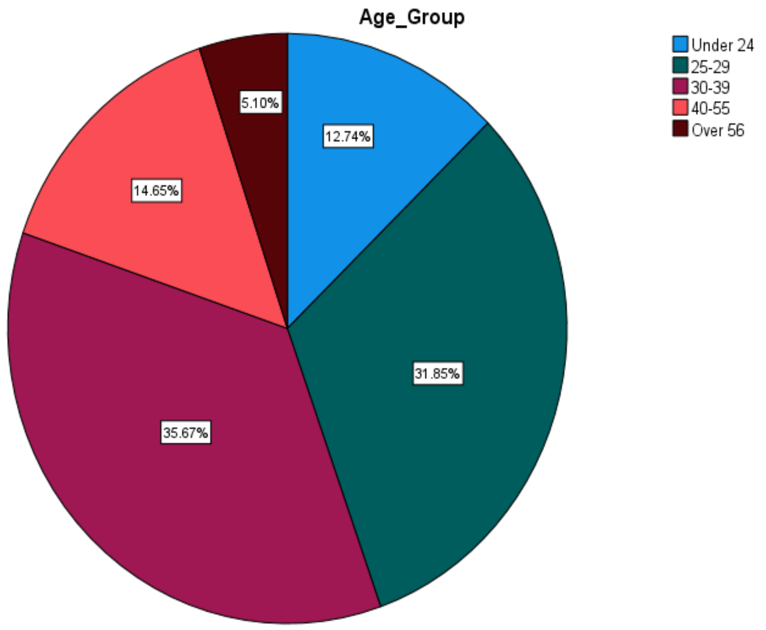
Country					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Norway	90	57.3	57.3	57.3
	Other	67	42.7	42.7	100.0
	Total	157	100.0	100.0	

Age Group					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Under 24	20	12.7	12.7	12.7
	25-29	50	31.8	31.8	44.6
	30-39	56	35.7	35.7	80.3
	40-55	23	14.6	14.6	94.9
	Over 56	8	5.1	5.1	100.0
	Total	157	100.0	100.0	

Gender					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	85	54.1	54.1	54.1
	Female	72	45.9	45.9	100.0
	Total	157	100.0	100.0	

Table 1: Descriptive Statistics





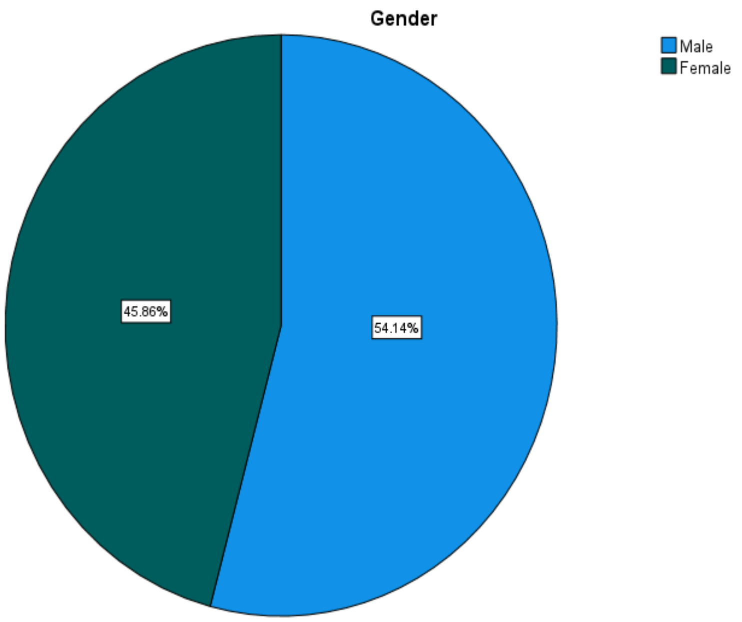


Figure 12: Country, Age Group, and Gender Distribution

4.2.1.2 Continuous Variable

There are eight types of continuous variables in this study, where most seven are measured on a 7 Likert scale from 1 to 7, which represents strongly disagree to strongly agree, respectively. This was done to assess how strongly respondents agree with a statement or disagree with a statement. After collecting the data, it was checked across in several steps for errors as it is cited earlier. After that, the final dataset was checked for the low or high mean values and maximum or minimum values, which is out of a scale of 1-7. In addition, Skewness[2] and Kurtosis[3] values were also checked for further inspection to ensure the normality of the data. Skewness is recognized as a measure of asymmetry by the support of three location measures (mean, median, and mode), whereas kurtosis measures help us to evaluate the relative peakedness or flatness of the data numerically (Shanmugam and Chattamvelli, 2016). Skewness and kurtosis value will be zero if the distribution is perfectly distributed except for any unusual occurrence in the social sciences (Pallant, 2011). In this study, the Kolmogorov-Smirnov[4] test of normality was also included to check the normality distribution of the data [Appx: 2]. The accepted result of this test is the p-value of more than .05 to accept the null hypothesis "the data are normally distributed."

Furthermore, the mean of a 7-point Likert scale should be 3.5 in theory; however, this is not the case in social science. In this study, there are 25 indicators or items in total, which have been constructed based on six independent variables and one dependent variable. All the items contain mean statistics above 3.5. The highest grand mean[5] is 6.21, belongs to construct SI, and the lowest grand mean belongs to 4.74 for the construct PR, shown in the ANOVA table in the appendix [Appx: 3].

In this study, the kurtosis values are not evenly distributed. Among 25 items, 17 items generated positive kurtosis values, and the rest are negative. In contrast, the skewness values are found all negative. However, the kurtosis and skewness values are both inside the critical range of threshold, which is ±2 for both skewness and kurtosis (George and Mallery, 2019). However, we can see some skewness and kurtosis are bigger than arguably two or three times of their respective standard error, which indicates that the data are not symmetric, therefore; not normally distributed (Charles Zaiontz, 2016).

[2] The Skewness value provides an indication of the symmetry of the distribution. Positive values indicate positive skew (scores clustered to the left) while negative skewness values indicate a clustering scores to the right -hand side of the graph (Pallant, 2011).

[3] Kurtosis provides information about the 'peakedness' of the distribution. Positive kurtosis indicates the distribution as peaked, values below zero indicates distribution rather flat and too many cases in the extremes (Pallant, 2011).

[4] A non-significant result (sig. more than .05) implies the normality of the data in Kolmogorov-Smirnov test. Achieving the sig. .000 is violation of the asuumption of normality, however; this is quite common when a sample size is relatively large (Pallant, 2011).

[5] The grand mean of a multiple subsamples is the mean of all observations every data point, divided by the joint sample size (Statistics How To, 2018).

As the results fit within the crucial range by the consideration of kurtosis and skewness value, therefore; the next step is directed to check the Kolmogorov-Smirnov test for normality. However, the test has found an insignificant result of normality (p-value .000), which also states that all indicators are not normally distributed. Therefore, in the next step, the normal QQ plot was investigated, and here also found the distribution of all indicators are not normally distributed, which concludes that for the further analysis, it was admitted a non-normal distribution for all items.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
EE_1	157	3	7	6.31	.831	-1.320	.194	1.807	.385
EE_2	157	3	7	6.29	.849	-1.239	.194	1.395	.385
EE_3	157	3	7	6.13	.875	-.717	.194	-.013	.385
EE_4	157	2	7	5.96	.986	-1.019	.194	1.978	.385
SI_1	157	3	7	6.17	.928	-.984	.194	.555	.385
SI_2	157	4	7	6.40	.775	-1.171	.194	.765	.385
SI_3	157	3	7	6.01	.987	-.633	.194	-.359	.385
SI_4	157	3	7	6.25	.876	-.986	.194	.406	.385
HM_1	157	1	7	5.73	1.308	-1.112	.194	1.217	.385
HM_2	157	1	7	5.75	1.245	-1.018	.194	1.014	.385
HM_3	157	1	7	5.85	1.310	-1.199	.194	1.136	.385
PV_1	157	4	7	6.46	.693	-1.019	.194	.240	.385
PV_2	157	3	7	6.11	1.180	-1.161	.194	.224	.385
PV_3	157	1	7	5.94	1.343	-1.282	.194	1.114	.385
PR_1	157	1	7	4.70	1.483	-.284	.194	-.676	.385
PR_2	157	1	7	4.70	1.448	-.388	.194	-.518	.385
PR_3	157	1	7	4.60	1.300	-.406	.194	.162	.385
PR_4	157	2	7	4.96	1.363	-.346	.194	-.574	.385
BI1_1	157	1	7	5.49	1.096	-.835	.194	1.220	.385
BI1_2	157	3	7	5.71	.906	-.185	.194	-.524	.385
BI1_3	157	3	7	5.86	.950	-.668	.194	.222	.385
BI2_1	157	1	7	5.96	1.208	-1.295	.194	1.904	.385
BI2_2	157	3	7	6.03	1.006	-.625	.194	-.644	.385
BI2_3	157	3	7	6.38	.828	-1.433	.194	1.986	.385
BI2_4	157	4	7	6.22	.896	-.835	.194	-.351	.385
Valid N (listwise)	157								

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Usage_Frequency	157	2	5	4.48	.821	-1.531	.194	1.487	.385
Valid N (listwise)	157								

Table 2: Descriptive Statistics of Continuous Variables

Apart from the mentioned continuous variables above, there is another continuous variable that exists in this study that was done to formulate the ultimate dependent variable for the second half of the model, where Behavioural Intention (BI_2) becomes an independent variable and Usage Likelihood (UL) becomes dependent variable. As it was mentioned earlier, in the analysis, the relationship between BI_2 and UL was moderated by types of services participants use, and UL was controlled by country, age generations, and gender. The UL was not formed directly by asking questions to respondents based on different indicators like other constructs; rather, it was formed based on participants' usage frequency of the Fintech services. The respondents' answers varied from 'twice a month' to 'five or more times a month.' Later for ease of analysis, it has been categorised low (1 to 2 times a month), medium (3 to 4 times a month), and high (5 or more times a month). The variable was renamed to Usage Category in the analysis so that it is easily findable, however; it is actually determining the UL in the study. To make it clear for the readers, the Usage Category and UL are the same.

4.3 Constructs' Validity and Reliability

The validity and reliability of constructs were checked if the constructs are valid and reliable for further tests. Reliability is the degree to which the studied variables measure the 'true' value, and it is error-free. It is concerned with transforming raw data into 'analysing form' (Hair et al., 2014). On the other hand, data validity signifies the degree where a sample or a measure accurately represents its value, what it is supposed to.

4.3.1 Factor Analysis

Factor analysis[6] is a data reduction procedure that takes a larger set of variables and tries to find out a way if there is a way to reduce or summarize it to use as a reduced set of factors or components (Pallant, 2016). The factor analysis was done twice, once for all independent variables and another one for the dependent variable (BI_2) using principal component analysis (PCA). The varimax[7] method was used for rotation, and items value less than .40 were not loaded during the analysis. Before conducting PCA, data were evaluated if it is sustainable for factor analysis. The appropriateness of the data was measured by checking the Kaiser-Meyer-Olkin (KMO). KMO determines if the data is expected to factor built upon correlation or partial correlation and helps to identify which variables to opt-out from the factor analysis due to multicollinearity issue. In this study, all the items were included in the analysis, and the reason for that will be cleared during the rest of the analysis. To conduct a factor analysis, KMO value over .60 or above is good for factor analysis, and additionally, Bartlett's Test of Sphericity[8] value should be significant ($p \leq .05$) (Pallant, 2011). However, Kaiser himself allocated the level of KMO over .90 as marvellous, over .80 as meritorious, over .70 as middling, over .60 as mediocre, over .5 as miserable, and less than .50 as unacceptable (George and Mallery, 2019).

After the assessment to verify the data is sustainable for factor analysis, I have conducted the analysis and found the KMO for six independent variables .838 and Bartlett's Test of Sphericity sig. level .000. As per Kaiser's scale of KMO, the KMO achieved in this study is meritorious for independent variables. On the other hand, the dependent variable BI_2 also achieved KMO .741 and the sig. level of Bartlett's Test of Sphericity .000. This concludes the KMO and Bartlett's Test of Sphericity both are good in this study; therefore, the factor analysis is appropriate. Additionally, when examining the Correlation Matrix[9] table [Appx:

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[6] The technique is used in developing scales and measure to identify the underlying structure (Pallant, 2011).
[7] SPSS provides Varimax, Quartimax, Equamax, Direct Oblimin, Promoax rotation techniques; however, the most common orthogonal approach is the Varimax method which minimizes the tendency of high loadings on each other for the factors (Pallant, 2011).
[8] A sig. value <.05 in Bartlett's Test of Sphericity refers that the data do not produce an identity matrix and it is approximately multivariate normal and accepted for factor analysis (George and Mallery, 2019).
[9] If there are not many correlation coefficients ≤.30, we have to reconsider doing factor analysis (Pallant, 2011).

4]. Most correlation coefficients are found above .30 or above, which also proves that the factor analysis is applicable.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.838
Bartlett's Test of Sphericity	Approx. Chi-Square	1546.273
	df	210
	Sig.	.000

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.741
Bartlett's Test of Sphericity	Approx. Chi-Square	120.041
	df	6
	Sig.	.000

Table 3: KMO and Bartlett's test Independent Variables and Dependent Variable

In the next step, to get an idea about how many components have been extracted, we need to check some information provided in the Total Variance Explained table [Appx: 5]. In this analysis, we must find out how many components have eigenvalue 1 or more. From the table, we have the first six components with eigenvalue more than 1 (6.470, 2.231, 2.067, 1.387, 1.369, 1.042). These six components explain a total of 69.358% of the variance.

Finally, from the Rotated Component Matrix table [Appx: 6], we get an overview of the extracted values of the six constructs on six components. All the values are loaded with either strong or very strong loadings except for SI_4 (.467); moreover, there are no cross-loadings among any components. Therefore, the data is adequate for further analysis, and no items were excluded for the analysis.

4.3.2 Reliability Analysis

The subsequent step is to analyse the reliability of the scales. During this analysis, we have to check our Cronbach alpha value first. The accepted Cronbach alpha value is above .70, which is considered reliable; however, .80 is desirable (Pallant, 2011). However, the rule of thumb for Cronbach alpha value over .90 is excellent, over .80 is good, over .70 is acceptable, over .60 is questionable, over .50 is poor, and below .50 is unacceptable (George and Mallery, 2019).

The reliability coefficient of the Effort Expectancy scale provided a Cronbach alpha value of .756, which includes indicators EE1, EE2, EE3, and EE4. It is worth mentioning that deleting the item EE_4 would increase the (α) value by 5 percent to .810; however, it would lead to fewer items left in further analysis though I have found there is no significant increase of the results in further analysis (e.g., increase in R square or adjusted R square) without it. Next, the Cronbach alpha for Social Influence is .720, which is also above the accepted level. The items included in Social Influence are SI1, SI2, SI3, and SI4. The Hedonic Motivation scale provided a coefficient of reliability score of .874, which is nearly excellent, including the indicators HM1, HM2, HM3, HM4, and none of the items would increase the (α) value. The next construct is Price Value, and the scale produced a Cronbach alpha value .760, and the deletion of indicator PV1 would increase it to .839, but in that case, only two items would be left in the construct, which might not contribute satisfactorily in providing accurate results for the model, that is the reason none of the items were deleted, and Price Value consists of items PV1, PV2, and PV3. The reliability coefficient of the construct Perceived Risk scale revealed an (α) value of .883, which is again near to excellent score, and it includes the indicators of PR1, PR2, PR3, and PR4. The Brand Image scale demonstrated a Cronbach alpha value of .718, which has three items BI1_1, BI1_2, and BI1_3; the alpha value is above the accepted level. Finally, the dependent variable Behavioural Intention scale provided a reliability coefficient of .710, and it consists of BI2_1, BI2_2, and BI2_3. Below an overview of all Cronbach alpha values are presented in a tabular form; the rest relevant tables are presented in the appendix.

Variables	Construct	α value
IV1	Effort Expectancy	.756
IV2	Social Influence	.720
IV3	Hedonic Motivation	.874
IV4	Price Value	.760
IV5	Perceived Risk	.883
IV6	Brand Image	.718
DV	Behavioural Intention	.710

Table 4: Reliability Analysis

4.3.3 Descriptive Statistics of Summate Scales

After reliability analysis was done, the summated scales were developed from all dependent and independent variables. A summated scale is formed by combining several individual items into a single construct. The scale is developed by summing up all indicators of a construct and then divided by the same number of items. The highest mean value belongs to Social Influence (6.2102) construct, while the lowest mean belongs to Perceived risk (4.7404). The details are presented in the appendix [Appx: 7].

4.3.4 Measurement of Central Tendencies of the Constructs

In this part, the mean and standard deviation of the variables related to Fintech services is presented. As in the earlier part, the summated scale was prepared for each variable for the first part of the model combining 7 variables in total. The mean values range from 4.7404 to 6.2102 for all the variables. It represents most of the participates responded "Slightly agree" or "Agree." In terms of standard deviation, the lowest value is .65993, and the highest 1.20425.

Variables	Constructs	N	Mean	Std. Deviation
IV1	EE	157	6.1736	.67443
IV2	SI	157	6.2102	.65993
IV3	HM	157	5.7771	1.15123
IV4	PV	157	6.1677	.91023
IV5	PR	157	4.7404	1.20425
IV6	BI1	157	5.6879	.78961
DV	BI2	157	6.1481	.72774

Table 5: Measurement of Central Tendencies-Fintech Adoption

Now the table below shows the mean and standard deviation of likelihood to use Fintech services based on the usage frequency for the second part of the model. For this test, the frequency of use has been categorised as low, medium, and high. The category is designed on, respondents who use Fintech services 1 to 2 times a month are in the low category, respondents who use 3 to 4 times a month are in the medium category, and respondents who use five or above times a month are in the high category. The mean value of the construct is 2.6178, which represents most of the respondents are from the medium to the high category, while the standard deviation is .56085.

Variable	Construct	N	Mean	Std. Deviation
DV	Usage Likelihood	157	2.6178	.56085

Table 6: Measurement of Central Tendencies-Usage Likelihood

4.4 Correlation Analysis

A Pearson Correlation analysis is performed to investigate the linear relationships among dependent and independent variables. It is designed to study the intensity of the relationship between two independent variables, and it might provide both positive and negative strength of the relationship. A positive correlation implies that as one variable increases, so does the other, and a negative correlation implies as one variable increases, another decrease (Pallant, 2011). This analysis can take values only from -1 to 1. A perfect correlation signifies with 1 and -1 signifies a negative correlation. If correlation indicates of 0 then there is no relation between two variables.

4.4.1 Correlation Analysis between the Constructs

A Pearson Correlation was conducted to study the linear relationship among constructs following the last step. From the table below, we can see none of the correlation values are equal to zero; hence, we can say there is a presence of a linear relationship between the dependent and independent variables, and it is required to carry on a multiple linear regression analysis. The correlation between dependent and independent variables is positive in all cases except one, which is Brand Image (BI_1). Brand Image has a negative (-0.78) correlation with Behavioural Intention (BI_2) in this case. Moreover, BI_2 strong correlation to Price Value (PV), Hedonic Motivation (HM), and Effort Expectancy (EE).

Besides, it is also noticeable that among independent variables, HM has a strong correlation with EE and SI, PV is also highly correlated with EE and HM.

Construct	EE	SI	HM	PV	PR	BI1	BI2
EE	1						
SI	.386**						
HM	.498**	.449**	1				
PV	.428**	.322**	.527**	1			
PR	.289**	.457**	.321**	.464**	1		
BI1	-.011	-.181*	.037	-.002	-.017	1	
BI2	.505**	.254**	.560**	.600**	.291**	-.078	1

Table 7: Pearson Correlation Matrix

Now the table below shows an overview of the intention to use Fintech service and the likelihood to use the service, which is contingent on some other factors. The outcome indicates there is a positive correlation between BI_2 as an independent variable and UL as the dependent variable. The correlation is also significant at .001 level (2-tailed).

Thus, it concludes the relationship between all independent variables and the dependent variable is significant in model-1, and it is also true for the model-2.

		BI2	UL
BI2	Pearson Correlation	1	.257**
	Sig. (2-tailed)		.001
	N	157	157
UL	Pearson Correlation	.257**	1
	Sig. (2-tailed)	.001	
	N	157	157

Table 8: Correlation Analysis: Behavioural Intention and Usage Likelihood

4.5 Inferential Analysis

Inferential statistics refers to reach to a conclusion that expands beyond the immediate data alone. The inferential technique allows us to use a selected sample to make generalizations about the population from which samples are chosen. Therefore, in this method, it is essential that the sample truly represents the population.

In this part, a discussion on the outcomes of Multiple Linear Regression for model-1, Ordinal Regression for model-2, and there will also be a brief discussion on results attained using General Linear Model through Univariate to verify the results against attained in Ordinal Regression.

4.5.1 Multiple Linear Regression (MLR)

In this analysis, the hypotheses were analysed using Multiple Linear Regression. This analysis allows a more advanced way to investigate the interrelations between independent variables and dependent variables. This analysis facilitated to understand how well EE, SI, HM, PV, PR, and BI_1 influence users to make intentions to use a service.

4.5.1.1 Analysis of Direct Effects

Initially, a Linear Regression was run using six independent variables (EE, SI, HM, PV, PR, BI_1) and the dependent variable (BI_2) for model-1 to check the direct effects of independent variables over the dependent variable. To verify if the model is fit and appropriate, we have to look at the model summary and ANOVA table. Looking at the model summary table, we see the R^2 value[10] is .493. Assessment of the R^2 effect size value suggests what percentage of the dependent variable is accounted for by all involved independent variables (George and Mallery, 2019). The value of R^2 can range from 0 to 1. If the Regression model is appropriately utilized, and it provides a high R^2, the explanatory power of the regression equation can be assumed a better prediction of the dependent variable. On the other hand, adjusted[11] R^2 depends on the sample size and the number of predictors involved in the model, which entails that Adjusted R^2 tends to get smaller than R^2 as there are fewer observations per predictor in the model. In this study, the attained Adjusted R^2 is .472. This means all the independent variables (EE, SI, HM, PV, PR, BI_1) included in the model can explain 47.2% of the variation in the dependent variable (BI_2), and the remaining 52.8% can be explained by other factors that were not included in this study. There is no standard for the acceptance range of $R^{2,}$ though. Several authors explained it differently in their papers about R^2. R^2 value between .30 to .50 has a low

[10] When a small sample is involved, the R^2 value in the sample rather optimistic observations of the true value in the population (Tabachnick & Fidell, 2007).

[11] The adjusted R^2 corrects the value of R^2 value that provides a better understanding of the true population (Pallant, 2011)

effect, and .50 to .70 has a moderate effect size (Moore et al., 2015, p. 1085). Furthermore, Henseler defines R^2 values of .67, .033, and .19 as substantial, moderate, and weak accordingly (Henseler et al., 2009, p. 303). Therefore, according to the first statement, the R^2 value has an almost moderate effect, but according to the second statement, the R^2 has a moderate effect in this study.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.702[a]	.493	.472	.52867

Table 9: Model Summary

After the analysis of the model summary, the ANOVA table from Regression analysis was checked [Appx: 8]. The ANOVA table shows the model's explained part (40.696) is lower than the unexplained part (41.923). The F value is with 6- and 150-degree freedom (df) at 24.268, and but the probability of occurrence by chance is less than .000 if there is no significant effect between the predictors. Therefore, we can predict the variables (EE, SI, HM, PV, PR, BI_1) can be used to describe the dependent variable (BI_2), and as the model provides the result of statistically significant .000 ($p \leq .05$); which means we can reject the null hypothesis.

The coefficients table below represents how much each predictor has a contribution towards the dependent variable (BI_2). The table below shows that there are three predictors that have contributions towards BI_2, and they are statistically significant ($p \leq .05$). These predictors are EE, HM, and PV, and conversely, three predictors (SI, BI_1, and PR) do not have any contributions towards BI_2.

Constructs	Unstandardized B	Coefficient Std. error	Standardized Coefficients Beta	t	Sig.
EE	.255	.076	.237	3.376	.001
SI	-.123	.081	-.112	-1.529	.128
HM	.188	.048	.297	3.875	.000
PV	.302	.060	.377	5.035	.000
PR	.001	.043	.002	.023	.982
BI1	-.098	.055	-.106	-1.771	.079

Table 10: Coefficients of MLR for BI_2

In addition, now there are some additional findings be reported from the coefficients table [Appx: 9]. The Collinearity Tolerance[12] in the coefficients table indicates how much of the variability of a particular predictor is not explained by other predictors. If any of the value of tolerance is less than .10, it implies that the predictor has high multiple correlations with other variables, that concludes the model has multicollinearity issues (Pallant, 2011). However, in this study, there is no predictor that has a tolerance value below .10 in direct effect. The next statistic to be reported is the Variance Inflation Factor[13] (VIF), which is opposite to the collinearity tolerance value. It assesses how much multicollinearity problems raise the variance of the regression coefficients. If the VIF value is above 10 it indicates multicollinearity (Pallant, 2011). However, some authors limit the VIF by 3 or 5, but 10 is the maximum level of VIF acceptance for further analysis (Hair et al., 1998). A VIF 1 means is no correlation among independent variables, and variance is not inflated at all. The VIF values in this study ranged between 1.057 to 1.736, which implies the variance is not highly inflated, and there are small correlations exist but not enough to cause a problem.

4.5.1.2 Analysis of Controlling Effects

In this step, the Regression Analysis was run by keeping the same predictors and dependent variable along with some additional categorical variables (country, gender, and age) to analyse if there are any control effects from these variables towards BI_2. The results are shown in the appendix [Appx: 10]. During the analysis, similar categorical variables were selected that were selected for the analysis of control effects in the model-2 (e.g. age: iGen/millennials/xennials, country: Norway/other, gender: male/female). While running the Regression, these categorical variables were entered in the block-1, and the predictors were entered in the block-2. The Normal Probability Plot [Appx: 11] was also checked during this analysis and found that the existing points followed and approached the diagonal line from left to the upper right. It means the residual value is normally distributed; therefore, the multicollinearity assumption was not violated.

It is also mentionable that control variables were tested one by one and altogether, one from each category. Although during the test, the model summary shows a slight improvement of R^2 after controlling at .50; however, there are no control effects found from the categorical

[12] In multiple regression tolerance is estimated by $1\text{-}R^2$.
[13] VIF is calculated by $1 \div (1\text{-}R^2)$

variables towards BI_2. Thus concludes, towards BI_2 only three predictors (EE, HM, and PV) have contributions in the model.

4.5.2 Ordinal Regression

The Ordinal Regression is the second last stage of the data analysis of this study, and this analysis was used for model-2 only, where the ordinal dependent variable is UL derived from usage category low, medium, and high. In this analysis, BI_2 is the predictor; country, age, and gender are control variables; type of service is the moderator, which was used to see the moderating relationship between BI_2 and UL through interaction. After everything was finalized, Ordinal Regression was run in two-stage, first to test the direct effect of BI_2 over UL and then in the second stage to test the control and moderating effects on UL with additional variables along with sole predictor BI_2. The findings are presented below.

As the output was produced, the Descriptive results [Appx: 12] show 157 analysis with no missing value for UL where category low has 6 respondents (3.80%), the medium has 48 respondents (30.60%), and category high has 103 respondents (65.60%).

4.5.2.1 Analysis of Direct Effect

This analysis shows if there is any effect of BI_2 alone on UL. The first table we have in the analysis is Model Fitting Information [Appx: 13]. The table provides the -2 log-likelihood values for the baseline and as well as the for the final model. The Chi-Square was performed by SPSS, and it shows the result of significance ($p < .05$). That means the model is fit, and the null hypothesis is rejected[14]. This also means the final model gives a better prediction than the prediction just based on the marginal probabilities for the outcome categories.

Following the Model Fitting Information Table, next table we have is the Goodness-of-Fit[15] table [Appx: 14]. This table contains Pearson's chi-square and another chi-square statistic based on deviance. However, we must check the Pearson's value; the attained significant value

[14] In ordinal regression null hypothesis is "there is no significant difference between baseline model and the final model" where baseline model is without any predictors and final model is with predictors.
[15] Goodness-of-Fit table intend to test if the observed data are consistent with the fitted model. The null hypothesis here is "the observed data has goodness of fit with the fitted model."

in this test is .583 ($p > .05$). It concludes the Goodness-of-Fit data is consistent with the fitted model, and thus we accept the null hypothesis in this case.

The next table we have in the analysis is Pseudo R-Square [Appx: 15] and as we can observe, the Nagelkerke value in this table is .09; this means 9% of the variance is explained by BI_2 on UL in this regression model. In this case, the Pseudo R-Square is only 9% because this analysis contains only one independent variable. If we include more independent variables in this regression analysis, the R^2 will increase.

Afterwards, the Parameter Estimates table [Appx: 16] was analysed for further analysis. In this table, BI_2 has a positive estimate value, which means BI_2 has a positive impact on UL; the significant value was also found significant at .001 ($p < .05$). Moreover, the Threshold[16] (usage category 2) was found significant in the table that refers medium to high users are statistically significant than low and medium users.

The last table we have in the analysis is the Test of Parallel Lines [Appx: 17]. In this table, we have a significant value of .162 ($p > .05$); since the value is greater than .05, the null hypothesis is accepted.

4.5.2.2 Analysis of Control and Moderation Effects

In the second stage, the control variables[17] (country, gender, and age) were used to test if there is any effect on UL any of these variables have. Moreover, the moderator variable[18] (types of service) was used between BI_2 and UL through interactions. The results are discussed below.

The first table we need to check again is Model Fitting Information [Appx: 18] that shows the final model is significant than the baseline model at .000. The inclusion of control variables and the moderator with BI_2 improved the result a lot compare to the earlier stage where BI_2 was used as only independent variable. Base on the generated outcome, we can reject the null hypothesis, and the final model predicts better than the baseline model towards UL.

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[16] Threshold estimates 1 is cut-off value between low and medium category users and threshold estimate 2 is cut-off value between medium and high category users (Statistical Consulting, 2020).

[17] Control variables are variables which is not a part of experiment, but they could affect the outcome (Science Notes, 2020).

[18] Moderators are those third-party variables that influence the strength or direction of the relationship between and independent and dependent variable (Statistics Solutions, 2020).

The next table, Goodness-of-Fit, also shows much improved results as Pearson's chi-square is .374, which was previously at .583 when just sole predictor was used. As the Goodness-of-Fit has a non-significant value ($p > .05$), we are also able to reject the null hypothesis in this stage.

	Chi-Square	df	Sig.
Pearson	116.753	137	.894
Deviance	102.481	137	.988

Table 11: Goodness-of-Fit

In the Pseudo R-Square table [Appx: 22], now we have Nagelkerke value at .292, which means BI_2 now explains over around 29% of the variance of UL with other control variables. That means if we could include more independent variables in this stage, the R^2 value would certainly increase.

The next table to interpret is the Parameter Estimates table presented below. In this analysis, Norway was chosen from the country category, male was chosen from gender, xennials from age group/generation as control variables. As the moderator, payment was chosen through interaction with BI_2. These variables were altered to see if any other variables have any impact as the control variables or as moderators with BI_2. However, after this alteration; none was found significant except age group/generation: iGen as a control variable. The outcome of this variable (iGen) will be discussed following the discussion of the outcomes achieved in the table presented below.

		Estimate	Std. Error	Wald	df	Sig.
Threshold	[Usage Category = 1.00]	2.007	1.557	1.663	1	.197
	[Usage Category = 2.00]	4.960	1.591	9.717	1	.002
Location	Norway	.275	.375	.538	1	.463
	Male	-.006	.375	.000	1	.987
	Sum_BI2 * Payment	.233	.085	7.411	1	.006
	Sum_BI2	.769	.256	9.014	1	.003
	Xennials	1.644	.469	12.273	1	.000

Table 12: Parameter Estimates

From the table, we can see again 'Threshold' (usage category 2) is significant ($p = .002$), which means if the respondents who are in the medium category and if they push themselves a little bit more and jump into the higher usage category they are more likely to adopt the Fintech services. In other words, we can say users who are in the medium to higher category; they are more likely to use or adopt the services. Next, in the 'Location' section, we can see as a country Norway is insignificant (.463) that means country of birth does not have any impact on the adoption of Fintech, so as gender as male is insignificant (.987) and also found female insignificant during the test. As a sole independent variable BI_2 is significant at .003 and, on the other hand, from age group xennials (age 30-39) are very significant at .000, which was expected as xennials (part of millennials), and they are the most Fintech service users by the literature. Besides, as service types payment was found significant at $p = .006$ (interactions with BI_2), it means xennials who use payment as their service are most likely to adopt Fintech services. In addition, from the Estimate column, we can see all the variables which are significant have positive estimate values (xennials have high impact), which states; for each unit increase on an independent variable or control variable, there is a predicted increase (a certain amount) in the log odds of falling at a higher level of the dependent variable.

Previously it was mentioned that iGen (under 24) was found significant as well during the tes. When it was analysed with the same variables from the above table (except xennials) the result came out interesting [Appx: 23]. Although they were found significant ($p = .001$) however, their contribution in the Estimates column is -1.671 (negative). It means, for every unit increase on an independent variable or control variable, there is a predicted decrease (a certain amount) in the log odds of falling at a higher level of the dependent variable. Which refers under this age group they seem; use payment as a service a lot; however, they are not very confident to use Fintech services as their medium of payment.

Now, if we give a look at the Test of Parallel Lines[19] table presented below, we can see the significant value is greater than .05; therefore, we can accept the null hypothesis as the achieved p-value is .496.

[19] The null hypothesis state that the location parameters (slope coefficients) are the same across response categories.

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	150.915			
General	146.531	4.384	5	.496

Table 13: Test of Parallel Lines

4.5.3 General Linear Model

As it was mentioned previously, the last step of data analysis was done to verify the results achieved during the Ordinal Logistic Regression analysis, and this step is involved with General Linear Modelling. The analysis was done twice, first with only the independent variable's direct effect on UL was done. Then the same control variables, moderator, and predictor were used to see the interaction effects on UL.

4.5.3.1 Analysis of Direct Effects

The first table we have is the Tests of Between-Subjects Effects table [Appx: 19]. We can see that BI_2 was found significant ($p = .001$) while predicting UL; therefore, the null hypothesis[20] is rejected in this case.

Moreover, in the Parameter Estimates table [Appx: 20] we find the BI_2 also significant. If we look at the values under column (B), it shows BI_2 has a positive impact on predicting UL, which implies if we increase the independent variable by one unit, the dependent variable's value will also increase. The results show the consistency to the results were achieved in Ordinal Regression analysis.

4.5.3.2 Analysis of Control and Moderation Effects

Alike the previous stage first, we have the Tests of Between-Subjects Effects table, which is presented below. From the table, we can see that the results in Ordinal Regression xennials have significant ($p = .001$) effects towards UL. On the other hand, when we look at the interaction effect of payment with BI_2 we find it significant ($p = .006$). Moreover, the independent variable BI_2 by itself is significant at .004. Similar to the previous analysis, we do

[20] The null hypothesis in this analysis is "there is no impact of predictor on dependent variable".

not see any significant impact of country and gender while adopting Fintech services. Based on the results, the null hypothesis was rejected in this analysis.

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	9.860[a]	5	1.972	7.594	.000	.201
Intercept	4.147	1	4.147	15.970	.000	.096
Sum_BI2 * Payment	2.034	1	2.034	7.835	.006	.049
Male	.028	1	.028	.108	.743	.001
Norway	.126	1	.126	.485	.487	.003
Sum_BI2	2.187	1	2.187	8.422	.004	.053
Xennials	3.231	1	3.231	12.441	.001	.076
Error	39.210	151	.260			
Total	1125.000	157				
Corrected Total	49.070	156				

Table 14: Tests of Between-Subjects Effects

On the Parameter Estimates table [Appx: 21], when we see (B) column, the moderator effect between (between BI_2 and payment), and control variable (xennials) all have positive values, which means all these variables have a positive effect towards defining UL. This also implies if we increase the independent variable by one unit, the dependent variable's value will also increase.

This analysis shows that the results in Ordinal Regression are constant to the results; this study achieved in General Linear Model, and the calculations are effective.

4.6 Hypothesis Assessment

H_1: Effort Expectancy (EE) has a significant effect on Behavioural Intention (BI_2) to use Fintech services.

The significant value of EE is .001, and it is smaller than the accepted level of .05, which implies there is a substantial linear relationship between EE and BI_2 to use Fintech services. Moreover, the B coefficients of EE is .255, which means it is statistically distinct from 0 and has a positive effect on the behavioural intention to use Fintech services. It confirms that the hypothesis is supported.

H_2: Social Influence (SI) has a significant impact on Behavioural Intention (BI_2) to use Fintech services.

The p-value of SI is .128 and it is greater than the accepted level .05, and B coefficient is -.123, which means there is a negative correlation between and SI and BI_2. Therefore, SI does not influence users to use Fintech services and, it has a negative effect on BI_2 to use the services. Thus, the hypothesis is not accepted.

H_3: Hedonic Motivation (HM) has a significant impact on Behavioural Intention (BI_2) to use Fintech services.

The significant value of HM is .000, which proves that it has a great significant impact on BI_2. Moreover, the B coefficient is .188 proves there is a positive linear relationship between HM and BI_2 to use or adopt Fintech services. Therefore, the hypothesis is supported.

H_4: Price Value (PV) has a significant effect on Behavioural Intention (BI_2) in terms of using Fintech services.

The p-value of PV is .000 ($p < .05$), which is very much significant, and the B coefficient (.302) is highest among all other predictors, and it is statistically significant to use Fintech services. It implies there is a great linear relationship between PV and BI_2 in this model. Hence, the hypothesis is accepted.

H_5: Perceived Risk (PR) has a significant effect on Behavioural Intention (BI_2) to use Fintech services.

The significant value of PR is .982, which is not statistically significant, and the B coefficient is .001, which suggests there is an insignificant relationship between PR and BI_2. In other words, consumers are not apprehensive about perceived risk while using Fintech services. Thus, the hypothesis is not supported.

H_6: Brand Image (BI_1) has a significant impact on Behavioural Intention (BI_2) to use Fintech services.

BI_1 has a significant value of .079, which is beyond the accepted significant level of .005; moreover, the B coefficient is -.098, which implies there is no linear relationship between BI_1 and BI_2 to use Fintech services. Therefore, the hypothesis is rejected.

H_7: Behavioural Intention (BI_2) has a significant influence on Usage Likelihood (UL) to use Fintech services.

The p-value of BI_2 is significant at .004 after types of service has a moderation effect on the relationship between BI_2 and UL, which is smaller than the accepted level .05. Besides, the B value of BI_2 is .168, which implies there is a positive effect of BI_2 on UL. Therefore, the hypothesis is supported.

DISCUSSION & CONCLUSION

The last chapter of this thesis discusses the substantial findings of the study. First, there will be an overview of the summary of the hypothesis; following it, there will be an overview of the revisited model with new results with three predictors and other controlling and moderating factors. Moreover, a brief discussion of findings based on EE, HM, and PV to answer the research questions and to compare the results of this study with previous studies will be presented. Afterwards, the theoretical and practical implications, limitations, and future scope of the research will be discussed. Then the chapter will end with a conclusion based on the relevant outcomes.

5.1 Summery of the Hypothesis Assessment

Hypotheses	Outcomes
H_1: Effort Expectancy (EE) has a significant effect on Behavioural Intention (BI_2) to use Fintech services.	Accepted
H_2: Social Influence (SI) has a significant impact on Behavioural Intention (BI_2) to use Fintech services.	Rejected
H_3: Hedonic Motivation (HM) has a significant impact on Behavioural Intention (BI_2) to use Fintech services.	Accepted
H_4: Price Value (PV) has a significant effect on Behavioural Intention (BI_2) in terms of using Fintech services.	Accepted
H_5: Perceived Risk (PR) has a significant effect on Behavioural Intention (BI_2) to use Fintech services.	Rejected
H_6: Brand Image (BI_1) has a significant impact on Behavioural Intention (BI_2) to use Fintech services.	Rejected
H_7: Behavioural Intention (BI_2) has a significant influence on Usage Likelihood (UL) to use Fintech services.	Accepted

Table 15: Summary of Hypothesis Assessment

5.2 Model Revisitation

The foremost goal of the research was to find out the factors that are affecting the behavioural intention of users or banking customers to use Fintech services, and the secondary aim was to check if their specific needs for services influence them to use the alternative services rather than their banks. In this study, a conceptual model has been developed based on previous research on IS and technology acceptance. The based model is known as Unified Theory of Technology Acceptance 2 (UTAUT2), and it was altered by dropping constructs like Performance Expectancy, Facilitating Conditions, Habit, Trust and moreover, by adding one additional construct in the model that is Brand Image to predict the Usage Likelihood of the Norwegian consumers. The first half of the model includes six hypotheses connected to the factors that affect consumers' intention to use Fintech services. On the other hand, the second half of the model is based on the evaluation of consumers' probability to use the services, which might affect by some other factors like their nationality, their gender, their age group, and their desire to use a particular type of service. In this research, a quantitative approach was carried out on the collected data from an online survey. After the evaluation of hypotheses, the following revisited model was developed from the final significant results.

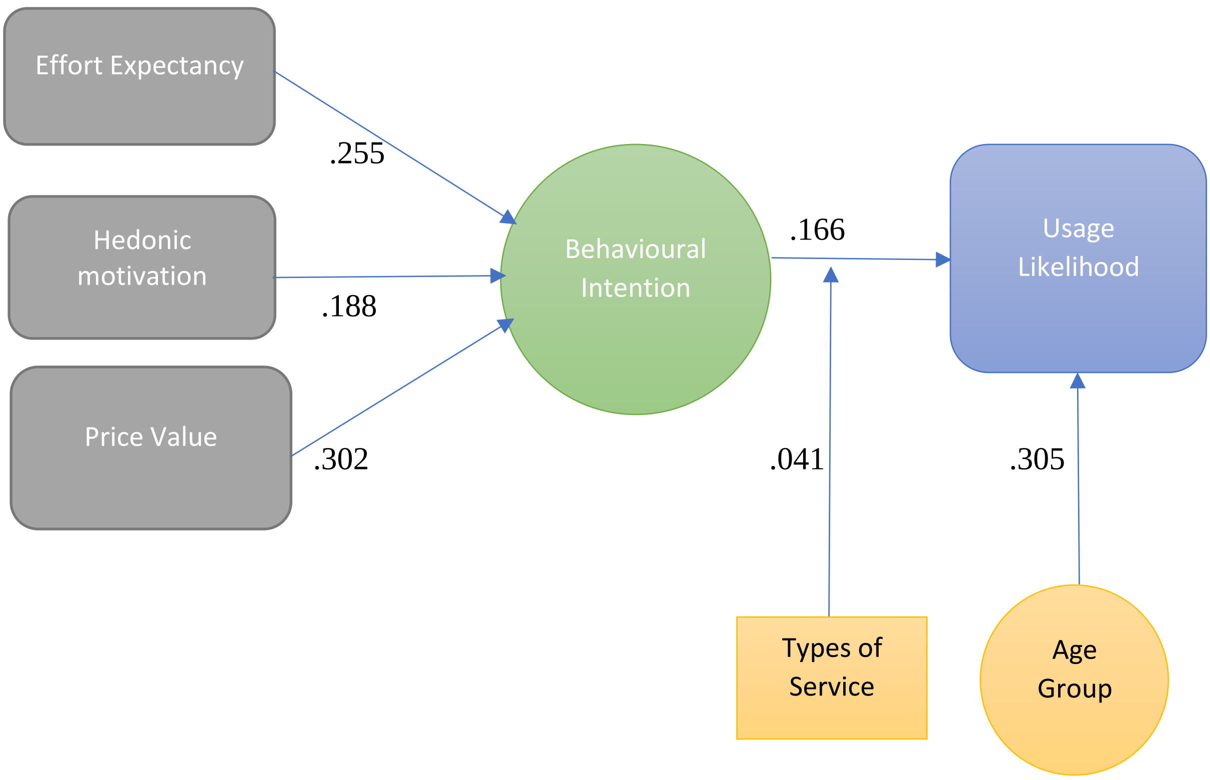


Figure 13: Revisited Conceptual Model

5.3 Discussion on the Results

This study has two research questions, based on which whole research was conducted. Now there is a short discussion presented below to get a clear picture of the overall results and answers to the two research questions.

1. *What factors influence behavioural intention towards usage likelihood of fintech services among Norwegian bank users?*

After testing the hypothesis formulated on Effort Expectancy, Social Influence, Hedonic Motivation, Price Value, Perceived Risk, and Brand Image, the results above demonstrated that these predictors have effects on Fintech usage or Fintech adoption. However, among all six predictors, three of them were found significant, and the rest are not significant. Among the independent variables, Price Value has the strongest effect on choosing Fintech services over banks. This implies most of the respondents think Fintech companies provide cheaper services than their regular banks, while it comes to payment or any other kind of similar services offered by these firms or banks both. The sconed strongest predictor in this study is Effort Expectancy, which means the respondents believe Fintech services are easier to interact with rather than their banks. It might be interaction through the app or online use or ease of services or getting the services; Fintech companies hold the advantage over banks. The last predictor, which has a strong influence on using Fintech services is Hedonic Motivation. As previous literature found it has a strong influence in terms of technology use, this study found as well that the predictor has a solid impact on Norwegian consumers choosing Fintech services over their banks while getting specific services. Conversely, Social Influence, Perceived Risk, and Brand Image were found, having an insignificant impact on Behavioural Intention. Which denotes Norwegian consumers are not influenced by social pressure or any other types of influence when it comes to using Fintech. Moreover, they do not think the risk factor is important when choosing alternative financial services. Lastly, they also do not believe the financial company's reputation is essential to use its service.

In terms of predicting users' behavioural intention, the result of this study (47.2% variance explained of Behavioural Intention) nearly matches Venkatesh's research on "Consumer Acceptance and Use of Information Technology" where the author found 52% variance explained in Behavioural Intention by the predictors Effort Expectancy, Hedonic Motivation, and Price Value (Venkatesh et al., 2012). In terms of other technology adoption research works, it was also found having positive effects of Effort Expectancy, Hedonic Motivation, and Price value towards Behavioural Intention (Baabdullah, 2018); (Mehta et al., 2019); (Teo et al., 2015). Moreover, in terms of Fintech adoption by banking users with extended TAM model achieved quite similar results, which is consistent with this study (Hu et al., 2019).

Furthermore, the findings of Social Influence, Perceived Risk, and Brand Image as predictors towards predicting Behavioural Intention were found inconsistent compare to previous research in technology adoption, m-payment, and e-learning system (Abrahão et al., 2016); (Shin, 2010); (Koenig-Lewis et al., 2015).

2. *Does behavioural intention influence actual behaviour after controlling for the effects of different financial service types?*

The second half of the model was used to answer the second research question. There are five types of Fintech services were used in this study. They are deposit, financial advice, financing, insurtech, and payment. All these services were checked one by one if they have any impact on the relationship between Behavioural Intention and Usage Likelihood. The only payment was found having a significant impact on this relationship. About 4.1% variance was explained of this relationship by the types of service. Therefore, it concludes the service type has a positive influence on the actual behaviour or intention to use the services.

There are some additional findings of this thesis that are now being reported below.

During the Ordinal Regression, the conceptual model provided a significant result of R^2 via Nagelkerke test, which implies the model explains about 29.2% of the dependent variable of Usage Likelihood. This is a great result in terms of predicting the final usage of similar technological services (Leong et al., 2013); (Shin, 2009). Moreover, it was also found respondents who are high users category most prone to adopt the service when they always use a particular service(s) offered by Fintech firms. Besides this, the category medium might also shift to the high category if they push themselves slightly towards per month usage, which is also proved by the cut-off score (Threshold) in the Parameter Estimates table that means the medium to high users are significant to adopt or use the service.

Next, there were three types of control variables used in the study to see whether they influence users' behavioural intention during the adoption of service. The variables were used are country (determined by respondents' birth), age group (categorised by generations), and gender (male or female). First, the country was found insignificant in the test, which indicates, people who born outside of Norway, once they moved inside the country and were exposed to use any technology or service, behave similarly to Norwegians. Moreover, the gender was found insignificant also during the final usage; the probable reason for this could be Norway has high egalitarian values in its society, which facilitate equal participation in all kinds of services, which is true for Fintech usage as well. The last control variable was the age group, which has basically five groups (four groups for the ease of analysis mentioned earlier) in terms of the generations. Age group 25 to 29 and 30 to 30 are basically the generation millennials, but some sources and authors divided this group into two generations, which was used in this study too as millennials or y1 and xennials or y2 to see if they have some kind of similarity or dissimilarity. The use of two generations from millennials was successful as in this study millennials found insignificant and xennials found significant. This implies xennials who are high users of Fintech are more likely to adopt the services. Besides, there was one interesting result which shows iGen (under 24) are more likely to depend on their banks in terms of getting financial services.

5.4 Theoretical and Practical Implications

The intent of this thesis was to have a look into the factors that influence Fintech adoption in Norway. The outcomes provide a significant contribution to the Fintech industry as well as the banking industry in Norway.

In this study, Venkatesh's UTAUT2 was modified in the scenario of Norwegian culture, banking and financial industry, and infrastructure of the country. The experiment of this modification illustrates the outcome is significant in terms of the Norwegian context. For example, predictor perceived risk was found insignificant, which reflects Norwegian society's high level of trust in services, gender as control was found insignificant, which also represents society's egalitarian value. Moreover, payment (moderator) as a service was found having a significant effect, which also demonstrated the society is moving towards a cashless society by the use of local or international mobile payment or mobile wallet systems like Vipps, Coopay, Apple/Google pay (Bambora, 2020). Thus, people are accepting cheaper and easy to use financial services from alternative sources other than their traditional banks.

The current research works in this field were done in the context of mobile payment or mobile wallet adoption in Norway. Moreover, there are exploratory research on Fintech's effects on traditional banking and financial sectors. However, there is no quantitative research which shows that what factors are driving Norwegian consumers to use Fintech services. This thesis fills up this research gap by using the UTAUT2 model, which is a combination of sociology, psychology, and human behaviour research to explore what factors are working behind this shift. Moreover, it is also mentionable now payment as a service is mostly used by Norwegian consumers; however, in a future context, there are some other popular services like financial advice and insurtech which might also attract these consumers towards using Fintech.

The practical implication of this study is involved with Fintech firms, banks, financial companies, engineers, app developers, managers, and so on. They can understand what the consumers want, for instance, what is the importance of ease of use a service. For reaching out to the customers, it is very important that the services are easy to interact with so that consumers feel the motivation to use the service and to grow willingness to know more about it. Data collected on perceived usefulness and perceived ease of use can be implemented to enhance the features and usefulness of a service's interface and functionality so that both parties in the business can get the benefits (Davis, 1989).

In addition, the practical implications are also related to the infrastructural environment, which facilitates Fintech adoption as it is based on modern technology. The development of infrastructure and new regulations have lowered the hurdle shifting to alternative financial services if consumers intend to use. These have also created a new practice among consumers to lower their hesitancy to try and accept these new types of firms. Moreover, getting the opportunity to use more modern and effective services at cheaper costs affects their pattern of use of financial services, which creates a more competitive environment in the financial and banking arena. This ultimately benefits firms to get and provide more modernized services at a competitive price and consumers to get more options to choose from better financial services which they find useful and trustworthy for themselves at a lower price.

5.5 Limitation and Future Scope of Research

The study has several limitations, which are reflected in the results. First of all, roughly above three months was a bit difficult to conduct such kind of research at the master's level. Because of the time limit, it was not possible to gather more data from respondents. Moreover, it was a great restraint to manage time for sampling and writing this master's thesis alone in such a short time. Furthermore, the given time in data collection was over two weeks approximately. If more time would have given and it would be a much bigger sample than 157, then the results might get more significant and interesting. Moreover, it felt the respondents felt biased at a point that is the reason almost half of the respondents were removed from the initial dataset after inspection.

Next, it was done in the context of Norway; therefore, it does not represent the represents the results in another region or another country. Moreover, it was said earlier the sample is not normally distributed, which also means this does not represent the opinions of the whole population, and it is also difficult to reflect the whole population's opinions with 157 respondents.

Besides, the conceptual model was made by opting out some important predictors from the original model; if more predictors had been included, the R^2 would be more significant toward Behavioural Intention. The author believes if the original model is tested by including some other factors like trust, government support, and in a contextual scenario, it will deliver more significant results, which will provide a better understanding of consumers' intention to use a service or technology adoption.

For future research, the second suggestion is to give more time in data collection to get a bigger sample in the first place if the quantitative study is conducted. The bigger the sample, the more significant results it will certainly produce in the Norwegian or any other context. The next recommendation is to conduct a longitudinal study, it will allow the researchers to study individuals' adoption practices over time, and that would be more beneficial to track changes in respondents' attitudes or behaviors. This will also help researchers to attain significant insights about individuals' behavioural intention to use any services. Moreover, other research designs can also be applied in this context, such as in-depth qualitative study can provide a greater intuition about respondents' behavioural and psychological attitudes.

Last but not least, it will be interesting for future research to consider contingency factors in adopting Fintech services from alternative sources. This will help future researchers to measure the environmental ecosystem of Fintech in different countries and in different setups. Especially the Fintech service (e.g. payment) ecosystem is quite developed but understudied. Contingency analysis will help to understand differences between different Fintech markets and their infrastructure, which are continuously developing. Moreover, it will also help to obtain an understanding of the environmental factors that are affecting Fintech adoption.

5.5 Conclusion

The thesis aimed to determine the factors that affect Fintech adoption in Norway, which the thesis successfully delivered. We got an insight into both direct influencers as well as indirect influencers that might all change users' intention towards final usage.

The study was based on an online survey among 157 respondents who are customers of different Norwegian banks. For the analysis of the conceptual model Multiple Linear Regression, Ordinal Regression, and General Linear Model were used as statistical techniques on SPSS. After the initial analysis for the first half of the model, it was found that 47.2% of the variation of dependent variable Behavioural Intention is explained by the independent variables Effort Expectancy, Social Influence, Hedonic Motivation, Price Value, Perceived Risk, and Brand Image. However, during the hypothesis testing, it was found Social Influence, Perceived Risk, and Brand Image do not have a significant impact on Behavioural Intention to use Fintech services, whereas Effort Expectancy, Hedonic Motivation, and Price Value were found having a significant effect. The findings show further, among the significant variables, Price Value is the strongest predictor of Behavioural Intention; following it, Effort Expectancy appears as the second strongest predictor and Hedonic Motivation as the third. In the second half of the model, the correlation between Behavioural Intention and Usage Likelihood is moderated by the types of service, which implies consumers' demand for cheaper financial services influences them to choose Fintech. In this moderation, relationship payment was found to have a significant impact compare to the other four types of services. The findings also reveal as a predictor Behavioural Intention explains about 29.2% of the dependent variable Usage Likelihood.

Lastly, it was also found that the age group has a significant effect on users' final usage. The findings show among five generations, xennials (age 30-39) have the strongest positive significant effect on the dependent variable, whereas; iGen (age under 24) was found to have a negative significant impact on Usage Likelihood. The findings of the study have theoretical and practical implications for the Fintech firms, banks, financial institutions, app developers, researchers, and managers who want to attain better understandings about what are consumers' priorities in the adoption of Fintech services.

References:

AARTS, H., VERPLANKEN, B. & VAN KNIPPENBERG, A. 1998. Predicting behavior from actions in the past: Repeated decision making or a matter of habit? *Journal of applied social psychology,* 28**,** 1355-1374.

ABRAHÃO, R., MORIGUCHI, S. & ANDRADE, D. 2016. Intention of adoption of mobile payment: An analysis in the light of the Unified Theory of Acceptance and Use of Technology (UTAUT). *RAI Revista de Administração e Inovação,* 13.

AIKEN, L. S., WEST, S. G., PITTS, S. C., BARALDI, A. N. & WURPTS, I. C. 2012. Multiple linear regression. *Handbook of Psychology, Second Edition,* 2.

AJIBADE, P. 2018. Technology acceptance model limitations and criticisms: Exploring the practical applications and use in technology-related studies, mixed-method, and qualitative researches. *Library Philosophy & Practice*.

AJZEN, I. 1985. From intentions to actions: A theory of planned behavior. *Action control.* Springer.

ALIAGA, M. & GUNDERSON, B. Interactive Statistics.

ARENAS GAITÁN, J., PERAL PERAL, B. & RAMÓN JERÓNIMO, M. 2015. Elderly and internet banking: An application of UTAUT2. *Journal of Internet Banking and Commerce, 20 (1), 1-23.*

ARNER, D. W., BARBERIS, J. & BUCKLEY, R. P. 2015. The evolution of Fintech: A new post-crisis paradigm. *Geo. J. Int'l L.,* 47**,** 1271.

BAABDULLAH, A. M. 2018. Consumer adoption of Mobile Social Network Games (M-SNGs) in Saudi Arabia: The role of social influence, hedonic motivation and trust. *Technology in Society,* 53**,** 91-102.

BAMBORA. 2020. Available: https://www.bambora.com/articles/why-the-nordics-are-going-cashless/ [Accessed 7/12/2020].

BANDURA, A. 1986. *Social foundations of thought and action: A social cognitive theory,* Englewood Cliffs, NJ, US, Prentice-Hall, Inc.

BANSAL, S. K., BANSAL, A. & BLAKE, M. B. Trust-based Dynamic Web service Composition using Social Network Analysis. 2010 IEEE International Workshop on: Business Applications of Social Network Analysis (BASNA), 15-15 Dec. 2010 2010. 1-8.

BAPTISTA, G. & OLIVEIRA, T. 2015. Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior,* 50**,** 418-430.

BERG, S. A. & EITRHEIM, O. Bank Regulation and Bank Crisis: The Main Developments in the Norwegian Regulatory System Before, During, and After the Banking Crisis of 1988-92. Financial Market Regulation in the Wake of Financial Crises: The Historical Experience Conference, 2009. 169.

BLAISE, R., HALLORAN, M. & MUCHNICK, M. 2018. Mobile commerce competitive advantage: A quantitative study of variables that predict m-commerce purchase intentions. *Journal of Internet Commerce,* 17**,** 96-114.

BOX, G. E., JENKINS, G. M. & REINSEL, G. C. 2011. *Time series analysis: forecasting and control*, John Wiley & Sons.

BROWN, S. A. & VENKATESH, V. 2005. Model of Adoption of Technology in Households: A Baseline Model Test and Extension Incorporating Household Life Cycle. *MIS Quarterly,* 29**,** 399-426.

BURNS, R. P. & BURNS, R. 2008. *Business research methods and statistics using SPSS*, Sage.

CBINSIGHTS 2018. Banks Are Finally Going After Fintech Startups.

CHANDRA, S., SRIVASTAVA, S. C. & THENG, Y.-L. 2010. Evaluating the role of trust in consumer adoption of mobile payment systems: An empirical analysis. *Communications of the association for information systems,* 27**,** 29.

CHANG, L. Y., WONG, S. F., LEE, H. & JEONG, S.-P. 2016. *What motivates chinese consumers to adopt FinTech services: a regulatory focus theory*.
CHARLES ZAIONTZ 2016. Analysis of Skewness and Kurtosis.
CHILDERS, T. L., CARR, C. L., PECK, J. & CARSON, S. 2001. Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of retailing,* 77**,** 511-535.
COMPEAU, D., HIGGINS, C. A. & HUFF, S. 1999. Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS quarterly***,** 145-158.
CROWTHER, D. & LANCASTER, G. 2012. *Research methods*, Routledge.
DAVIS, F. D. 1986. *A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results.* Ph.D., Massachusetts Institute of Technology, Cambridge, MA, USA.
DAVIS, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly***,** 319-340.
DAVIS, F. D., BAGOZZI, R. P. & WARSHAW, P. R. 1989. User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science,* 35**,** 982-1003.
DAVIS, F. D., BAGOZZI, R. P. & WARSHAW, P. R. 1992. Extrinsic and intrinsic motivation to use computers in the workplace 1. *Journal of applied social psychology,* 22**,** 1111-1132.
DECI, E. L. & RYAN, R. M. 1985. Cognitive evaluation theory. *Intrinsic motivation and self-determination in human behavior.* Springer.
DU, W., PAN, S. L., LEIDNER, D. E. & YING, W. 2019. Affordances, experimentation and actualization of FinTech: A blockchain implementation study. *The Journal of Strategic Information Systems,* 28**,** 50-65.
ERNST & YOUNG. 2019. *Global Fintech Adoption Index* [Online]. Available: https://www.ey.com/en_gl/ey-global-fintech-adoption-index [Accessed 21/08/2020 2020].
EUROPEAN COMMISSION. 2018. *Payment Services* [Online]. Available: https://ec.europa.eu/info/business-economy-euro/banking-and-finance/consumer-finance-and-payments/payment-services/payment-services_en#eu-rules-on-payment-servicesEuropean [Accessed 10/12/2020].
FISHBEIN, M. & AJZEN, I. 1977. Belief, attitude, intention, and behavior: An introduction to theory and research.
GABOR, D. & BROOKS, S. 2017. The digital revolution in financial inclusion: international development in the fintech era. *New Political Economy,* 22**,** 423-436.
GAI, K., QIU, M. & SUN, X. 2018. A survey on FinTech. *Journal of Network and Computer Applications,* 103**,** 262-273.
GEORGE, D. & MALLERY, P. 2019. *IBM SPSS Statistics 26 step by step: A simple guide and reference*, Routledge.
GERDRUP, K. R. 2003. Three episodes of financial fragility in Norway since the 1890s.
HAIR, J. F., BLACK, W. C., BABIN, B. J. & ANDERSON, R. E. 2014. Multivariate data analysis: Pearson new international edition. *Essex: Pearson Education Limited*.
HAIR, J. F., BLACK, W. C., BABIN, B. J., ANDERSON, R. E. & TATHAM, R. L. 1998. *Multivariate data analysis*, Prentice hall Upper Saddle River, NJ.
HALE, J. L., HOUSEHOLDER, B. J. & GREENE, K. L. 2002. The theory of reasoned action. *The persuasion handbook: Developments in theory and practice,* 14**,** 259-286.
HENSELER, J., RINGLE, C. M. & SINKOVICS, R. R. 2009. The use of partial least squares path modeling in international marketing. *New challenges to international marketing.* Emerald Group Publishing Limited.
HERMES, N. & LENSINK, R. 2008. Does financial liberalization influence saving, investment and economic growth? Evidence from 25 emerging market economies, 1973–96. *Financial Development, Institutions, Growth and Poverty Reduction.* Springer.

HERNAES. 2018. *The current state of Fintech in Norway* [Online]. Available: https://hernaes.com/2018/02/13/the-current-state-of-fintech-in-norway/ [Accessed 20/08/2020 2020].

HERNEAS. 2017. *Banking is necessary, banks are not* [Online]. Hernaes. Available: https://hernaes.com/2017/09/11/banking-is-necessary-banks-are-not/#:~:text=Banking%20is%20necessary%2C%20banks%20are%20not%20was%20stated%20by%20Bill,the%20first%20wave%20of%20fintech.&text=On%20the%20one%20hand%2C%20fintechs%20are%20agile%20and%20innovative. [Accessed 07/09/2020 2020].

HU, Z., DING, S., LI, S., CHEN, L. & YANG, S. 2019. Adoption intention of fintech services for bank users: An empirical examination with an extended technology acceptance model. *Symmetry,* 11**,** 340.

HUANG, Y. M. 2017. Exploring students' acceptance of team messaging services: The roles of social presence and motivation. *British Journal of Educational Technology,* 48**,** 1047-1061.

INNOPAY. 2015. *Open Banking Monitor: Banks Moving Beyond the PSD2 Requirements* [Online]. Available: https://www.innopay.com/en/publications/innopay-open-banking-monitor-banks-moving-beyond-psd2-requirements [Accessed 20/08/2020].

ISLAM, M. & HASAN, I. 2013. Intention to use advanced mobile phone services (AMPS). *Management Decision,* 51**,** 824-838.

JAKOBSSON, N. & KOTSADAM, A. 2010. Do attitudes toward gender equality really differ between Norway and Sweden? *Journal of European Social Policy,* 20**,** 142-159.

KASASA. 2020. *Boomers, Gen X, Gen Y, and Gen Z Explained* [Online]. Available: https://www.kasasa.com/articles/generations/gen-x-gen-y-gen-z [Accessed 26/10/2020].

KESHARWANI, A. & SINGH BISHT, S. 2012. The impact of trust and perceived risk on internet banking adoption in India: An extension of technology acceptance model. *International Journal of Bank Marketing,* 30**,** 303-322.

KHEDMATGOZAR, H. R. & SHAHNAZI, A. 2018. The role of dimensions of perceived risk in adoption of corporate internet banking by customers in Iran. *Electronic Commerce Research,* 18**,** 389-412.

KIM, K. & PRABHAKAR, B. 2000. Initial trust, perceived risk, and the adoption of internet banking. *ICIS 2000 Proceedings***,** 55.

KOENIG-LEWIS, N., MARQUET, M., PALMER, A. & ZHAO, A. L. 2015. Enjoyment and social influence: predicting mobile payment adoption. *The Service Industries Journal,* 35**,** 537-554.

KOTHARI, C. R. 2004. *Research methodology: Methods and techniques*, New Age International.

KPMG. 2017. *Setting Course in a Disrupted Marketplace.* [Online]. Available: https://assets.kpmg/content/dam/kpmg/xx/pdf/2017/04/setting-course-in-a-disrupted-marketplace.pdf [Accessed 7/10/2020].

LÆRD STATISTICS. 2020. Available: https://statistics.laerd.com/spss-tutorials/ordinal-regression-using-spss-statistics.php [Accessed 9/12/2020].

LANCELOT MILTGEN, C., POPOVIČ, A. & OLIVEIRA, T. 2013. Determinants of end-user acceptance of biometrics: Integrating the "Big 3" of technology acceptance with privacy context. *Decision Support Systems,* 56**,** 103-114.

LEE, M.-C. 2009. Understanding the behavioral intention to play online games: An extension of the theory of planned behavior. *Online Information Review,* 33**,** 849-872.

LEE, N. & LINGS, I. 2008. *Doing business research: a guide to theory and practice*, Sage.

LEONG, L.-Y., HEW, T.-S., TAN, G. W.-H. & OOI, K.-B. 2013. Predicting the determinants of the NFC-enabled mobile credit card acceptance: A neural networks approach. *Expert Systems with Applications,* 40**,** 5604-5620.

LIN, H.-M., CHEN, W.-J. & NIEN, S.-F. 2014. The study of achievement and motivation by e-learning-a case study. *International Journal of information and education technology,* 4**,** 421.

LUNA-MARTINEZ, D. 2017. Financial inclusion in Malaysia: Distilling lessons for other countries. The World Bank.

MA, Q. & LIU, L. 2005. The Technology Acceptance Model.
MAGNI, M., SUSAN TAYLOR, M. & VENKATESH, V. 2010. 'To play or not to play': A cross-temporal investigation using hedonic and instrumental perspectives to explain user intentions to explore a technology. *International Journal of Human-Computer Studies,* 68**,** 572-588.
MCCULLAGH, P. & NELDER, J. A. 1989. Generalized Linear Models 2nd Edition Chapman and Hall. *London, UK*.
MEDALLIA. 2015. *Experience Factors' Have Biggest Impact on Millennials' Banking Choices, New Study Finds* [Online]. Medallia. Available: https://www.prnewswire.com/news-releases/experience-factors-have-biggest-impact-on-millennials-banking-choices-new-study-finds-300172866.html [Accessed].
MEHTA, A., MORRIS, N. P., SWINNERTON, B. & HOMER, M. 2019. The Influence of Values on E-learning Adoption. *Computers & Education,* 141**,** 103617.
MOEN, I. M. & HELGØY, H. H. 2018. *The revised Payment Services Directive (PSD2): implications of PSD2 on Norwegian banks.*
MOMANI, A. & JAMOUS, M. 2017. The Evolution of Technology Acceptance Theories. *International Journal of Contemporary Computer Research (IJCCR),* 1**,** 50-58.
MOORE, D. S., NOTZ, W. I. & FLIGNER, M. A. 2015. *The basic practice of statistics*, Macmillan Higher Education.
MOORE, G. C. & BENBASAT, I. 1996. Integrating diffusion of innovations and theory of reasoned action models to predict utilization of information technology by end-users. *Diffusion and adoption of information technology.* Springer.
MOROSAN, C. & DEFRANCO, A. 2016. It's about time: Revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. *International Journal of Hospitality Management,* 53**,** 17-29.
MORRIS, M. G. & VENKATESH, V. 2000. Age differences in technology adoption decisions: Implications for a changing work force. *Personnel psychology,* 53**,** 375-403.
MUN, Y. Y., JACKSON, J. D., PARK, J. S. & PROBST, J. C. 2006. Understanding information technology acceptance by individual professionals: Toward an integrative view. *Information & Management,* 43**,** 350-363.
NAKASHIMA, T. 2018. Creating credit by making use of mobility with FinTech and IoT. *IATSS Research,* 42**,** 61-66.
PALLANT, J. 2011. Survival manual. *A step by step guide to data analysis using SPSS*.
PALLANT, J. 2016. SPSS Survival Guide Manual 6th edition. Two Penn Plaza. New York, NY: McGraw Hill Education.
PARK, E., KIM, H. & OHM, J. Y. 2015. Understanding driver adoption of car navigation systems using the extended technology acceptance model. *Behaviour & Information Technology,* 34**,** 741-751.
PRIEM, R. L., LI, S. & CARR, J. C. 2011. Insights and New Directions from Demand-Side Approaches to Technology Innovation, Entrepreneurship, and Strategic Management Research. *Journal of Management,* 38**,** 346-374.
PRIEM, R. L. & SWINK, M. 2012. A Demand-side Perspective on Supply Chain Management. *Journal of Supply Chain Management,* 48**,** 7-13.
PWC GLOBAL 2019. Financial services technology 2020 and beyond: Embracing disruption.
RIYADH, A. N., BUNKER, D. & RABHI, F. 2010. Barriers to e-finance adoption in small and medium sized enterprises (SMEs) in Bangladesh. *Available at SSRN 1726262*.
ROBINSON, M. T. 2016. The generations: Which generation are you? Available from: https://www.careerplanner.com/Career-Articles/Generations.cfm [Accessed 15/11/2020.
ROVAI, A. P., BAKER, J. D. & PONTON, M. K. 2013. *Social science research design and statistics: A practitioner's guide to research methods and IBM SPSS*, Watertree Press LLC.
RUTHERFORD, A. 2001. *Introducing ANOVA and ANCOVA: a GLM approach*, Sage.
RYAN, R. M. & DECI, E. L. 2000. Self-Determination Theory and the

Facilitation of Intrinsic Motivation,

Social Development, and Well-Being.
SANDER, K. 2020. *Forskningsprosessen* [Online]. Available: https://estudie.no/forskningsprosessen/ [Accessed 05/12/2020].
SCHECHTER, J. 2013. Deductive reasoning. *The Encyclopedia of the Mind*, 226-230.
SCHMIDT, M. J. & HOLLENSEN, S. 2006. *Marketing research: An international approach*, Pearson education.
SEMUEL, H. & LIANTO, A. S. 2014. Analisis ewom, brand image, brand trust dan minat beli produk smartphone di Surabaya. *Jurnal Manajemen Pemasaran,* 8**,** 7-54.
SHANMUGAM, R. & CHATTAMVELLI, R. 2016. Skewness and Kurtosis.
SHAW, N. & SERGUEEVA, K. 2019. The non-monetary benefits of mobile commerce: Extending UTAUT2 with perceived value. *International Journal of Information Management,* 45**,** 44-55.
SHIN, D.-H. 2009. Towards an understanding of the consumer acceptance of mobile wallet. *Computers in Human Behavior,* 25**,** 1343-1354.
SHIN, D.-H. 2010. Modeling the interaction of users and mobile payment system: Conceptual framework. *International Journal of Human-Computer Interaction,* 26**,** 917-940.
SIKDAR, P. & MAKKAD, M. 2015. Online banking adoption: A factor validation and satisfaction causation study in the context of Indian banking customers. *International Journal of Bank Marketing,* 33**,** 760-785.
SNKI 2018. Financial Inclusion Insights Indonesia.
TARHINI, A., TEO, T. & TARHINI, T. 2015. A cross-cultural validity of the E-learning Acceptance Measure (ElAM) in Lebanon and England: A confirmatory factor analysis. *Education and Information Technologies,* 21.
TAYLOR, S. & TODD, P. 1995. Decomposition and crossover effects in the theory of planned behavior: A study of consumer adoption intentions. *International journal of research in marketing,* 12**,** 137-155.
TEIGEN, M. & WÄNGNERUD, L. 2009. Tracing gender equality cultures: Elite perceptions of gender equality in Norway and Sweden. *Politics & Gender,* 5**,** 21.
TEO, A.-C., TAN, G. W.-H., OOI, K.-B., HEW, T.-S. & YEW, K.-T. 2015. The effects of convenience and speed in m-payment. *Industrial Management & Data Systems*.
THE GLOBAL ECONOMY. 2017. Available: https://www.theglobaleconomy.com/Norway/percent_people_bank_accounts/ [Accessed 26/10/2020 2020].
THEFACTORY 2019. Fintech Beat.
THOMPSON, R. L., HIGGINS, C. A. & HOWELL, J. M. 1991. Personal Computing: Toward a Conceptual Model of Utilization. *MIS Quarterly,* 15**,** 125-143.
TORNATZKY, L. G. & KLEIN, K. J. 1982. Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on engineering management***,** 28-45.
TRIANDIS, H. C. Values, attitudes, and interpersonal behavior. Nebraska symposium on motivation, 1979. University of Nebraska Press.
VENKATESH, V. & DAVIS, F. D. 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science,* 46**,** 186-204.
VENKATESH, V., MORRIS, M. G., DAVIS, G. B. & DAVIS, F. D. 2003. User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly,* 27**,** 425-478.
VENKATESH, V., THONG, J. Y. L. & XU, X. 2012. Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly,* 36**,** 157-178.
VENKATESH, V. & ZHANG, X. 2010. Unified Theory of Acceptance and Use of Technology: U.S. Vs. China. *Journal of Global Information Technology Management,* 13**,** 5-27.

ZATWARNICKA-MADURA, B., STECKO, J. & MENTEL, G. 2016. Brand image vs. consumer trust. *Актуальні проблеми економіки*, 237-245.
ZAVOLOKINA, L., DOLATA, M. & SCHWABE, G. 2016. The FinTech phenomenon: antecedents of financial innovation perceived by the popular press. *Financial Innovation,* 2.
ZHOU, T., LU, Y. & WANG, B. 2010. Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior,* 26, 760-767.

Appendixes

Appx: 1 Survey Questionnaire

Q.1 Where were you born?

Norway

Other

Q.2 What is your gender?

Male

Female

Q.3 What is your age group?

Under 24

25-29

30-39

40-55

Over 56

Q.4 Do you use any Fintech services?

Yes

No

Used before

- Respondents who answered “Yes” or “Used before” could proceed to next section.

Q.5 Which following service do you use or have used?

Deposit

Financial advice

Financing

Insurtech

Payment

Q.6 How frequently do you use or used to use the service?

Once a month

Twice a month

Three times a month

Four Times a month

Five or more times a month

Variables	Indicators	Description
Effort Expectancy: EE	EE1	I find Fintech services are easy to learn.
	EE2	It is simple and understandable to interact with a Fintech service.
	EE3	The system is flexible to interact with.
	EE4	I do not have any confusion about “what I am doing” while using the service.
Social Influence: SI	SI1	My friends, family and surroundings value the use of Fintech services.
	SI2	Many of my friends use Fintech services.
	SI3	Family and friends’ suggestions influence my decision to use Fintech services.
	SI4	I find usage of Fintech trendy.
Hedonic Motivation: HM	HM1	To me using a Fintech app or service is fun.
	HM2	It is something I like doing.
	HM3	I feel the motivation to explore more about Fintech.
Price Value: PV	PV1	Price plays a crucial role for me to select a financial service.
	PV2	I find Fintech services are cheaper to use.
	PV3	I think Fintech services are cheaper than my regular bank considering other associated costs to use it.
Perceived Risk: PR	PR1	I feel unsafe by providing personal information to use the system.
	PR2	I feel unprotected to send confidential data while using the mobile app of the service providers.
	PR3	I feel the chances of happening something wrong on these types of services higher than my regular bank.
	PR4	There is a high risk of breaching my financial data if I lose my phone as Fintech services are mostly based on mobile apps.
Brand Image: BI_1	BI1_1	I feel brand name is important to choose a financial product.
	BI1_2	I feel a service provider with good brand image is more trustworthy to use.
	BI1_3	I feel safe to use a Fintech service if it is from a renowned brand.
Behavioural Intention: BI_2	BI2_1	I shall prefer to pay with Vipps or with other mobile payment systems over my regular bank card.
	BI2_2	I shall try to use Fintech services for the cross-border payments rather than my regular bank.
	BI2_3	I intend to use Fintech services in the future.
	BI2_4	I shall recommend others to use Fintech services.

Appx: 2

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
EE_1	.287	157	.000	.755	157	.000
EE_2	.288	157	.000	.766	157	.000
EE_3	.248	157	.000	.821	157	.000
EE_4	.204	157	.000	.821	157	.000
SI_1	.272	157	.000	.800	157	.000
SI_2	.334	157	.000	.737	157	.000
SI_3	.249	157	.000	.830	157	.000
SI_4	.299	157	.000	.781	157	.000
HM_1	.212	157	.000	.844	157	.000
HM_2	.205	157	.000	.854	157	.000
HM_3	.230	157	.000	.816	157	.000
PV_1	.349	157	.000	.728	157	.000
PV_2	.310	157	.000	.752	157	.000
PV_3	.270	157	.000	.782	157	.000
PR_1	.172	157	.000	.937	157	.000
PR_2	.200	157	.000	.933	157	.000
PR_3	.188	157	.000	.933	157	.000
PR_4	.199	157	.000	.922	157	.000
BI1_1	.220	157	.000	.884	157	.000
BI1_2	.205	157	.000	.878	157	.000
BI1_3	.240	157	.000	.863	157	.000
BI2_1	.251	157	.000	.802	157	.000
BI2_2	.260	157	.000	.825	157	.000
BI2_3	.326	157	.000	.729	157	.000
BI2_4	.298	157	.000	.785	157	.000

a. Lilliefors Significance Correction

Appx: 3

ANOVA

		Sum of Squares	df	Mean Square	F	Sig
Between People		271.755	156	1.742		
Within People	Between Items	12.395	3	4.132	8.477	.000
	Residual	228.105	468	.487		
	Total	240.500	471	.511		
Total		512.255	627	.817		

Grand Mean = 6.21

(SI)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig
Between People		904.943	156	5.801		
Within People	Between Items	11.342	3	3.781	5.557	.001
	Residual	318.408	468	.680		
	Total	329.750	471	.700		
Total		1234.693	627	1.969		

Grand Mean = 4.74

(PR)

Appx: 4

Correlation Matrix[a]

		EE_1	EE_2	EE_3	EE_4	SI_1	SI_2	SI_3	SI_4	HM_1	HM_2	HM_3	PV_1	PV_2	PV_3	PR_1	PR_2	PR_3	PR_4	BI1_1	BI1_2	BI1_3
Correlation	EE_1	1.000	.596	.606	.320	.221	.262	.120	.172	.313	.418	.449	.206	.331	.322	.175	.222	.229	.107	-.035	.103	.048
	EE_2	.596	1.000	.562	.350	.220	.307	.156	.278	.360	.380	.396	.249	.365	.297	.187	.291	.299	.165	-.038	-.023	-.076
	EE_3	.606	.562	1.000	.266	.304	.416	.250	.350	.383	.436	.469	.421	.415	.411	.321	.314	.338	.230	-.079	.038	.022
	EE_4	.320	.350	.266	1.000	.147	.129	.099	.145	.156	.211	.174	.120	.070	.129	.102	.073	.068	-.015	.006	-.027	.008
	SI_1	.221	.220	.304	.147	1.000	.527	.536	.308	.329	.388	.279	.195	.246	.261	.187	.268	.344	.340	-.134	-.124	-.125
	SI_2	.262	.307	.416	.129	.527	1.000	.337	.235	.208	.259	.191	.240	.134	.136	.267	.296	.479	.421	-.075	-.045	-.141
	SI_3	.120	.156	.250	.099	.536	.337	1.000	.396	.325	.300	.254	.207	.252	.213	.257	.330	.319	.272	-.041	-.032	-.080
	SI_4	.172	.278	.350	.145	.308	.235	.396	1.000	.423	.336	.251	.207	.172	.155	.187	.273	.276	.218	-.198	-.150	-.149
	HM_1	.313	.360	.383	.156	.329	.208	.325	.423	1.000	.753	.662	.200	.426	.406	.114	.215	.189	.228	-.055	-.016	-.030
	HM_2	.418	.380	.436	.211	.388	.259	.300	.336	.753	1.000	.685	.196	.477	.489	.202	.270	.241	.270	.064	.083	.029
	HM_3	.449	.396	.469	.174	.279	.191	.254	.251	.662	.685	1.000	.194	.450	.487	.307	.389	.312	.227	.108	.051	.009
	PV_1	.206	.249	.421	.120	.195	.240	.207	.207	.200	.196	.194	1.000	.464	.383	.290	.272	.305	.290	-.079	.006	.011
	PV_2	.331	.365	.415	.070	.246	.134	.252	.172	.426	.477	.450	.464	1.000	.729	.378	.398	.283	.337	-.121	.029	.042
	PV_3	.322	.297	.411	.129	.261	.136	.213	.155	.406	.489	.487	.383	.729	1.000	.428	.350	.308	.324	-.018	.069	.043
	PR_1	.175	.187	.321	.102	.187	.267	.257	.187	.114	.202	.307	.290	.378	.428	1.000	.785	.652	.562	.024	.074	-.053
	PR_2	.222	.291	.314	.073	.268	.296	.330	.273	.215	.270	.389	.272	.398	.350	.785	1.000	.692	.559	.024	.032	-.091
	PR_3	.229	.299	.338	.068	.344	.479	.319	.276	.189	.241	.312	.305	.283	.308	.652	.692	1.000	.675	-.005	.011	-.077
	PR_4	.107	.165	.230	-.015	.340	.421	.272	.218	.228	.270	.227	.290	.337	.324	.562	.559	.675	1.000	-.009	-.019	-.064
	BI1_1	-.035	-.038	-.079	.006	-.134	-.075	-.041	-.198	-.055	.064	.108	-.079	-.121	-.018	.024	.024	-.005	-.009	1.000	.549	.337
	BI1_2	.103	-.023	.038	-.027	-.124	-.045	-.032	-.150	-.016	.083	.051	.006	.029	.069	.074	.032	.011	-.019	.549	1.000	.519
	BI1_3	.048	-.076	.022	.008	-.125	-.141	-.080	-.149	-.030	.029	.009	.011	.042	.043	-.053	-.091	-.077	-.064	.337	.519	1.000
Sig. (1-tailed)	EE_1		.000	.000	.000	.003	.000	.067	.016	.000	.000	.000	.005	.000	.000	.014	.003	.002	.091	.330	.101	.277
	EE_2	.000		.000	.000	.003	.000	.025	.000	.000	.000	.000	.001	.000	.000	.009	.000	.000	.020	.317	.385	.172
	EE_3	.000	.000		.000	.000	.000	.001	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.002	.163	.317	.394
	EE_4	.000	.000	.000		.033	.053	.108	.035	.026	.004	.015	.068	.193	.054	.102	.183	.199	.424	.472	.370	.461
	SI_1	.003	.003	.000	.033		.000	.000	.000	.000	.000	.000	.007	.001	.000	.010	.000	.000	.000	.047	.061	.059
	SI_2	.000	.000	.000	.053	.000		.000	.001	.005	.001	.008	.001	.047	.045	.000	.000	.000	.000	.176	.287	.039
	SI_3	.067	.025	.001	.108	.000	.000		.000	.000	.000	.001	.005	.001	.004	.001	.000	.000	.000	.303	.347	.159
	SI_4	.016	.000	.000	.035	.000	.001	.000		.000	.000	.001	.005	.016	.026	.009	.000	.000	.003	.007	.031	.031
	HM_1	.000	.000	.000	.026	.000	.005	.000	.000		.000	.000	.006	.000	.000	.078	.003	.009	.002	.245	.419	.353
	HM_2	.000	.000	.000	.004	.000	.001	.000	.000	.000		.000	.007	.000	.000	.006	.000	.001	.000	.213	.152	.358
	HM_3	.000	.000	.000	.015	.000	.008	.001	.001	.000	.000		.007	.000	.000	.000	.000	.000	.002	.088	.264	.455
	PV_1	.005	.001	.000	.068	.007	.001	.005	.005	.006	.007	.007		.000	.000	.000	.000	.000	.000	.164	.468	.448
	PV_2	.000	.000	.000	.193	.001	.047	.001	.016	.000	.000	.000	.000		.000	.000	.000	.000	.000	.066	.358	.300
	PV_3	.000	.000	.000	.054	.000	.045	.004	.026	.000	.000	.000	.000	.000		.000	.000	.000	.000	.412	.195	.296
	PR_1	.014	.009	.000	.102	.010	.000	.001	.009	.078	.006	.000	.000	.000	.000		.000	.000	.000	.383	.178	.256
	PR_2	.003	.000	.000	.183	.000	.000	.000	.000	.003	.000	.000	.000	.000	.000	.000		.000	.000	.381	.346	.128
	PR_3	.002	.000	.000	.199	.000	.000	.000	.000	.009	.001	.000	.000	.000	.000	.000	.000		.000	.475	.448	.169
	PR_4	.091	.020	.002	.424	.000	.000	.000	.003	.002	.000	.002	.000	.000	.000	.000	.000	.000		.456	.405	.215
	BI1_1	.330	.317	.163	.472	.047	.176	.303	.007	.245	.213	.088	.164	.066	.412	.383	.381	.475	.456		.000	.000
	BI1_2	.101	.385	.317	.370	.061	.287	.347	.031	.419	.152	.264	.468	.358	.195	.178	.346	.448	.405	.000		.000
	BI1_3	.277	.172	.394	.461	.059	.039	.159	.031	.353	.358	.455	.448	.300	.296	.256	.128	.169	.215	.000	.000	

a. Determinant = 2.94E-005

Appx: 5

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.470	30.807	30.807	6.470	30.807	30.807	3.136	14.932	14.932
2	2.231	10.623	41.430	2.231	10.623	41.430	2.756	13.125	28.057
3	2.067	9.843	51.273	2.067	9.843	51.273	2.426	11.553	39.610
4	1.387	6.606	57.880	1.387	6.606	57.880	2.263	10.774	50.384
5	1.369	6.517	64.397	1.369	6.517	64.397	2.008	9.562	59.945
6	1.042	4.962	69.358	1.042	4.962	69.358	1.977	9.413	69.358
7	.855	4.073	73.431						
8	.790	3.762	77.194						
9	.659	3.138	80.331						
10	.638	3.039	83.371						
11	.494	2.353	85.723						
12	.461	2.193	87.917						
13	.397	1.890	89.806						
14	.382	1.817	91.624						
15	.362	1.724	93.348						
16	.298	1.417	94.765						
17	.279	1.329	96.094						
18	.239	1.140	97.234						
19	.223	1.064	98.297						
20	.198	.944	99.241						
21	.159	.759	100.000						

Extraction Method: Principal Component Analysis.

Appx: 6

Rotated Component Matrix[a]

	Component					
	1	2	3	4	5	6
PR_1	.864					
PR_2	.856					
PR_3	.813					
PR_4	.722					
HM_1		.829				
HM_2		.804				
HM_3		.776				
EE_1			.772			
EE_2			.760			
EE_3			.654			
EE_4			.643			
SI_1				.778		
SI_3				.721		
SI_2				.669		
SI_4				.467		
BI1_2					.865	
BI1_1					.767	
BI1_3					.755	
PV_2						.744
PV_1						.737
PV_3						.653

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 7 iterations.

Appx: 7

Descriptive Statistics

	N	Mean	Std. Deviation
Sum_BI2	157	6.1481	.72774
Sum_EE	157	6.1736	.67443
Sum_SI	157	6.2102	.65993
Sum_HM	157	5.7771	1.15123
Sum_PV	157	6.1677	.91023
Sum_PR	157	4.7404	1.20425
Sum_BI1	157	5.6879	.78961
Valid N (listwise)	157		

Appx: 8

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	40.696	6	6.783	24.268	.000[b]
	Residual	41.923	150	.279		
	Total	82.619	156			

a. Dependent Variable: Sum_BI2

b. Predictors: (Constant), Sum_BI1, Sum_PV, Sum_SI, Sum_EE, Sum_PR, Sum_HM

Appx: 9

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	2.942	.632		4.651	.000	1.692	4.191					
	Sum_EE	.255	.076	.237	3.376	.001	.106	.405	.505	.266	.196	.688	1.454
	Sum_SI	-.123	.081	-.112	-1.529	.128	-.282	.036	.254	-.124	-.089	.634	1.578
	Sum_HM	.188	.048	.297	3.875	.000	.092	.283	.560	.302	.225	.576	1.736
	Sum_PV	.302	.060	.377	5.035	.000	.183	.420	.600	.380	.293	.602	1.660
	Sum_PR	.001	.043	.002	.023	.982	-.084	.085	.291	.002	.001	.676	1.480
	Sum_BI1	-.098	.055	-.106	-1.771	.079	-.207	.011	-.078	-.143	-.103	.946	1.057

a. Dependent Variable: Sum_BI2

Appx: 10

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	6.268	.094		66.998	.000	6.083	6.453					
	Country_Birth=Other	-.014	.118	-.010	-.121	.904	-.247	.218	-.025	-.010	-.010	.989	1.011
	Gender=Female	-.218	.117	-.150	-1.866	.064	-.449	.013	-.148	-.149	-.149	.990	1.010
	iGen	-.112	.174	-.051	-.640	.523	-.456	.233	-.045	-.052	-.051	.994	1.006
2	(Constant)	3.058	.646		4.737	.000	1.782	4.334					
	Country_Birth=Other	-.038	.089	-.026	-.431	.667	-.215	.138	-.025	-.036	-.025	.918	1.089
	Gender=Female	-.117	.087	-.080	-1.338	.183	-.289	.056	-.148	-.110	-.078	.947	1.056
	iGen	-.030	.130	-.014	-.233	.816	-.288	.227	-.045	-.019	-.014	.948	1.055
	Sum_EE	.254	.076	.235	3.318	.001	.103	.405	.505	.264	.194	.678	1.475
	Sum_SI	-.132	.082	-.120	-1.607	.110	-.295	.030	.254	-.131	-.094	.612	1.634
	Sum_HM	.179	.049	.283	3.646	.000	.082	.276	.560	.288	.213	.566	1.767
	Sum_PV	.308	.060	.386	5.114	.000	.189	.428	.600	.389	.298	.598	1.672
	Sum_PR	.002	.044	.003	.042	.966	-.085	.088	.291	.003	.002	.648	1.543
	Sum_BI1	-.092	.056	-.100	-1.648	.101	-.203	.018	-.078	-.135	-.096	.923	1.083

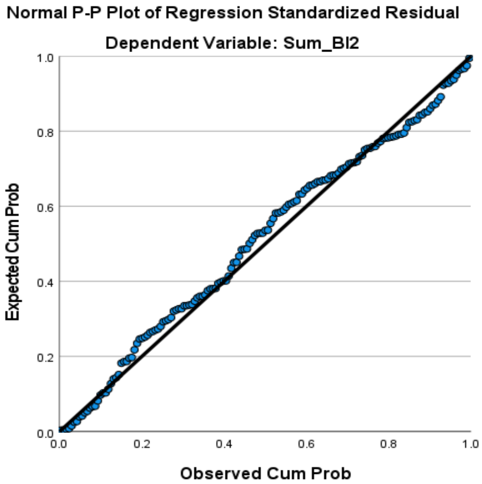
a. Dependent Variable: Sum_BI2

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	5.990	.115		51.927	.000	5.762	6.218					
	Xennials	.116	.124	.077	.943	.347	-.128	.361	.077	.076	.075	.961	1.040
	Payment	-.025	.130	-.015	-.189	.850	-.282	.233	.008	-.015	-.015	.959	1.043
	Gender=Male	.214	.117	.147	1.828	.070	-.017	.445	.148	.147	.146	.990	1.010
	Country_Birth=Norway	.014	.118	.010	.119	.905	-.219	.247	.025	.010	.010	.989	1.011
2	(Constant)	2.887	.649		4.449	.000	1.605	4.169					
	Xennials	.041	.092	.027	.447	.656	-.141	.223	.077	.037	.026	.926	1.080
	Payment	-.009	.098	-.006	-.094	.925	-.203	.185	.008	-.008	-.006	.901	1.109
	Gender=Male	.116	.088	.080	1.324	.188	-.057	.290	.148	.109	.077	.942	1.061
	Country_Birth=Norway	.038	.090	.026	.422	.674	-.139	.215	.025	.035	.025	.918	1.089
	Sum_EE	.257	.078	.238	3.289	.001	.103	.412	.505	.263	.192	.652	1.533
	Sum_SI	-.132	.082	-.120	-1.622	.107	-.293	.029	.254	-.133	-.095	.625	1.599
	Sum_HM	.176	.050	.279	3.562	.000	.078	.274	.560	.283	.208	.558	1.792
	Sum_PV	.307	.061	.384	5.029	.000	.187	.428	.600	.384	.294	.586	1.707
	Sum_PR	.003	.044	.005	.064	.949	-.085	.090	.291	.005	.004	.638	1.566
	Sum_BI1	-.093	.056	-.101	-1.657	.100	-.204	.018	-.078	-.136	-.097	.925	1.081

a. Dependent Variable: Sum_BI2

Appx: 11



Appx: 12

Case Processing Summary

		N	Marginal Percentage
LowMediumHigh	1.00	6	3.8%
	2.00	48	30.6%
	3.00	103	65.6%
Valid		157	100.0%
Missing		0	
Total		157	

Appx: 13

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	74.457			
Final	62.449	12.008	1	.001

Link function: Logit.

Appx: 14

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	22.915	25	.583
Deviance	24.572	25	.487

Link function: Logit.

Appx: 15

Pseudo R-Square

Cox and Snell	.074
Nagelkerke	.094
McFadden	.050

Link function: Logit.

Appx: 16

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Usage_Category = 1.00]	1.427	1.420	1.011	1	.315	-1.355	4.210
	[Usage_Category = 2.00]	4.134	1.438	8.266	1	.004	1.316	6.952
Location	Sum_BI2	.785	.235	11.134	1	.001	.324	1.247

Link function: Logit.

Appx: 17

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	62.449			
General	60.497	1.952	1	.162

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

Appx: 18

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	191.588			
Final	150.915	40.673	5	.000

Link function: Logit.

Appx: 19

Tests of Between-Subjects Effects

Dependent Variable: LowMediumHigh

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	3.250[a]	1	3.250	10.993	.001	.066
Intercept	4.216	1	4.216	14.263	.000	.084
Sum_BI2	3.250	1	3.250	10.993	.001	.066
Error	45.820	155	.296			
Total	1125.000	157				
Corrected Total	49.070	156				

a. R Squared = .066 (Adjusted R Squared = .060)

Appx: 20

Parameter Estimates

Dependent Variable: LowMediumHigh

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	Partial Eta Squared
Intercept	1.399	.370	3.777	.000	.667	2.130	.084
Sum_BI2	.198	.060	3.316	.001	.080	.316	.066

Appx: 21

Parameter Estimates

Dependent Variable: LowMediumHigh

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	Partial Eta Squared
Intercept	1.398	.350	3.996	.000	.707	2.089	.096
Sum_BI2 * Payment	.041	.015	2.799	.006	.012	.070	.049
Male	-.027	.083	-.329	.743	-.191	.137	.001
Norway	.058	.083	.697	.487	-.106	.221	.003
Sum_BI2	.166	.057	2.902	.004	.053	.279	.053
Xennials	.305	.087	3.527	.001	.134	.476	.076

Appx: 22

Pseudo R-Square

Cox and Snell	.228
Nagelkerke	.292
McFadden	.170

Link function: Logit.

Appx: 23

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Usage_Category = 1.00]	1.656	1.533	1.167	1	.280	-1.349	4.661
	[Usage_Category = 2.00]	4.613	1.552	8.836	1	.003	1.571	7.654
Location	Norway	.242	.368	.433	1	.511	-.479	.964
	Male	.035	.369	.009	1	.925	-.689	.759
	Sum_BI2 * Payment	.307	.093	10.901	1	.001	.125	.490
	Sum_BI2	.814	.253	10.379	1	.001	.319	1.309
	iGen	-1.671	.514	10.567	1	.001	-2.678	-.663

Link function: Logit.