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# User adoption of mobile applications:
## Extension of UTAUT2 model

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## Preface

This master thesis is one of a series of papers and reports published by the Center for Service Innovation (CSI). Centre for Service Innovation (CSI) is a coordinated effort by NHH to focus on the innovation challenges facing the service sector and involves 20 business and academic partners. It aims to increase the quality, efficiency and commercial success of service innovations and to enhance the innovation capabilities of its business and academic partners. CSI is funded through a significant eight-year grant from the Research Council of Norway and has recently obtained status as a Centre for Research-based Innovation (SFI).

## Executive summary

The purpose of the following research is to build the holistic model that predicts the consumer adoption mechanism for the third-party mobile applications. The research model for this study is based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). The original antecedents of the UTAUT model are supplemented with effects from online rankings and reviews and herd behavior. Also the moderating effect of mobile application type in the research model is tested.

The results of the study showed that some constructs from UTAUT2 model do explain user acceptance of mobile applications. Performance expectancy, price value and habit confirmed to be significant in the influence on the user behavioral intention to adopt mobile applications. The expected effect of online rankings and reviews and of herd behavior on the behavioral intention was not confirmed. The test of the moderating effect of mobile application type in the research model confirmed the presence of differences in the influences of some of antecedents in the model across hedonic and utilitarian mobile applications.

This research contributes to the UTAUT research, advances the mobile application adoption research and establishes directions for the future research in the area of mobile application adoption.

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# 1. Introduction

## 1.1. Background and motivation

The market for products and services in the modern world to big extent depends on the development of technology and internet. With rise of Internet of Things (IoT) era, new opportunities open for businesses; enhanced customer service, access to big data, innovation of business models and increased revenues (Harvard Business Review, 2014). The need new IoT-based solutions also comes from consumer markets; such trends as increased mobility, need to permanently be online, increased value of time and the need to use time efficiently reflect future consumer preferences and are important for business development (Andreassen, Lervik-Olsen, & Calabretta, 2015). For companies that want to follow the consumer demand for mobility and time efficiency and to use the benefits of IoT, mobile applications are popular and easily available solution. Inspiring examples of Uber, Netflix, Amazon, Vipps, etc. prove that mobile apps carry big potential for innovation as an enabling technology. In contrast to these optimistic prospects, recent statistics show that the number of new mobile application downloads tends to decrease, while both smartphone and tablet users spend most of their time on around 4-5 favorite applications (Pedotto & Chen, 2016). This tendency indicates that mobile application market becomes more concentrated and competitive. The market for mobile applications reached the point when the demand is intense but at the same time the proposition market is crowded. Mobile application technology is one of the easiest and obvious ways for businesses to keep up with the digital hype, but the increased competitiveness on the market for mobile applications makes it hard for business to effectively utilize the benefits of mobile applications. That is why before investing into development of mobile application, businesses face the need to understand the crucial factors that make mobile applications competitive and attract users. Firms that want to deploy mobile application as enabling technology encounter a question: what makes the market adopt newly introduced mobile applications?

Information technology acceptance research provides us with several theoretical models that use different constructs to explain the technology adoption mechanism. Potentially, these theoretical models could be relevant for explaining the adoption of mobile applications as well. Yet, the detailed review of the existing theoretical research reveals several gaps that prevent applicability of these theories in the modern setting to full extent.

First theoretical gap is connected with the fact that existing theoretical models don’t include all variables that describe potential important factors that may influence the consumer intention to

adopt mobile application. Fast development of digital technologies has strong influence on consumer demands, expectations and market trends. Main research in the area of information technology adoption was developed in the period from 1989 to 2003 (e.g. Davis et al., 1989; Taylor & Todd, 1995; Venkatesh & Davis 2000; Venkatesh et al., 2003). In that period information technology was limited to computer/desktop solutions, or so-called Internet of Computers era (Mattern & Floerkemeier, 2010). The mobile applications technology started to develop in the beginning of Internet of Things era. Based on this and with account for new consumer demand trends (Andreassen, Lervik-Olsen, & Calabretta, 2015) we assume that drivers for user acceptance confirmed by earlier models may not completely describe the process of mobile application user adoption and should be supplemented by new ones. In this research we will test the mobile application adoption process using the established information technology adoption research and supplement it with variables that describe new ways for consumers to collect the information about mobile application.

As it was mentioned earlier, the market for mobile applications is crowded and highly competitive. In such case it becomes impossible for modern consumers, who aim to be time efficient and mobile, to test the functionalities and benefits of numerous new offerings on the market. One of the solutions in such case for consumers is to collect information about mobile application online or copy the behavior of other consumers on the market when adopting the application. In the existing information technology adoption theoretical models, such as TAM (Davis et al., 1989), TRA (Ajzen & Fishbein, 1980), UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012), variables that describe such behavior of consumers are not included. To research how the online rankings and reviews and herd behavior influence consumer decision to adopt mobile applications, in our study, we will supplement the classical technology adoption model with variables that describe online reviews and rankings and herd behavior.

Secondly, in addition to holistic model for all categories of mobile applications, in our research we will test the effects of the proposed antecedents separately for utilitarian and hedonic mobile applications. Ahmad (2012) introduced classification of mobile services based on the relative importance of utilitarian and hedonic benefits they create for the users. In our study we will use the same logic and will also differentiate between the type of value that mobile applications create for the user and group mobile apps into utilitarian and hedonic. Hirschman & Holbrook (1982) introduced hedonic motives in consumer decision making as one of the important areas for understanding the consumer behavior and decision making. Whitten, Hightower & Sayeed (2014) in their research of the mobile device adoption, confirmed that utilitarian and hedonic value have significant influence on the overall value that user connects with the specific technology. Based on

this, we expect that consumers may also perceive adoption of utilitarian and hedonic mobile applications differently.

Finally, the review of the research literature conducted for the purpose of our study shows that theoretical research of the process of mobile application adoption is very limited. Third party mobile applications technology is relatively new, not centralized and the development of mobile applications is available to numerous third-party contractors (Rajput, 2017). And that is one of the reasons for why the technology of third-party mobile applications has developed rapidly since 2008. The theoretical research did not follow this fast development; in scientific literature the topic is relatively new and is not discovered to large extent. Review of research available in the area of mobile application adoption shows that big part of theoretical research on mobile applications focuses on specific functionalities of mobile applications and the service that they provide (e.g. security apps (Han, Wu & Winsdor, 2014), mobile shopping apps (Taylor & Levin, 2014), mobile banking applications (Verissimo, 2015), mobile instant messaging apps (Oghuma et al., 2015) instead of investigating mobile apps as a holistic and universal technology. Such studies don't create a holistic understanding of what features of mobile applications as an enabling technology, can enhance or even determine its adoption. In our study we have interest in understanding how users view mobile applications as a holistic technology and what factors define the user intention to adopt mobile application.

## 1.2 Purpose and research question

The purpose of this research is to build the holistic model that predicts the consumer adoption mechanism of third-party mobile applications. As a basis for our research we will use the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). UTAUT model is the most holistic and unified model describing the new technology adoption; it synthesizes eight well-established and validated technology acceptance models and theories (Yang & Forney, 2013). UTAUT model incorporates the benefits of other technology acceptance models and explains as much as 70 percent of the variance in intention, what is much more than the variance explained by any other of the general models on technology acceptance (Venkatesh et al., 2016). Moreover, the strong benefit of UTAUT model is that it integrates all important variables from multiple models for technology acceptance research. Since the research in the area of mobile application adoption is not yet developed and established, applying such holistic and generic model as UTAUT will be useful for identifying key factors that influence attitude towards adoption of mobile applications and for establishing a baseline, holistic model for mobile applications adoption research.

Since in our research we specifically focus on consumer context of mobile application adoption, we will base our model on the UTAUT2 model, which was developed specifically for consumer context (Venkatesh et al., 2012). As it has already been described, the research on user adoption of mobile applications is quite limited. Most of research focuses on specific functionalities and services that mobile apps deliver to the user, without researching mobile applications as a holistic enabling technology. Even less studies utilized UTAUT or UTAUT2 models to discover the adoption mechanism for mobile applications (Hew et al., 2015). In our study we will develop a UTAUT extension. The research category of UTAUT extensions has the greatest potential for making significant theoretical contributions to new technology adoption research (Venkatesh et al. 2016). UTAUT and UTAUT2 models are widely adopted by researchers to examine the information technology adoption thanks to its validity and reliability in influencing technology acceptance (Wong et al., 2014) and utilizing it for understanding process of mobile application adoption will be of a big value for both businesses and researchers.

As a result of the following study we expect to enrich the UTAUT-related research base and to make the findings applicable for the modern business setting. We assume that user acceptance of mobile applications is characterized by specific high-level and individual-level contextual factors that are not described in the original UTAUT2 model. Thus, in this work we will investigate these factors and test how they influence user acceptance of mobile applications. In the following work we aim to build a technology acceptance model that explains the adoption mechanisms only for voluntary market setting where consumers have the full decision power to adopt the technology.

With a purpose to explain the mobile application adoption mechanism on the market we will answer the following research questions:

RQ1: Do constructs from UTAUT2 model explain user acceptance of mobile applications?

RQ2: How Online Reviews and Rankings and Herd Behavior complement the UTAUT2 antecedents in explaining acceptance of mobile applications?

RQ3: What are the moderating effects of the type of mobile application?

### 1.3 Contributions

This research will have several theoretical contributions, which correspond to recommendations that Venkatesh et al. (2016) outlined in their study “Unified theory of acceptance and use of technology: a synthesis and the road ahead”. Following the recommendations from Venkatesh et al. (2016) we will extend the UTAUT2 model with new effects from additional high-level contextual factors and with individual level contextual factors connected with task attributes.

As new high-level contextual factors we will introduce Online Rankings and Reviews and Herd Behavior. We expect that these two antecedents will represent additional social factors that may influence user intention to adopt mobile application. As new individual level contextual factors we will test moderating effects from utilitarian and hedonic task attributes that users associate with different categories of mobile applications.

The review of research on the adoption and usage of mobile applications shows the importance of online rankings and reviews and of herd behavior for the adoption of some specific types of mobile applications (e.g. Hyrynsalmi et al., 2015, Liang et al., 2015, Shen et al., 2015). Yet the importance of Online Rankings and Reviews and Herd Behavior for adoption of mobile application as a holistic technology is not properly discovered. Extending the existing UTAUT2 model with effects from Online Rankings and Reviews and from Herd Behavior extends the classical Social Influence construct with new dimensions; in the original UTAUT model the social influence is limited to opinions of important others. Additionally, this study integrates the original UTAUT2 model with the model of Herd Behavior in the adoption and continued use of technology by Sun (2013). Thanks to these theoretical contributions this research enriches the knowledge on user acceptance of information technology by identifying and testing the existing user acceptance models in additional boundary conditions and extends the original UTAUT2 model with new contextual factors. The results of the following study are valuable for testing the applicability of existing UTAUT model for different technologies and show the generalizability of the model.

The results of this research will be valuable for application in a business setting and will fill the knowledge gap on the adoption of mobile applications for both business managers and developers. The results of this study will provide managers with understanding of the mechanism of technology adoption on consumer markets and specifically, user acceptance of mobile applications. Such knowledge will become valuable for businesses in making a decision to invest into mobile application development. Firstly, it will allow managers to reasonably evaluate the decision to supplement their market offering with a mobile application before launching the development process. The results of this study will allow for deeper understanding of what functionalities users expect their mobile application to have. Secondly, knowledge of the features that are important for user adoption of mobile applications is necessary for development and marketing of the application. Finally, we expect the model to become a powerful tool for marketers that will give them more insights into consumer attitudes and behaviors related to mobile applications. For example, understanding of the importance of hedonic and price value as well as of online rankings and reviews for utilitarian and hedonic mobile applications will help marketers choose the relevant launch strategy for the newly introduced app on the market. With such knowledge it will be possible to not only design mobile application that will win user loyalty on the market, but also to

develop a launch and promotional campaign targeted specifically on users who may be less likely to adopt the mobile app in other case.

This will also have a methodological contribution to the existing research base. For this study new measures for the construct called Online Rankings and Reviews were developed. This construct was developed and introduced specifically for the purpose of our research and conceptually is based on the commonly used in the literature constructs called Online WOM, e-WOM or Online reviews. Even though the influence of Online Rankings and Reviews on the adoption of mobile applications has already been researched, other methods than self-reported survey were used for measuring this construct. For example, Liang et al., (2016) used multifacet sentiment analysis and collected data from Apple Store for measuring this construct. Similar approach was used by (Hyrynsalmi et al., 2014) where they examined the effects of e-WOM by gathering a set of application data from Google Play. For this reason, it was not possible for us to adopt the survey measurement items from previous research. The measurement items for Online Rankings and Reviews developed in our study can be used in the future research for confirmation of the following findings as well as for research aimed at specific types of mobile applications.

### 1.4 Outline

To answer the abovementioned research questions and to deliver on the declared theoretical and managerial contributions, we will build this research paper in a following way. First, we will present the three main models that explain the theories of adoption. These theories will help us gain the perception of new technology adoption process and discover the studies that can potentially be used for researching the mobile application user adoption. These theories will be also used as a reference for defining the potential antecedents and moderators in our research model. In the adoption literature review we will also specifically focus on the details and relevance of UTAUT2 model as a baseline model for our research. After reviewing the theories of adoption we will present the existing research and findings on the mobile application adoption. We will also describe characteristics that differentiate mobile applications from other information systems and technologies. Based on this theoretical background we will present our research model and describe the hypotheses for our research. We will present the sample and methods for our data analysis. Finally, we will describe the results, conclusions and directions for future research.

# 2. Theories of adoption

## 2.1. General models

### *2.1.1. Theory of reasoned action*

One of the most popular general models used to predict and explain usage behavior is the Theory of Reasoned Action (TRA). This model has been used for more than 30 years as a fundamental theory to explain human behaviors and behavioral intentions. Initially described with the aim to explain the connection between the attitude towards behavior and the actual behavior (Fishbein & Ajzen, 1975), the model became a foundation for research in social psychology and was used to predict a wide range of behaviors with regard to conditions determined by initial goal, availability of choice situation etc. (Sheppard et al. 1988). The model proved its relevance and generalizability in numerous settings for various decision situations; voting on elections (e.g. Bowman & Fishbein, 1978, Davidson et al., 1985), having a child (e.g. Vinokur-Kaplan, 1978, Davidson and Jaccard, 1979), losing weight (Sejwacz, Ajzen & Fishbein, 1980), purchasing behavior (Glassman & Fitzhenry, 1976, Miniard, Fishbein & Ajzen, 1980, Obermiller & Page, 1982), leisure choices (Warshaw & Davis, 1985), etc. According to Fishbein & Ajzen (1975) the actual behavior of the person is determined by the behavioral intention while two main constructs that influence the Behavioral Intention are the Attitude towards behavior and the Subjective norms. The benefit of TRA is that it is applicable for explaining a wide range of human behaviors. But at the same time, TRA model is also a very general one. Precise explanation of specific behaviors in TRA model requires initial eliciting of salient beliefs about the behavior (Ajzen & Fishbein, 1980). In adoption research literature TRA is often used as a mediating model of impact of uncontrollable and controllable variables on user behavior and to describe how the psychological internal variables influence the external variables and user acceptance (Davis et al., 1989).

### *2.1.2. Theory of Planned Behavior*

Another important theory that is relevant for our research is the Theory of Planned Behavior (TPB). This theory was developed with an aim to overcome limitations of TRA in explaining behaviors over which people don’t have a complete volitional control (Ajzen, 1991). Just as it was in the original TRA model, the actual behavior in TPB depends on the attitude towards behavior as well as on the subjective norms. Yet, TPB model is supplemented by a third construct, Perceived Behavioral Control, which describes the perceived difficulty of performing the behavior (Ajzen, 1991). In contrast to the previous two constructs, in TRA the Perceived Behavioral Control

influences not only the behavioral intention but the actual behavior. This construct adds to the model explanation of non-motivational factors such as availability of opportunities and resources (e.g. time limits, money, skills) (Ajzen, 1985). Though the model itself may seem very general and simplistic, with only three constructs determining behavioral intention and the actual behavior, the author also dedicated separate studies explaining the complexity of constructs described in the model, for example, clarifying the role of self-efficacy and controllability and presenting the unified nature of these two constructs in forming the perceived behavioral control (Ajzen, 2002). Just like the TRA model, TPB gained numerous extensions and proved to be applicable for wide range of behavioral choices. For example, the model was tested to explain the small business executives' decision to adopt information technology (Harrison et al., 1997), the adoption of Computing Resource Center by business school students (Taylor & Todd, 1995), etc. One of the most relevant extensions of TPB is decomposed TPB (DTPB) that was developed to better explain usage intention. In DTPB attitude, subjective norm and perceived behavioral control were decomposed into underlying belief structure within technology adoption contexts what made possible recognition of the relationships and crossover effects between decomposed constructs (Taylor & Todd, 1995). In this model the belief measures used for TRA and TPB used salient belief elicitation measure. The relationship between the constructs that determine these attitudes remained obscure.

### *2.1.3. Technology Acceptance Model*

Finally, the third model, which can be relevant for our study, is the adaptation of TRA developed by Davis (1986) to explain the computer usage behavior - Technology Acceptance Model (TAM). The TAM was developed for tracing the impact of external factors on internal beliefs, attitudes and intentions. In contrast to TRA model, TAM model assumes that Behavioral Intention in addition to being determined by the attitude towards behavior is also directly influenced by Perceived Usefulness and Perceived Ease of Use. Variables Usefulness and Ease of Use are in turn influenced by other external antecedents (Davis et al., 1989). The author incorporated these two variables in the model arguing that they are specifically relevant for the acceptance of technology. Usefulness represents the user view on how new technology will increase his performance, while Ease of Use is the evaluation of level of effort needed to use the new system (Davis et al., 1989). Though developed to explain the computer systems adoption, TAM has also proved to be applicable for other information systems (Mathieson, 1991). Important difference between TRA and TAM is that TAM does not include Subjective Norm as a third variable that determines Behavioral Intention, the reason for that is that Subjective Norm is the most complicated and the least explained part of TRA; its influence on Behavioral Intention may be both, mediated by Attitude towards behavior and at the same time it may have a direct influence on the Behavioral Intention, and it is difficult to distinguish between these two types of influence (Fishbein & Ajzen, 1975). The research of importance of

Subjective Norm for technology acceptance showed contradicting results (e.g. Mathieson, 1991; Taylor & Todd, 1995). To investigate these contradicting results TAM2 model was developed. In TAM2 the complex nature of direct and indirect influences of Subjective Norm on Behavioral Intention were researched. It was confirmed that Subjective Norm has significant influence on Behavioral Intention via Usefulness and has a direct effect on Behavioral Intention for mandatory usage contexts (Venkatesh & Davis, 2000).

Emergence of TAM raised a question about the differences between TAM and other, more general models and gave rise to studies that compared the effectiveness of TAM, TRA and TBP in explaining the process of technology acceptance. In the study comparing how TAM and TRA explain user acceptance of computer technology, Davis et al. (1989) reported that both models proved that attitude towards behavior is the main determinant of Behavioral Intention for acceptance of IS and concluded that both models are applicable for explanation of technology acceptance. Yet it was observed that though the models came to the same conclusion and weight of constructs, they had different lines of reasoning; TRA required eliciting specific perceived consequences for the specific technology researched. Moreover, the importance of Subjective Norm in both models was put into question, since it didn't prove to be significant (Davis et al., 1989). In the study aimed at comparing the TAM and TPB models, Mathieson (1991) showed that both models are relevant for explaining the technology acceptance, yet there are some differences that may influence the choice of the model. For example, it was reported that TAM explained the attitude towards using IS better than TPB, at the same time, TPB proved to be better in providing more specific information on the outcomes and barrier factors, what is relevant for digging deeper into the salient and incontrollable factors (e.g. answering why the system is not easy to use) that determine technology acceptance (Mathieson, 1991).

Such long and sophisticated line of research along with its results show both, the relevance of the existing models for explanation of technology acceptance as well as need for more complex and detailed research in this area. It is important to determine the salient beliefs and antecedents for the new technology acceptance, which influence the significance of the main general constructs described in the existing models. Moreover, another issue under question is the role of the Subjective Norm in the models and for the technology acceptance process.

### 2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

One of the important conclusions in the studies that compared TAM and TRA (Davis et al., 1989) and TAM and TPB (Mathieson, 1991) is that these models can be effectively used together and that they supplement each other in a way that can help explaining and predicting user acceptance of technology. All three abovementioned models have their limits and imperfections. Choosing among

quite different models where some were developed to fit the general purposes while others were made specifically to explain adoption of certain technology can be a difficult task and may result in distorted evidence and imprecise conclusions. Even more complicated this choice becomes when we take into account models that are extensions or a hybrids of one the main models, for example TAM2, Decomposed TPB or Combined TAM and TPB. For the purpose of our study we decided to base our research on the holistic model that incorporates the benefits and strengths of the previously mentioned models and at the same time is the most relevant for explaining the technology acceptance process. Unified Theory of Acceptance and Use of Technology (UTAUT) is a truly holistic model that explains as much as 70 percent of the variance in Behavioral Intention, what is much more than any of the general models discussed above are able to explain (Venkatesh et al., 2003). The fact that UTAUT model also integrates important variables and moderators from multiple models for technology acceptance research makes UTAUT the most comprehensive solution for researching individual app adoption mechanism.

By integrating 8 prominent models on individual adoption mechanisms, UTAUT hypothesizes that three main constructs, which are Performance Expectancy, Effort Expectancy and Social Influence, determine Behavioral Intention. Behavioral Intention in turn, together with Facilitating Conditions influences Perceived Usefulness. The model also includes numerous moderating effects which determine the influence of the main constructs on Behavioral Intention as well as on Perceived Usefulness. Among these moderators are different combinations of gender, age, experience and voluntariness of use (Venkatesh et al., 2003). Initial model was developed to explain the individual adoption of IS in organizations but quickly became a basis for research of individual technology acceptance in slightly different settings and areas. Though being based on strong adoption models and confirmed in various settings, the original UTAUT model was widely criticized for its limitations to predict consumer intention to use new technology in terms of performance expectancy measures. It was claimed that the utilitarian performance expectancy from original UTAUT model should be supplemented with hedonic performance expectancy (Yang, 2010). In the extended UTAUT2 model the original model was supplemented with Hedonic Motivation, Price Value and Habit constructs and was developed specifically for explaining the individual consumer use of technology. Several new moderating effects were added to the model, and it was reported that Habit, in addition to indirect effect on Use Behavior through Behavioral Intention had a direct effect on Use Behavior (Venkatesh et al., 2012).

### *2.2.1 Adoption of mobile technologies using UTAUT*

Literature review through EBSCO Business Source Complete showed a limited amount of research on individual adoption of mobile technologies. For this literature review we used the

following search term combinations: “mobile + UTAUT”, “app + UTAUT”, “application + UTAUT” “Mobile application + adoption” “Mobile app + adoption”. In this literature research we considered only the results for which the abovementioned search terms we present in the title of the article and the results that mentioned combination of these search terms in the article abstract. One of the criteria for the research was that the work should be a peer reviewed article. Later the results of the literature research were adjusted according to the ABS Academic Journal Guide 2015. The results of this literature review are presented in Table 2.1. After this review, a manual revision of the articles was also conducted; the main criterion for the manual revision was that the research should be focused specifically on adoption of mobile technology, not on other technologies connected with mobile phones. Moreover, for the UTAUT and UTAUT2 studies the preference was given to articles that were mentioned in the overview of UTAUT adoptions and extensions described by Venkatesh et al. (2016).

Table 2.1

*Results of literature review*

| | Search terms | | | | |
|---|---|---|---|---|---|
| | mobile + UTAUT | app + UTAUT | application + UTAUT | Mobile application + adoption | Mobile app + adoption |
| EBSCO Business Source Complete | 34 | 2 | 19 | 104 | 53 |
| ABS adjusted | 7 | 1 | 7 | 11 | 12 |

This literature research showed that among the available works using UTAUT and UTAUT2 models for the research of mobile technologies adoption, almost half focuses on adoption of mobile banking and mobile payments. Yu (2012) used UTAUT model to explain the mobile banking adoption; in the study the key constructs from initial model were supplemented with influences from Perceived Credibility, Perceived Financial Cost and Perceived Self-efficacy. After this study by Yu (2012) more research of individual mobile technology adoption process were published. The UTAUT model became a basis for and extended model that explained the determinants of stock investors’ intention towards using mobile stock trading, where in addition to main UTAUT effect a significant negative effect of security risk, economic risk and functional risk on behavioral intention was revealed (Tai & Ku, 2013). Another extended UTAUT model for mobile banking supplements the constructs in UTAUT model with influences from task technology fit (TTF) model and initial trust model (ITM). In this model the positive influence of initial trust, performance expectancy,

technology characteristics and task technology fit on behavioral intention was confirmed (Oliveira et al., 2014). The perceived risk and trust constructs were confirmed to be significant for the mobile payments adoption in other extensions of UTAUT model that focused on adoption from consumer centric perspective (Slade et al., 2015). In addition to mobile services research, UTAUT also proved to be efficient for acceptance of other new technologies, for example for radio frequency identification enabled services (Nysveen & Pedersen, 2014), mobile health services (Sun et al., 2014; Dwivedi et al., 2016), mobile TV (Wong et al., 2013), mobile shopping services (Yang, 2010). Dwivedi et al. (2016) also showed the importance of self-concept for mobile health service adoption, yet highlighting a strong, country specific moderating effect. Hew et al. (2015) used UTAUT2 model to test the process of mobile application adoption.

# 3. Mobile Applications

## 3.1 Features of mobile apps

Despite the growing popularity of mobile apps, research in this area is quite limited and fragmented. For the convenience of the further review we separated the studies on the main features of mobile apps into groups based on what type of features of mobile applications the study describes. The first group of studies is the most general – it describes how mobile apps create value for consumers, businesses and what features of mobile applications make them attractive for the customer. These studies confirm that the main features that differentiate applications from other competing technologies, is that mobile apps are flexible and easily portable while allowing simultaneous delivery of real-time information to large user population. For example, in the research of how mobile apps create value for businesses Nah et al. (2005) highlighted the importance of app *efficiency* and *effectiveness* in creating value for users by minimizing delays and saving time in retrieving, updating and communicating information (Nah et al., 2005). The research on features that attract consumers to use mobile applications describes that *vividness*, *novelty*, *convenience*, *control*, *customization* and *feedback opportunity* are the attributes that can be employed to attract consumers to the app, while the readily available *interactivity* makes apps attractive and can increase customers' enjoyment and willingness to reuse the app (Kim, Wang, & Malthouse, 2015). Another study shows that just as other mobile services, mobile apps are attractive for the user because they offer *ubiquity*, *instant connectivity*, *personalization* and *timeliness* (Legner, Urbach,, & Nolte, 2016). Using the example of Mobile Instant Messaging (MIM) apps, Oghuma et al. 2015, described *enjoyment*, *ability to create networks* and groups and *time/money saving* with access to wide range of communication channels as features that make mobile apps attractive to users. The research on hotel app adoption reported that *service personalization* is important for app adoption process, which can also be enhanced by consumer innovativeness and gamification (Morosan, & DeFranco, A., 2016). Study by Hong, Cao & Wang (2017), reported that social mobile applications depend on the size of the network that has adopted the mobile application and that users perceive that mobile application is more useful and more fun based on how many people are already using the mobile application. As a result users make judgments about perceived benefits and satisfaction under influence of network externalities and herd behavior.

The second group of research describes mobile app features from the perspective of how specific technical characteristics of mobile applications influence the value creation and thus the

attractiveness of the app to the customer. For example, among features that differentiate mobile apps from other technologies, is increased *need to be adaptive and functional on various devices*. Cugola et al. (2014) illustrated how the *functional differences of physical devices* impact the app ability to satisfy consumer requirements (Cugola et al., 2014). Other studies on this topic confirmed that in contrast to traditional applications designed for PCs, increased interactivity of mobile apps also makes them depended on the *environment* in which mobile application is executed. This in turn can affect the app value created and the user acceptance of the technology (Legner, C., Urbach, N., & Nolte, 2016).

The third group of research describes the features and attributes of mobile apps that directly determine the app sales and marketing. Theoretical arguments for importance of *online rankings and reviews, e-word of mouth and online word of mouth (WOM)* for sales of mobile apps are strong, but empirical research show conflicting results in this case (Liang et al., 2015). To resolve this confusion, Liang et al. (2015) conducted a multifacet sentiment analysis (MFSA) of consumer feedback. In their study they reported positive influence of the comments about product quality in online reviews on sales of mobile apps. Interestingly, negative comments about service quality had stronger influence on mobile app sales than the positive comments. Shen (2015) revealed the importance of rating-scores and top charts for the formation of attitude towards mobile application. Moreover, Huang & Korfiatis (2015) run a test that showed how online reviews of mobile applications influence user judgments about app experience during trial period. Among other attributes that influence the app sales researchers also reported the *price (paid/free subscription basis),* that also moderates the importance of online reviews for the purchase (Huang & Korfiatis , 2015). Finally, another important technical feature that influences the process of how the customer gets acquainted with the app and how it is disseminated is the type of the app. In the study of mobile app adoption on Malaysian market Hew et al. (2015) highlighted that based on how customer gets access/ downloads the app, mobile apps can be divided into three types: *native*, *web* and *hybrid*. The difference among these types is that native apps can be downloaded only from app stores and are not connected to website URL (e.g. Angry Birds), web apps are basically websites that are made to look similar to native apps but can be accessed by entering a specific URL address into the browser, where the user will be asked whether he wants to install the app onto the device (e.g. Financial Times). Finally, hybrid apps include characteristics of both native and web apps (Hew et al., 2015). Though in their research Hew et al. mentioned and described in detail these features of the apps, they didn't differentiate on how these features may influence on the adoption of the app.

### 3.2 Adoption studies

Many mobile app adoption studies describe the adoption of mobile apps from the perspective of the functional value they create for the user. Such studies focus on a specific category of the app, such as mobile banking, shopping, traveling apps etc. For example, Verissimo (2015) conducted a study on mobile banking app adoption with specific focus on configurations of features which increase the mobile banking usage. The study aimed at presenting findings on mobile banking app use and identifying the potential barriers that restrict wider adoption of these applications. For the research author used a fuzzy set qualitative comparative analysis (fsQCA) with an aim to identify how the antecedents of mobile banking usage combine together to provide similar usage or non-usage outcomes as well as to discover which antecedents are essential or just sufficient to achieve usage/non-usage of mobile banking app. As a result, the study showed that *perceived risk*, *compatibility*, *perceived ease of use*, *perceived usefulness* are antecedents that determine use of mobile banking apps. It was reported that these antecedents are significant for usage situation in configuration as well as separately. At the same time the necessary condition for non-use of mobile banking app is the configuration of age, income with other abovementioned individual variables. The authors assume that for older people it may be more difficult to adopt mobile banking apps and that the main users of such applications are middle-aged customers. The effect of age in this case works in configuration with effect of income, predicting that the probability for older customers with lower incomes to use mobile banking applications is very low.

Another category of mobile apps described in the app adoption research are messaging apps, news apps, shopping apps and social apps. For example, Oghuma et al. (2015) investigated how and why mobile instant messaging apps (MIM) replace telecommunications operators' short message service and how the messaging apps are changing the customer attitude end expectations on how to connect and interact. Researchers used the benefit – confirmation model to show how the continuous intention to adopt mobile instant messaging (MIM) apps is developed. The research is based on the data obtained during a comparative analysis of mobile applications in South Korea. The study reports a crucial role of benefit seeking in determining continued MIM usage; perceived usefulness stands as an important factor for usage. Moreover, the authors assumed that distinguishing features of MIM apps such as available services, storage capacity and compatibility may influence users' perceptions of their ability to use the app. Also, it was expected that such add-ons as gaming, e-commerce, media content and other innovative service may enhance the hedonic value. This hypothesis was confirmed and authors also highlighted that the importance of the hedonic value depends on the usage situations implying that for customers that use MIM app for communication with friends and family hedonic features of the app may be more important. As a result of the research it was proved that perceived net benefits (users' perception of the sum of all

benefits with consideration for the costs of technology usage) and perceived network benefits (perception of benefits derived from network with other users) can explain users' continuance use intention of MIM applications.

In the research of mobile app adoption it is also quite common to build a model that focuses specifically on variables that are relevant for the type of service provided by mobile app. For example Han, Wu & Winsdor (2014) did research of the adoption of free third-party security apps, where they evaluated variables that are relevant specifically for adoption of security apps. In their research they put a strong emphasis on the difference between adoption and acceptance, highlighting that in the adoption research the individual's cognitive factors such as perceived ease of use and perceived usefulness form TAM should not be used as the determinant factors of the individual adoption intention and behavior. The reason for not taking these variables into consideration is that in case of adoption process individual tries the technology for the first time, and thus is not able to evaluate the usefulness and ease of use. Instead, they research two other dimensions that they assume will determine the intention to adopt security apps. First dimension is Awareness which includes Technology Awareness and Threat Awareness and the second dimension is Trust, which includes Trust in Third-Party Apps and Trust in Operation System. In this study it was expected that user Threat Awareness may be very important for the adoption of mobile security apps. In contrast to this the results of the study showed that crucial factor for user intention to adopt security mobile app is the user trust in these apps and their developers. Moreover, the study reported a significant effect of technology awareness and trust into technology on the intention to adopt the security app.

Rather popular approach in app adoption research is also to treat mobile apps as an innovative form of e-commerce. Taylor & Levin (2014) examined the consumer's interest in the mobile app as an attitudinal predictor of two behavioral outcomes, which are the use of the app for shopping and/or information-sharing. As a result, the researchers reported strong correlations between interest in retailer's app and intention to engage in purchasing and information sharing activities. By providing these results, the study proved the worthiness of developers' and retailers' investments into mobile apps. The study also showed that users of retail mobile apps are interested in simplicity of transaction and would prefer having less of distracting and irrelevant features. Following the mobile apps e-commerce research, Morosan & DeFranco (2016) studied user acceptance of hotel-branded mobile applications. In the research it was highlighted that specific feature of mobile applications services is that they offer uniqueness of the firm-consumer interactions, opportunity to gather rich personal information, while they are also vulnerable to breach of signal and may interfere the privacy of users. The authors researched how the intention to use the mobile application is developed with regard to personalization and privacy challenges. They

viewed personalization as a feature of mobile application that can both increase the value of overall consumption experience while potentially endanger the privacy of the user and force consumers disclose personal information. Moreover, authors also added to the model variables that describe personal innovativeness, assuming that consumer's natural inclination to engage into novel experiences and interest in innovative IS may negatively influence their app-related privacy concerns when using the hotel apps to access personalized hotel services. As a result, the study confirmed that consumer's personalization and privacy perceptions as well as reflectors of innate consumer characteristics can be used to predict the hotel service app utilization. It was reported that benefits of personalization drive mobile consumer behavior even when privacy concerns exist. Moreover, innovative consumers who are able to cope with uncertainty are likely to diminish their privacy concerns if they can better understand the privacy implications of using hotel apps.

Though these studies reported significant results and are based on fundamental adoption theories, they cannot be fully generalized to understand the process of mobile applications adoption. They don't allow a holistic understanding of what features of the app, regardless of the application functional purpose, can enhance or even determine its adoption. Our literature review through EBSCO Business Source Complete using "app", "application" and "adoption" as search terms showed only two fundamental and generalizable studies that investigate adoption of mobile apps as a holistic technology, without a regard for the type and functionality of the app. In the first one, researchers used the TAM model to investigate the process of mobile app adoption (Shen, 2015), while in the second one the process of mobile application adoption was researched based on UTAUT2 model (Hew et al., 2015).

In the first one, Shen (2015) in the research of users' adoption of mobile applications aimed at developing a conceptual framework to outline users' behavior regarding apps. He researched the effects of product type and message framing moderation effects. His model became the extension of TAM with signaling theory and reputation and regulatory focus theory. Author suggested that app type may moderate the app reputation effect on user's attitude towards using the app and that perceived risk (of online purchasing) moderates app reputations effect on users' attitude towards using the app. This means that for free apps the importance of reputation effect will be not that strong. It was also expected that regulatory/promotion message framing will also moderate the app type effect on users' perceived usefulness, in other words consumers that are interested in hedonic benefits of the app will overestimate its hedonic attributes and vice versa. As a result, the study confirmed that TAM explains the user's intention to adopt the app. It was reported that app type and perceived risk moderate reputation source's influence on users' attitude toward using apps, while message framing moderates the effect of app type on perceived usefulness of the app. It was proved that high rating-score reputation's effect is greater for utilitarian apps; top charts reputation's effect

is greater for hedonic apps. Similar to findings of Liang et al. (2015), it was confirmed that rating scores from other users' experience mat have a greater effect for consumers in high perceived-risk situations (e.g. paid app subscription). In contrast, consumers might perceive low risk of monetary loss when procuring a free app and instead rely on the app popularity in top charts. Importantly, the study incorporated the regulatory focus theory to show how regulatory focus framing moderates app type's effect on users' perceived usefulness and showed that promotion message's effect is greater for hedonic apps than for utilitarian apps; in contrast, a prevention message's effect is greater for utilitarian apps.

In the second study, Hew et al., (2015) used the UTAUT2 model to research the adoption of mobile applications on Malaysian market. The study has a strong focus on Malaysian market, emphasizing the low adoption rate of the locally developed mobile apps on the market. In general the motivation behind the study is quite narrow and focuses on a specific market. Researchers describe the Malaysian market as underdeveloped in terms of mobile app adoption. For us the findings of this study are interesting but we should be aware that they have limited generalizability, as the study focuses on a specific, not yet mature market. The more detailed results of the study will be described in the next chapter presenting UTAUT mobile app research baseline.

### 3.3 UTAUT studies

Our literature review also shows that while several research models used TAM or TPB to explain and predict the usage intention and usage behavior for mobile applications, the research of application adoption that employ UTAUT or UTAUT2 models is very scarce. As it was described above, our literature review through EBSCO Business Source Complete revealed only one study that used UTAUT2 model to investigate the adoption of mobile apps; Hew et al. (2015) used UTAUT2 model to research mobile app adopting on Malaysian market. Hew et al. (2015) also highlighted that UTAUT research base for mobile app adoption is very scarce. The main reasoning for choosing UTAUT2 model for their research is that it is developed for consumer context. Researchers replicated the UTAUT2 with the variables that Venkatesh et al. (2012) confirmed to be significant for information technology adoption in consumer context. Hew et al. (2015) tested the hypotheses that Performance Expectancy, Effort Expectancy, Price Value, Facilitating Conditions, Habit, Social Influence, Hedonic Motivation have a positive influence on the Behavioral Intention to use mobile applications. Moreover, researchers also tested a hypothesis that Effort Expectancy has positive effect on Performance Expectancy and assumed that gender and education level may play a moderating role in all the above-mentioned relationships.

Out of the abovementioned potential antecedents for Behavioral Intention to adopt mobile applications, we would like to have a special discussion on Facilitating Conditions, since we expect that this one can have different dimensions when it comes to mobile app adoption process. In the original UTAUT2 model Venkatesh et al. (2012) explains Facilitating Conditions rather broadly and we would like to compare this explanation with how Hew et al. (2015) used it in their study and what was the reasoning for including this variable into the model on mobile app adoption. Hew et al. (2015, p. 1272) explained Facilitating conditions as "consumer perceptions of how much support, online help and assistance is available for the certain mobile application". Additionally, they also mentioned accessibility and quality of internet connection as another example of what facilitating conditions can be.

Hew et al. (2015) reported that Habit is the most significant predictor of Behavioral Intention, followed by Effort Expectancy, Facilitating Conditions and Performance Expectancy for Malaysian market. Interestingly, it was discovered that Price Value and Social Influence have non-significant relationship with Behavioral Intention, while gender and education level did not moderate the relationship between the constructs. It was also confirmed that Effort Expectancy has a Positive influence on the Performance expectancy. We find it interesting that the researchers reported the insignificant influence of Price Value on Behavioral intention what accordingly would mean that consumers would not intend to use mobile apps though they perceive the benefits received outweigh the money paid. It is worth mentioning one more time that the study be Hew et al. (2015) was conducted on Malaysian market and is among the first ones that apply UTAUT2 model to research the adoption of mobile apps. That is why for better and more precise insights into the process of consumer app adoption further replications and extensions are needed. The study by Hew et al. (2015) lacks precise adjustments and explanations of the model and variables directly connected with specific features of mobile applications as a service.

The review of the literature on app adoption shows that the knowledge on how consumer market adopts and accepts mobile applications is quite scarce and fragmented. A few studies that research adoption and acceptance of mobile apps exist and to large extent these studies focus on antecedents that are relevant only for specific service that mobile app provides. Moreover, most of the models used a TAM or TPB model as a basis for the research while a few studies used UTAUT or UTAUT2 model to research the consumer mobile app adoption.

# 4. Research model and hypotheses

## 4.1 Choice of the research model

### *4.1.1 UTAUT2 model*

As a base model for our study we will use the UTAUT2 model. There are several reasons for choosing UTAUT2 among other models that potentially could be used for researching the user adoption of mobile applications.

Firstly, after the review of four fundamental theories of adoption (TRA, TPB, TAM and UTAUT) as well as of some of their extensions, we saw strong benefits of UTAUT and UTAUT2 models over other models for our research. One benefit of UTAUT over other models is that UTAUT model was developed for research of technology adoption and is much more specific for the needs of our study than other models. In contrast to this the TRA model is more general one; for research of specific behaviors it requires initial eliciting of salient beliefs about the behavior (Ajzen & Fishbein, 1980). The constructs from TRA model are covered in both UTAUT and UTAUT2 models and UTAUT research. That is why we find the UTAUT2 model more relevant for our study in this case. Similarly to TRA model, the TPB model is also quite general and simplistic. The biggest benefit of TPB model is that it includes the construct called Perceived Behavioral Control that explains non-motivational factors such as availability of opportunities and resources (Ajzen, 1985). UTAUT and UTAU2 models were partially based on the findings from TBP model. That is why UTAUT and UTAUT2 models also include a variable that describes the Perceived Behavioral Control with the help of the construct called Facilitating Conditions (Venkatesh et al, 2003).

More relevant than the first two models for our research would be a model that was developed based on the TRA model specifically for the research of technology usage behavior – TAM. TAM proved to explain the attitude towards using the technology better than TBP (Mathieson, 1991). Yet, comparison of TAM model with UTAUT2 shows that UTAUT2 is still more beneficial model for our research. For example, the TAM model doesn't include the influence of Social Norm (Fishbein & Ajzen, 1975). For our research it was crucial to use the model that both describes the antecedents of specific technology adoption and at the same time allows for researching the mobile app technology as a product or services for which adoption is defined not only by its technological qualities but also by other factors that influence consumer decision to use product/ service, such as social influences, habits etc. Thus, using the UTAUT2 model for our study will allow us apply the findings of classical, generic user adoption models (TRA, TPB) while

making them more relevant for the technology adoption with the help of specific technology adoption theories that were also included in UTAUT2 model. Such approach is very relevant for research of mobile applications since mobile applications as an enabling technology may serve for different purposes and support various products as well as be an independent product.

A strong benefit of the UTAUT and UTAUT2 models compared to other adoption models is that UTAUT model has the highest explained variance. Such models as TRA, TPB and TAM reported to routinely explain over 40 percent of variance in individual intention to use technology (Venkatesh et al., 2003), while UTAUT and UTAUT2 models reported 70 percent of variance in usage intention (Venkatesh et al., 2012). Such difference in variance explained is quite substantial and proves the abovementioned benefits of UTAUT model for our study. Thus, the above described benefits of UTAUT model prove that this model offers most benefits for our research purpose compared with other models available. As a definitive model that synthesizes the benefits of other information technology adoption research it allows discovering more behavioral patterns and effects.

Another reason for choosing specifically UTAUT2 for our research is that UTAUT2 model was developed specifically for consumer use context. It is based on the original UTAUT model and has all the benefits of original UTAUT model but also includes more relevant predictors and mechanisms. Specifically, UTAUT2 model incorporates both main relationships from original UTAUT model, but also new constructs and relationships that are more relevant for a voluntary, consumer context of new technology adoption (Venkatesh et al., 2012). Utilizing the UTAUT 2 model for the research of mobile applications adoption will allow us discover more specific motivators which determine the user decision to adopt mobile applications.

Finally, the review of mobile app adoption studies and of mobile app specific features shows that the selection of variables presented in the UTAUT2 model as the ones that determine the Behavioral Intention to adopt new technology, corresponds to the list of factors and antecedents that we aim to test in our model based on the review of mobile app adoption literature. Performance Expectancy represents such features as efficiency, effectiveness (Nah et al., 2005), convenience, control (Kim, Wang, & Malthouse, 2015), timeliness (Legner, Urbach, & Nolte, 2016), time and money saving (Oghuma et al. 2015), usefulness (Verissimo, 2015) etc. described in the previous research among the features that attract consumers to mobile applications. Effort Expectancy and Facilitating Conditions represent such features as convenience (Kim, Wang, & Malthouse, 2015), personalization (Legner, Urbach,, & Nolte, 2016; Morosan, & DeFranco, 2016), compatibility with other functional devices (Cugola et al., 2014), perceived ease of use (Verissimo, 2015), etc. Most of the studies that investigate the features of mobile applications that make them attractive for the

users, confirm the importance of so-called enjoyment, vividness experience and entertainment dimension (e.g. Kim, Wang, & Malthouse, 2015, Oghuma et al. 2015, Morosan, & DeFranco, 2016). Hew et al., (2015) confirmed Hedonic Motivation as a second-most significant construct that determines the Behavioral Intention. That is why for the research of adoption of mobile applications it was important for us to include the influence of Hedonic Motivation in our model. UTAUT2 model is the only model out of the models described in chapter 2, which includes the variable that represents Hedonic Motivation. Moreover, in addition to the constructs that represent the specific features of mobile applications, UTAUT2 model also includes the constructs that are widely confirmed to be relevant for information technology adoption but are not yet properly researched in the mobile app context. These variables are Price Value and Habit. We also see that UTAUT model is designed in a way that allows us to measure the different types of Social Influence in the process of adoption of mobile application, what corresponds to the purpose of our research. UTAUT2 model already includes variable that represents the influence from significant others, such as friends, family and colleagues (Social Influence). In our study we aim to more explicitly investigate the influences for other social factors such as Online Rankings and Reviews and Herd Behavior. The design of UTAUT2 model and the selection of variables included into the model perfectly allow us to conduct such extension.

Based on these arguments we can see that UTAUT2 model is the most relevant model for our research as it allows us measure the model with most of the features that are described to influence the user intention to adopt mobile applications, while still combining them with the influences from overall technology adoption factors confirmed in previous UTAUT, TAM, TRA and TPB research. Moreover, the model is perfect for extending it with constructs that represent influences from new social dimensions.

### *4.1.2 Extension of UTAUT 2 model*

For the purpose of our research we will also supplement the UTAUT2 model with two constructs that we expect are additional factors that influence the behavioral intention to adopt mobile applications. These constructs are Online Rankings and Reviews and Herd Behavior. Testing these two constructs in our model will be important for gaining a better and more extensive understanding of what other types of social influence, except for the social influence from significant others, may have an influence on the user decision to adopt mobile application. Our literature review showed that online rankings and reviews and herd behavior have confirmed importance for adoption of mobile application as a holistic technology.

As it was mentioned earlier, the market for mobile applications is crowded and highly competitive. In such case it becomes impossible for modern consumers, who aim to be time

efficient and mobile, to actually test the functionalities and benefits of numerous offerings on the market for mobile applications. One of the solutions in such case for consumers is to collect information about mobile application online or copy the behavior of other consumers on the market when adopting the application. In the existing theoretical models that describe information technology adoption such as TAM (Davis et al., 1989), TRA (Ajzen & Fishbein, 1980) and UTAUT (Venkatesh et al., 2003) such variables and behavior of consumers is not described. To research how the online rankings and reviews and herd behavior influence consumer decision to adopt mobile applications, in our study, we will supplement the classical UTAUT2 technology adoption model with variables that describe online reviews and rankings and herd behavior.

Adding Herd Behavior in our model will help understand if users of mobile applications tend to follow the behavior of others and discount their own information. We assume that when deciding to adopt the newly introduced mobile application, users may still lack private information and experience with the app and will not only rely solely on their own private information. Instead, they will to some extent disregard their private information and imitate the behavior of others by adopting the application that is more popular. In the case of mobile applications we suggest that due to big amount of offerings on the market it becomes impossible for consumers to properly collect private information about the application and they may make their choice to imitate the adoption behavior of others. In such a way imitation of earlier adopters helps users to minimize uncertainty and save information search costs.

The reason for including Online Rankings and reviews into the research model is that quite often customers get acquainted with the mobile applications exactly through online articles, blogs, charts and rankings, accordingly, it is very likely that the impression about mobile applications, that customers get through Online Rankings and reviews influences the intention to adopt the app. There is a clear evidence for the importance of online feedbacks, ratings and feedbacks for the sales and attitudes towards mobile applications. Another reason for including this variable into our model is that when customers get acquainted with the mobile application and decide whether to install it or not they inevitably see the ranking of the app on the app store and also get an opportunity to read the customer feedbacks. This makes it is almost impossible to ignore the Online Rankings and reviews on app stores when downloading the mobile applications.

In the original UTAUT model (Venkatesh et al., 2003) and UTAUT2 model (Venkatesh et al., 2012) only few moderating effects from the initial hypothesis were confirmed (Venkatesh et al. 2016). The later adaptions and extensions of the UTAUT model have also revealed few new moderating effects. For example Wong et al., (2014) showed insignificance of gender as a moderator in UTAUT2 model. Brown et al., (2010), Liang et al., (2010), Xiong, Qureshi & Najjar

(2013) have neither revealed significant moderating influences in adapted UTAUT models. Finally, Hew et al. (2015) revealed no significant moderating effects for gender and level of education in their adoption of UTAUT 2 model. That is why we will not dig into the moderating effects of age, gender, education level and experience and will rather test the moderating effect of mobile app type on the direct effects in the model.

Our review of mobile app adoption studies indicated that there are more variables that can be added into our extended UTAUT model, such as privacy and perceived risk described by Han, Wu & Winsdor (2014), personalization and customization (Morosan, & DeFranco, 2016), personal innovativeness (Morosan, & DeFranco, 2016), personal technology traits (Yang, 2012), negative Online WOM (Liang et al., 2015) etc. Due to limitations of our research setting we didn't include these constructs as potential antecedents of Behavior Intention and decided to focus only extending the model with new dimensions of social influence such as Online Rankings and Reviews and Herd Behavior.

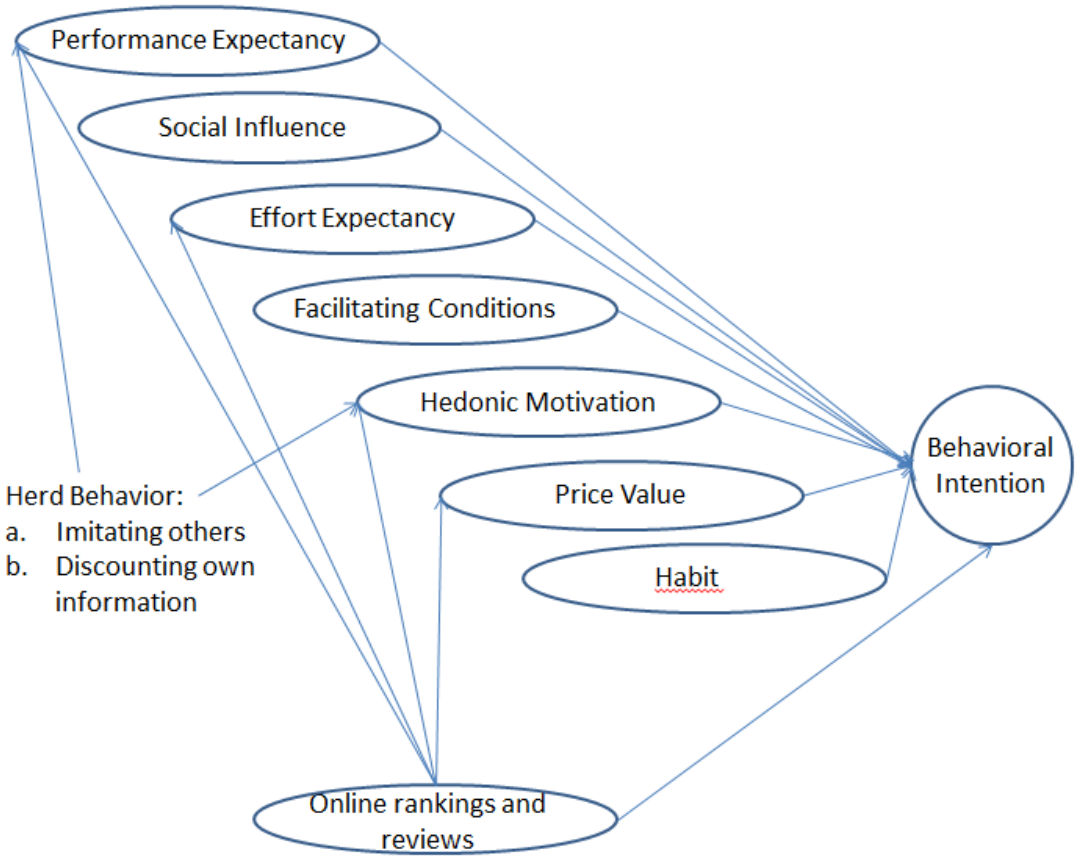
### 4.2 Main Research Model

In our research model, following the logic established by TRA and TBP models we will test the constructs that define user behavioral intention and influence the actual usage behavior. Due to limitations of our research setting we will focus only on researching the influence of such endogenous mechanisms (individual reactions to using mobile applications) as Performance Expectancy, Social Influence, Effort Expectancy, Facilitating Conditions, Hedonic Motivation, Price Value, Herd Behavior and Online Rankings and Reviews on the Behavioral Intention (Figure 4.1). The actual usage behavior will not be measured in this study due to limitations of the survey setting. Based on the previous research on how much of the actual usage behavior does the behavioral intention explain, we can expect that in our model the behavioral intention will explain approximately 30% of the variance in the actual usage behavior. The study by Ajzen, Brown & Carvajal (2004, p.1119) on explaining the discrepancy between intentions and actions and hypothetical bias in contingent valuation confirmed "the existence of a strong bias for people to overestimate the likelihood that they will engage in a socially desirable behavior". The test of bias in the TBP model confirmed that intentions account on average for approximately 28% of variance in the actual behavior. Venkatesh et al. (2012) in their study on adoption of the mobile internet supported the applicability and validity of UTAUT as a theoretical base for predicting consumer behavioral intention and technology use. Specifically, the variance explained in the technology use with direct effects from behavioral intention was 33% (Venkatesh et al., 2012, p.170), what means that there are many other factors that define the actual use of technology even when the user intention to adopt exists. That is why in our study we will focus solely on the mechanism of how

the behavioral intention to adopt the mobile application is framed and what factors define this process.

Picture 4.1

*Research model*




*Performance Expectancy*

The first construct included in our model is Performance Expectancy, which is "the degree to which user believes that using a technology will provide him with benefits in performing certain activities" (Venkatesh et al., 2003, page 447). The construct itself was formulated in the UTAUT model and developed as a result of incorporating conceptually similar variables from previous user acceptance research into one called Performance Expectancy. Performance Expectancy variable will represents perceived usefulness (Davis, 1989; Davis et al., 1989), extrinsic motivation (Davis et al., 1992), job-fit (Thompson et al., 1991), relative advantage (Moore and Benbasat, 1991) and outcome expectations (Compeau and Higgins 1995) constructs from previous research on technology acceptance. Performance Expectancy construct proved to be a strong predictor of behavioral intention (Venkatesh, 2003; Venkatesh 2012); in both UTAUT and UTAUT2 models Performance Expectancy was reported to have a significant influence on user decision to adopt the researched technology. Moreover, research that used the UTAUT model to explain behavioral

intention for mobile applications also proved the importance of this variable for the intention to use mobile applications (Hew et al., 2015). These results of previous research give us a strong argument to include Performance Expectancy in our research model. Another reason for including this variable into our model is that we expect that this variable will represents such features as efficiency, effectiveness, time/money saving, benefit seeking, etc. that are known to attract users to mobile application. For example, Nah et al. (2005) described that mobile applications create value for customers through efficiency and effectiveness, by saving customer time and money. Kim, Wang, & Malthouse (2015) also mentioned convenience among the features that may draw consumers to mobile applications and differentiate mobile applications from other competing technologies. Oghuma et al. (2015) proved the crucial role of benefit seeking for the adoption of mobile instant messaging applications. Based on the abovementioned arguments we suppose that consumers expect that mobile applications may create additional value for them and will perform better and more efficiently than competing technologies, what leads us to the following hypothesis:

*Hypothesis 1: Performance Expectancy has a positive influence on behavioral intention to use mobile applications.*

*Social Influence*

The second variable we will introduce and test in our model will be Social Influence. This variable was introduced in the initial UTAUT model (Venkatesh et al., 2003) and originally comes from TRA model where it was presented as Subjective Norm. In the UTUAT and UTAUT2 model, authors explained and interpreted the construct called Social influence similarly to Subjective norm construct from earlier adoption models (e.g. Fishbein & Azjen 1975, Davis et al., 1989, Mathieson 1991, Ajezen, 1991, Taylor & Todd 1995). Venkatesh et al. (2003) and Venkatesh et al. (2012) in UTAUT and UTAUT2 models described Social Influence as “degree to which an individual perceives that important others believe he or she should use the new system” (Venkatesh et al., 2003, page 451) In the previous theoretical research this construct proved to have influence on the intention to adopt the technology. For example, in the UTAUT model from 2003 the Social Influence construct proved to have a significant effect on the behavioral intention in mandatory organizational setting. UTAUT2 model, developed to research the voluntary consumer context, reported a positive effect of social influence on the behavioral intention to use mobile internet (Venkatesh et al., 2012). In the study on mobile commerce adoption on Chinese and Malaysian markets Chong et al. (2012) reported a significant effect of social influence on behavioral intention to adopt mobile commerce. Wong et al. (2014) also confirmed positive effect of Social Influence in intention to adopt mobile TV, yet, in their research they have also generalized the concept to more

than so called “important others” but also included social media and mass media in this concept. Finally, Yang (2010) also confirmed significant influence of Subjective Norm on the Behavioral Intention to use mobile shopping services. Based on the findings from UTAUT2 model as well as referring to the previous research in the area we expect that Social Influence has a positive influence on Behavior Intention to use mobile applications. We expect that the mechanism for such influence will work in a following way; in an everyday life setting it may be the family, friends or influential colleagues who may be using the mobile application and influence the consumer intention to adopt the application.

*Hypothesis 2: Social Influence has a positive influence on behavioral intention to use mobile applications.*

*Effort Expectancy*

Another variable in our model is Effort Expectancy, which according to UTAUT model is defined as “the degree of ease associated with the use of the system” (Venkatesh et al., 2003, page 450). The construct concept was first formulated in the UTAUT model and originated from the findings of the earlier technology acceptance models which proved that perceived ease of use (Davis, 1989; Davis et al. 1989), complexity (Thompson et al., 1991) and ease of use (Moore and Benbasat, 1991) have significant influence on the behavioral intention. The variable was reported to be significant for the adoption of new technology in the original UTAUT model but only for inexperienced users; it was also reported that when users gain experience in using the technology and learn more about it, the effort expectancy construct becomes not significant for behavioral intention (Venkatesh et al., 2003). The importance of the effort expectancy construct was also proved in other technology acceptance models; Davis et al. (1989) used the construct called perceived ease of use to explain the adoption of computer systems. In the UTAUT2 model Venkatesh et al. (2012) also confirmed the importance of Effort Expectancy for the voluntary consumer context. The replications of TAM and models based on TAM and UTAUT provide us with numerous confirmations of the importance of Effort Expectancy and Perceived Ease of Use for the behavioral intention for mobile technology and mobile application. For example, Verissimo (2015) confirmed that Perceived Ease of Use is among the constructs that determine use of mobile banking applications, Taylor & Levin (2014) report that users of retail mobile applications are interested in simplicity of the technology and want to have less of distracting elements. Hew at al. (2015) report positive influence of small effort expectancy on behavioral intention to use mobile applications. Such findings from the previous research constitute strong argument for us to expect that in our model Effort Expectancy also will have a significant influence on the Behavioral

Intention. In addition to all the described arguments we also suppose that it is quite intuitive to assume that if users perceive that mobile apps are easy to use, they will have higher intention to use the application. The research by Kim, Wang & Malthouse (2015) mentions convenience, customization, and control among the main features that make mobile applications attractive for users. It is logical to suppose that thanks to that mobile application is convenient to use, easily adapts to customer needs and allows the user bigger control over the technology it takes less effort from the user to understand how to use it. Moreover, the research on the features of mobile applications that differentiate mobile applications from other technologies shows that customers want their mobile applications to be adaptive and functional on various devices (Cogola et al., 2014) what leads us to conclusion that customers want to put less effort into learning how to use mobile apps and into actually using mobile application. Finally, the research of mobile application as a shopping and/or information sharing technology by Taylor & Levin (2014) reported that users of mobile applications are interested in simplicity of transaction and would prefer mobile applications that have less of distracting and irrelevant features. Based on this, in our study we assume that users may want to put less effort into learning how to use the mobile application and into actually using it and would accordingly prefer to adopt mobile application that they expect will be easier to use.

*Hypothesis 3: Effort expectancy has positive influence on behavioral intention to use mobile applications.*

*Facilitating conditions*

Another construct that we will test in our model is Facilitating Conditions. This construct was first formulated in the model of PC Utilization (Thompson et al., 1991) and later was used to formulate the Facilitating Conditions construct described in the UTAUT model (Venkatesh et al., 2003). In the formulation of this concept Venkatesh et al. (2003) also showed how Facilitating conditions construct from model of PC Utilization (Thompson et al., 1991) is similar to Perceived Behavioral Control described by Ajzen (1991) and Taylor & Todd (1995) and to Compatibility from Moore & Benbasat (1991). For the purpose of our research we will use the definition of Facilitation Conditions developed by Venkatesh et al. (2003, page 453) explaining this construct as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system." As it was formulated in the original UTAUT model Facilitating Conditions were hypothesized and proved to have positive influence only on the actual usage behavior. Yet, in the UTAUT2 model that focuses on the consumer voluntary context, it was also assumed and confirmed that Facilitating Conditions have a positive effect on the behavioral

intention (Venkatesh et al., 2012). The main reason for such difference is that authors assume that in case of involuntary context all the training and support will be readily available for users, while in case of consumer market the availability of Facilitating Conditions may vary significantly across technology providers. For our research such argumentation makes perfect sense and makes the concept of Facilitating Conditions more similar to the Perceived Behavioral Control from the TPB model. For example, users with different level of access to information, tutorials and different models of mobile phones and phone functionalities and availability of support may find it more easy or complicated to start using the mobile application.

The described reasoning for including the construct for Facilitating Conditions can be also supported by the evidence from empirical research. First of all Facilitating Conditions proved to have a significant positive effect on Behavioral Intention in consumer context in the UTAUT2 model by Venkatesh et al. (2012). Other studies of the IS adoption also confirmed that availability of various Facilitating Conditions may be significant for consumer's intention to adopt or not adopt the service. For example, Yang (2012) in the study on mobile shopping adoption, based on extended TPB reported significant influence of Perceived Behavioral Control (the concept that is similar to Facilitating conditions in UTAUT2) on the user intention to adopt mobile shopping. In their research of mobile shopping adoption based on adaptation of UTAUT model, Yang & Forney (2013) also confirmed the significance of Facilitating Conditions for the Behavioral Intention. Chong (2013) in his study of m-commerce adoption reported a significant effect of Facilitating Conditions on the Behavioral intention. Finally, in their replication of UTAUT2 model Hew et al. (2015) also reported that the high level of users' perception of Facilitating Conditions, such as online support, m-devices, internet connection and so forth leads them to a high level of Behavioral Intention. Moreover, the findings from the research that describes the features that differentiate mobile applications from other IS and make mobile applications attractive for users show the mechanisms of how availability or absence of relevant facilitating conditions may become decisive for users' intention to adopt or not adopt mobile application. One of the features of mobile applications that may become a strong facilitating condition for the user is customization and personalization. For example, Kim, Wang & Malthouse (2015) named customization among the features that increase the user willingness to build the relationship with mobile application. Morosan & DeFranco (2016) also confirmed the importance of service personalization for the adoption of hotel mobile applications. Moreover, since the user experience in case of mobile application is highly dependent on the mobile device itself, technical characteristics and features of mobile phone may become a strong reason for the user to consider to adoption or not adopt mobile application. For example, research on mobile applications already described that it is important that mobile application can be adaptive and functional on different types of devices (Cugola et al.,

2014). Moreover, as mobile applications become more interactive, environment in which mobile application is executed may also become a strong facilitating condition for the intention to adopt or not adopt mobile app (Legner, Urbach & Nolte, 2016). Finally, some mobile applications are highly dependent on the permanent access to internet, while others may perfectly function without connection to internet. While not all users have an unlimited access to mobile internet, the extent to which mobile application functionality depends on the permanent access to internet may become another facilitating condition that may influence the intention to adopt mobile application. Based on this empirical evidence and on the reasoning described above, we propose the following hypothesis for our model:

*Hypothesis 4: Facilitating conditions have a positive influence on behavioral intention to use mobile applications.*

*Hedonic Motivation*

Another variable, which we find to be relevant for the process of consumer adoption of mobile applications, is Hedonic Motivation. Venkatesh et al. (2012) included this variable only into UTAUT2 model, which was designed specifically for the voluntary, consumer context. In formulating the concept of Hedonic Motivation in our model we will refer to the definition formulated by Brown & Venkatesh (2006, page 408) in their research of technology adoption in households and used by Venkatesh et al. (2012, page 161) in the UTAUT2 model; "hedonic motivation is the fun or pleasure derived from using a technology." In our study the hedonic motivation will represent the perceived value of enjoyment and will be used to measure to what extent the user expectations about joy and fun in using mobile app may influence his/her intention to adopt it. The evidence from the previous mobile technology adoption research, provide strong support in favor of including Hedonic Motivation in our model. Venkatesh et al. (2012) confirmed their hypothesis that Hedonic Motivation is a significant predictor of consumers' Behavioral Intention to use technology. In their study of consumer mobile TV adoption, Wong et al. (2014) reported that Hedonic Motivation to be one of the most significant motivators that define user intention to adopt mobile TV. Yang & Forney (2013) in their research of consumer technology anxiety in mobile shopping adoption have also confirmed that if hedonic performance expectancy is positive, the consumer intention to use mobile shopping will also be significant. Finally, Hew et al. (2015) reported that Hedonic Value has significant positive influence on the Behavioral Intention to adopt mobile applications. Moreover, Kim, Wang & Malthouse (2015) described vividness, novelty and interactivity as mobile app attributes that attract consumers to use mobile applications. Based on the example of Mobile Instant Messaging apps, Oghuma et al. (2015) mentioned enjoyment

among the features of mobile applications that attract consumers to using this service. Finally, Morosan & DeFranco (2016) reported that consumer mobile app adoption process can be significantly enhanced by gamification of mobile app. Such evidence for empirical research becomes a strong basis for us to assume in our model that Hedonic Motivation is one of the determinants in the formation of consumer Behavioral Intention to adopt mobile application. We suppose that there may be various ways of how Hedonic Motivation is created for the user through mobile applications and assume that to large extent it may depend on the mobile app developers. We expect that it may be possible that entertainment value, which mobile application creates for the user, is one of the significant factors that influence the user intention to adopt mobile applications.

*Hypothesis 5: Hedonic Motivation has a positive influence on the behavioral intention to adopt mobile applications.*

*Price Value*

Another variable we will test in our research is Price Value. There are different types of price and subscription basis that developers of mobile applications use to market their services on app market; it is common to offer free mobile applications, at the same time some developers offer their mobile applications for one-time pay while others create a subscription based pay. That is why it is important to define how the price of mobile applications influences the user intention to adopt mobile application. This variable was introduced in UTAUT2 model and can be defined as "consumers' cognitive tradeoff between perceived benefits of the applications and the monetary cost for using them" (Dodds et al., 1991, p. 312). The main reason for including this variable into the UTAUT2 model is that this model describes setting in which users should bear the cost of adopting the technology themselves. Venkatesh et al. (2012) described the influence mechanism of Price Value on the Behavioral Intention as follows: Price Value is considered to be positive when users perceive the benefits that the technology brings to them are higher than the monetary price of adopting the technology. The theoretical research confirmed the importance of Price Value for Behavioral Intention for user technology adoption. In the study by Venkatesh et al. (2012) the direct effect of Price Value on Behavioral Intention to adopt mobile internet was confirmed. Yet, in the later empirical research the significance of Price Value for other technology services was not confirmed. For example, in the research of the adoption of mobile TV, Wong et al. (2014) reported insignificant influence of Price Value on the intention to adopt the mobile TV technology. In case of mobile TV adoption it was assumed that insignificance of Price Value for the Behavioral Intention can be explained by the fact that users who see significant enjoyment values and low need for effort inputs are ready to adopt the new technology regardless of the price. Such inconsistency

in theoretical results can be connected to a specific type of technology and the price user would normally pay for this technology. In the case for mobile applications we know that it is quite common for mobile applications to be offered on the market for free or for a not significant price; the average price for mobile application in 2017 was $1,02 (statista.com). That is why we expect that such a small price for using a mobile application that creates significant value for the user will be reasonable one and they will be ready to pay it. At the same time, statistics shows that market is filled with mobile applications that are offered for free and also that users are cautious when it comes to upgrading their free mobile application to paid version; only 35% of users are ready to upgrade their free version of mobile app to a paid version (statista.com). this means that users are quite critical regarding the potential value the mobile application will offer to them and that the tradeoff between potential benefits and the monetary price will be important for users when making a decision to adopt mobile application or not. These findings and arguments give us reason to assume in our study, that the Price Value will be one of the important factors in the process of user adoption of mobile applications.

*Hypothesis 6: Price Value has a positive influence on the Behavioral Intention*

*Habit*

Mobile applications are normally created for a repetitive usage on a daily basis; that is why we find it relevant to test the variable Habit, which was also introduced in UTAUT2 model. Venkatesh et al. (2012, p. 161) defined Habit as "the extent to which people tend to perform behaviors automatically because of learning and can be described as perceptual construct that reflects the results of prior experiences". In the UTAUT2 model the influence of Habit on the Behavioral Intention to adopt mobile internet was confirmed, and moreover, it was reported that the influence of Habit in intention to adopt technology is stronger for older men with extensive usage experience. The same relationship was also confirmed in other relevant empirical research; Wong et al. (2014) in the research of mobile TV adoption reported that habit influences the continual use of informational systems, and that usage of new technology on a daily, routine basis leads to development of habit what in turn supports the adoption the new technology. Moreover, in the research of mobile app adoption on Malaysian market, Hew et al. (2014) confirmed Habit to be the most significant driver for the Behavioral Intention to adopt mobile applications. Similar relationship was also confirmed in the study by Nikou and Bouwman (2014). In the research of social networking sites Habit was reported to be an important predictor of Behavioral Intention to use social networking sites (Nikou & Bouwman, 2014). Based on such empirical findings from previous research we suggest in our study that in the case of mobile app adoption process Habit will

have significant influence on determining the Behavioral Intention to adopt mobile applications. The mechanism for such influence can be the following; since mobile applications are normally created for the usage on a daily basis, consumers will have to use the app during certain period of time to try it and discover its benefits, what contributes to the development of the habit to use certain application. Once the habit is developed – it will be harder for the user to switch towards another mobile application, and it is likely that users may not even consider using other mobile apps. In such a way habit will contribute to the intention to adopt mobile application.

*Hypothesis 7: Habit has a positive influence on the behavioral intention to adopt mobile applications.*

*Herd Behavior*

Herd behavior was reported as a significant construct for user adoption of wide range of technologies. Sun et al. (2013, page 1016) defined Herd Behavior in technology adoption as "the phenomenon according to which person follows others when adopting a technology, even when his/her private information suggests doing something else." Herd Behavior describes the so-called phenomenon "when everyone does what everyone else is doing, even when their private information suggests doing something quite different" (Banerjee, 1992) and thus, depends on both how person uses his own private information and evaluations and the information available from others. We suggest that when deciding to adopt the newly introduced mobile application, users may still lack private information and experience with the app and will not only rely solely on their own private information. Instead, they will to some extent disregard their private information and imitate the behavior of others by adopting the application that is more popular. Herd Behavior is fundamentally different from other concepts that describe social influence such as subjective norm. While subjective norm is a self-instruction about expectation of a reference group and means that information about technology is obtained primary from the messages received from others, Herd Behavior depends on observations of other people's behavior and is not influenced by what others may think about the final choice of, for example user of technology (Sun, 2013). The main purpose of Herd Behavior is to make a decision that will have the best result for the user, no matter if this choice will be made based on imitating others. In the case of mobile applications we assume that due to big amount of mobile applications on the market it becomes impossible to properly collect private information about the application and they may make their choice to imitate the adoption behavior of others. In such way imitation of earlier adopters helps users to minimize uncertainty and save the information search costs. In the initial research by Sun (2013), from which we adopt the concept to our model, it was introduced that Herd Behavior occurs under two conditions:

imitating others and discounting own information, where imitating others describes "the degree to which a person will follow other's decisions when adopting a technology" and discounting own information describes "the degree to which a person disregards his/her own beliefs about a particular technology when making an adoption decision" (Sun, 2013, p. 1017.) According to these findings we also assume that Herd Behavior builds on two preconditions, which are Imitating Others and Discounting own Information. In our study we will also measure Herd Behavior based on these two conditions.

Empirical research reported evidence that prove significance of Herd Behavior in consumer choices and technology adoption – for example software product downloads (Duan et al., 2009), information system adoption (Sun, 2013). These findings give us a foundation for hypothesis in our model. Hong, Cao & Wang (2017) conducted a research that reported a positive influence of Herd Behavior on perceived usefulness and a mediating effect of Herd Behavior on user satisfaction through perceived usefulness. In the research by Hong, Cao & Wang (2017) the findings were confirmed for social mobile applications. In our study we assume that such effect of Herd Behavior is relevant not only for social mobile applications but also for mobile application technology as a whole referring to research of Sun (2013). Sun (2013) revealed a significant positive effect of Herd Behavior for the adoption of Information Systems. Thus, we expect that Herd Behavior will have a positive influence on Performance Expectancy because users who are not able to collect precise information on how useful the mobile application will be for them will imitate the behaviors of other earlier adopters. Following the framework from Sun et al., (2013) for measuring Herd Behavior with the help of two conditions, which are Imitating Others and Discounting Own Information we pose the following two hypotheses:

*Hypothesis 8a: Imitating others has a positive influence on Performance Expectancy;*

*Hypothesis 8b: Discounting own Information has a positive influence on Performance Expectancy;*

Similar logic is for the influence of Herd Behavior on Hedonic Motivation; users will rely on experience of earlier adopters and thus, will evaluate the potential hedonic value they may obtain from using the mobile application based on how many other users have already adopted the mobile application. The reason for such assumption is that mobile application technology fulfills the social value, and social interaction and exposure is an important part of utilizing the value created by mobile applications. At the same time, the market for mobile applications is highly competitive and it is hard for users to collect the precise and detailed information on the best choice on the market and the best performance and hedonic value they can get from mobile app. That is why, being not able to collect the information about the best choice on the market and potential value created users

make choice by imitating the behavior of others, what constitutes the first precondition of the Herd Behavior variable. Sun et al. (2013) described that Herd Behavior occurs under the condition that user not only imitates the behavior of others, but also discounts own information. That is why to be able to measure the full influence of Herd Behavior on Performance Expectancy and on Hedonic Motivation we will also test the effect of Discounting Own Information dimension on Hedonic Motivation:

*Hypothesis 8c: Imitating Others has a positive influence on Hedonic Motivation;*

*Hypothesis 8d: Discounting own Information has a positive influence on Hedonic Motivation.*

*Online Rankings and Reviews*

The reason for including Online Rankings and Reviews into the research model is that quite often customers get acquainted with the mobile applications exactly through online articles, blogs, charts and rankings. That is why it is likely that the impression about mobile applications, which customers get through the influence of Online Rankings and Reviews, have influence on the behavioral intention to adopt the app. There is a clear evidence for the importance of online WOM, feedbacks, ratings and reviews for the sales and attitudes towards mobile applications. Hyrynsalmi et al. (2015) run a practical test of the effect of customer ratings on the sales of mobile applications and reported a statistically significant correlation between high valence and sales of mobile applications. Liang et al. (2015) reported the significance of both positive and negative comments about the mobile app service on the sales of mobile applications with a stronger effect of negative feedbacks on the intention not to adopt mobile app. Shen (2015) also confirmed the importance of rating-scores and top charts for the attitude towards mobile applications. Finally, Huang & Korfiatis (2015) in their work investigating the moderating effect of online reviews in the formation of attitude towards mobile applications during the trial, proved that users judge the performance of mobile applications not only by the usage experience itself but also based on the reviews they read about the product. Another reason for including this variable into our model is that when customers get acquainted with the mobile application and decide to install it on the phone they inevitably see the ranking of the app on the app store and also get an opportunity to read the customer feedbacks. This makes it is almost impossible to ignore the Online Rankings and Reviews on app stores when downloading mobile applications. Based on this we postulate that positive Online Rankings and Reviews have a positive effect on Behavioral Intention by influencing the Performance Expectancy, Effort Expectancy, Price Value and Hedonic Value.

We suggest that potential users of mobile application, in a need to collect information about the performance benefits that using the mobile application will search for the relevant information

online. With this aim users will refer to reviewing online charts, feedbacks and rankings on app stores. In such a way reviewing positive Online feedbacks will create a positive impression of potential performance users may get from using the mobile application, what in turn will influence the behavioral intention to adopt the mobile application. This assumption has also been confirmed in earlier empirical research, for example, Shen (2015) has revealed the importance of rating-scores and top charts for the formation of attitude towards mobile application.

*Hypothesis 9a: Online Rankings and Reviews have a positive influence on Performance Expectancy;*

Moreover, we assume that thanks to Online Rankings and Reviews it becomes easier for users to understand how much effort will it be needed to use the mobile application. Based on this they decide whether to adopt a mobile app or not. The mechanism here works similarly; first of all, online feedbacks and rankings make it possible for the user to search the technical descriptions of the mobile app and to understand how much effort it will take them to adopt the app. Moreover, based on the rankings and feedbacks users can see how many people have already adopted the app and are using it. This allows them to expect that if the majority of users were capable to adopt the app, than it will not require much effort from them to adopt the app. This assumption can be supported by the finding from Liang et al. (2015) where it was reported that negative comments about service quality had strong negative influence on app sales, what can be explained with that users who get negative feedback on service expect that it will require them more effort to adopt the app.

*Hypothesis 9b: Online Rankings and Reviews have positive influence on Effort Expectancy;*

It is also intuitive to assume that Online Rankings and Reviews help the users to reduce perceived risk related to adoption of the mobile application and make users more confident regarding the price value of the mobile application. In the study by Huang & Korfiatis (2015) it was reported that influence of the e-WOM (in our study – Online rankings and reviews) on the app purchase is moderated by the price of the mobile application (paid/ free/ subscription based), what means that users rely on the online WOM when they need to evaluate the purchase of the application. The more positive feedback and high ranking scores are available for user the less risk he associates with mobile application service and the more safe and confident they feel about buying the mobile application and storing personal information in the application.

*Hypothesis 9c: Online Rankings and Reviews have positive influence on Price Value;*

Finally, we suggest that positive online recommendations and high rankings create the perception that adopting a mobile application will offer the user a high level of hedonic value, what can become another reason to use the mobile application. There are several studies that confirmed such influence of Online Rankings and Reviews on the user perception of the experience that the app will offer them. For example, Huang & Korfiatis (2015) run a test that showed how online reviews of mobile applications influence user judgments about app experience during trial period. Based on this we put forward the following hypothesis:

*Hypothesis 9d: Online Rankings and Reviews have positive influence on Hedonic Motivation;*

In addition to this, we also suggest that Online Rankings and Reviews have a direct effect on the Behavioral Intention to adopt the mobile application through the mechanisms that are not captured in the abovementioned hypotheses. Direct effect of Online Rankings and Reviews on the sale of technology has been widely confirmed in the empirical research, what gives us reason to expect that such direct relationship can be also relevant for the adoption of the mobile applications. For example, the importance of online WOM for the e-commerce has been widely confirmed in theoretical research. Dellarocas (2003) shown that online WOM has a significant influence on sales of different types of products thanks to its large-scale feedback mechanisms, Chevalier, & Mayzlin, (2006) reported that online reviews and feedbacks have significant influence on online purchases of books, Zu & Zhang, (2006) showed a similar effect for experience goods such as video games, Duan, Gu & Whinston (2008) reported significant influence of online WOM influences on sales in the movie industry, Amblee & Bui (2011) reported the same effect for digital microproducts. Online Rankings and Reviews is a strong variable widely associated and connected with the sale of mobile applications. That is why we suppose that good reviews and positive online rankings may be one of the reasons why users want to adopt mobile applications; they trust the online WOM and follow the mobile application trends. Based on this we also suggest the following hypothesis:

*Hypothesis 9e: Online Rankings and Reviews have positive influence on the Behavioral Intention to adopt the application;*

*Moderating effect of app type*

In consumer behavior research it is common to categorize consumption motives into hedonic (entertainment and experience oriented) and into utilitarian (functional usefulness and practical benefits oriented) (e.g. Venkatesh & Brown, 2001, Okada, 2005, Chitturi et.al., 2007, Chitturi et.al., 2008, Kim & Han, 2011 etc.) Venkatesh & Brown (2001) in the research of user adoption of personal computers reported that hedonic and utilitarian focus is among the dimensions

that influence user intention to adopt personal computers. In the research of mobile application adoption it is common to distinguish among different types of mobile applications and the value that they create for the user. The previous research on adoption of mobile application services was done for different categories of mobile apps: mobile banking apps (Verossimo, 2015), messaging apps (Oghuma et al., 2015), security apps (Han, Wu & Winsdor, 2014), shopping apps (Taylor & Levin, 2014), hotel mobile services (Morosan & DeFranco, 2016) etc. All these studies research the adoption process for specific categories of mobile applications and reported different results. This gives us reason to expect that even though there may be common effects for mobile app adoption as an information technology, users may also perceive adoption of different categories of mobile applications differently. Kim & Han (2011) in their study on the role of utilitarian and hedonic values and their antecedents in a mobile data service environment, provided strong evidences suggesting that in the process of mobile data services adoption, users who have no previous experience with the services consider only utilitarian value that the service will create for them. Moreover, it was reported that users associate adoption of hedonic services with a sense of guilt and "it is easier for users to justify spending on utilitarian consumptions" (Kim & Han, 2011, p. 2314).

In the research of mobile app adoption Shen (2015) proved that app type has a moderating effect on the user attitude towards using the mobile app in their extension of TAM model. One of the hypotheses tested by Shen (2015) suggested that app type moderates the effect of app reputation on user's attitude towards using mobile application. The hypothesis was confirmed and it was reported that for hedonic mobile applications entertaining top charts had a significant influence on the attitude towards using the app, while for utilitarian mobile applications it was confirmed that user's reviews of true experiences have significant effect on the attitude towards using the app. Basically, the finding of the study confirmed that for hedonic mobile applications users rely on herd behavior and follow the recommendations of top charts of most popular mobile apps, while for utilitarian mobile applications users prefer to look for more reliable source of information and seeks for the reviews and feedbacks on real experience with the app. Such findings give us reason to expect that in our model the effect of the main antecedents may also be different for hedonic and utilitarian mobile applications.

When differentiating between hedonic and utilitarian mobile applications we expected that for the respondent it will be hard to define, what main type of value their mobile application creates for them and that different respondents may have different approach to interpreting the hedonic and utilitarian value. That is why we suggested the respondents to assign the mobile application they were responding about in the survey to one of the 10 main mobile application categories commonly used on the app store. Afterwards, when processing the data, we divided the 10 main categories into two main types: Hedonic and Utilitarian. In the process of assigning a Hedonic or Utilitarian value

to each of 10 main app categories we followed the logic of mobile product/ service attributes, motives and values described in the study of utilitarian and hedonic values of mobile services by Ahmad (2012). According to categorization of values that mobile services create for users (Ahmad, 2012, p. 77) Social Network Services create hedonic value, that is why in our study we will assign the category of mobile applications called “Social and Communication” to hedonic type of mobile apps. In the same classification Games, Online TV, Video Streaming, Phone Camera are also described to create hedonic value for mobile service users. In our study for such type of mobile service stand categories “Entertainment”, “Hobbies” and “Games and Music”. That is why we will assign mobile applications in these categories also to hedonic type of mobile apps. In the study by Ahmad (2012) it is not categorized what kind of value the “Causal Reading” service on mobile phones creates for the users, but is mentioned that educational reading and scheduling books create utilitarian value. Based on this, we intuitively conclude that causal reading will have an opposite value and assigned mobile applications in the category “Causal Reading” to hedonic type of mobile apps. Based on this description of the type of value different service attributes create for the user the app categories “Hobbies”, “Social and Communication”, “Causal Reading”, “Entertainment” and “Games and Music” were assigned to Hedonic applications. In the study by Ahmad (2012, p. 77) it was also described that Financial Service applications create utilitarian value for users of mobile services. Based on this, we assigned mobile applications in “Finance, banking and insurance” category to utilitarian type of mobile applications. The same logic was applied to mobile applications in the category “Tools and Productivity”. To this category normally are allocated mobile applications that provide planning and scheduling services as well as applications that read documents and provide other office support. Ahmad (2012) describes that such services create utilitarian value for the users. When it comes to the category “Shopping” it is hard to clearly define one value that mobile shopping services create for users. In the classification by Ahmad (2012) the services in this category are described to create both utilitarian and hedonic value. For the purpose of our research, we referred to another study by Parker & Wang (2016) which showed that users of mobile shopping apps report that the main motivators for them to use mobile shopping apps are efficiency and convenience that these apps create. Similarly to Parker & Wang (2016) we assigned mobile applications in category “Shopping” to Utilitarian type of mobile applications. Finally, when it comes to the categories “Travel and Life” and “Health and Fitness”, we recognized that these services rather create convenience, efficiency, timeliness and increased quality of life for their users, and based on definition of utilitarian value, we assigned mobile applications in these categories to utilitarian type of mobile apps. Based on this, for the purpose of our study, we assigned mobile applications in app categories “Finance, banking and insurance”, “Travel and

Life", "Tools and Productivity", "Shopping" and "Health and Fitness" to utilitarian mobile applications.

Based on the evidence from the earlier research on the moderating effects of app type on the mobile application adoption process as well as based on the logic for differentiating between Hedonic and Utilitarian types of mobile applications, we expect that users may perceive adoption of Hedonic and Utilitarian mobile applications differently and that there will be differences in the influences of some of antecedents in the model across hedonic and functional mobile applications. For this reason, in our study we propose the following:

*Proposition 1:* There will be differences in the influences of some of the antecedents in the model across Hedonic and Utilitarian mobile applications.

# 5. Method

## 5.1 Research design and procedure

### *5.1.1 Research survey*

To test the hypotheses described in our research model, we conducted an online survey created and distributed with the help of the research software Qualtrics. The questionnaire was distributed among bachelor and master students studying economics and business administration at Norwegian School of Economics in Norway. The survey was available for potential respondents for ten days. The respondents were asked to answer the questions in the survey related to the mobile app they have recently downloaded on their phone (Appendix A). The measurements for the main dependent and independent variables in our model were collected with the help of "7-point Likert scale". No special form of motivation or compensation was used to stimulate participants; the participation in the survey was voluntary and anonymous.

The questionnaire was set up based to the framework established for testing UTAUT model (Venkatesh et al., 2003) and UTAUT2 model (Venkatesh et al., 2012). In addition to the questions measuring the main constructs in the model, the survey also included questions on demographical background, experience with using mobile applications and category of mobile application the respondent is answering the questionnaire about. As a result, the survey included 20 questions that measured the following main variables in our model: Behavioral Intention, Performance Expectancy, Social Influence, Effort Expectancy, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Herd Behavior (measured with the help of Imitating Others and Discounting Own Information dimensions) and Online Rankings and Reviews. Additional 6 questions were included into the survey to collect background information about age, gender, education, experience with mobile applications and app type.

### *5.1.2 Respondent group*

As a target group for respondents we chose students. One of the reasons for selecting students and young people as a target group for our research was that we aimed at investigating behavioral patterns of a mature and experienced group of users who have already tried using different types of mobile applications. For such purpose students are the right audience to target. Students represent the age group of population that spends the most time using mobile applications. Statistic research shows that younger people aged 18-34 years tend to spend more average time

daily on mobile applications than other users (Pedotto & Chen, 2016). Students often use mobile applications not only for their private needs, but also as the part of education process or participation in student activities (e.g. Student ID app, Kahoot, ItsLearning etc). Finally, students are also a very social and interconnected segment of population that actively uses social media and that is widely exposed to various types of social influences, what is relevant for our purpose of testing how different types of social influences determine the behavioral intention to adopt mobile application among users.

### *5.1.3 Initial data preparation*

Before the data analysis and testing of the model was done, we conducted the initial preparation of the dataset. To ensure the better quality of analysis the dataset was cleaned. First we removed the responses that were not finished and careless responses. As a result of the data collection we received 277 responses. After initial screening of the data 77 responses were removed because they were not fully completed on the moment when the data was retrieved. During the second screening, eight more responses were recognized as careless responses and also were deleted. The careless responses we identified those where nine or more questions in same session had the same answer. As a result, after two rounds of data cleaning, we got a dataset with 192 responses.

To be able to test our model for the presence of moderating effects of utilitarian/hedonic app type, we transformed the variable that represented app type. We composed the variable that described app type using 10 measurement dimensions (“Finance, banking and insurance”; “Travel and Life”; “Hobbies”; “Social and Communication”; “Tools and Productivity”; “Shopping”; “Causal Reading”; “Entertainment and sports”; “Games and music”; “Health and Fitness”) into 2 measurement dimensions – Utilitarian mobile applications and Hedonic mobile applications. In the research survey, to make it easier for the respondent to define the category of the mobile application, we used the traditional app categories that are widely applied in the app stores. Yet for the purpose of our study we were interested in differentiating only between Hedonic and Utilitarian mobile applications. For this reason the initial data on the app type variable, composed of 10 different dimensions, was transformed into two main variables, where all the responses for “Hobbies”, “Social and Communication”, “Causal Reading”, “Entertainment and Sports” and “Games and Music” were assigned to Hedonic applications (64 responses) and all the responses for “Finance, banking and insurance”, “Travel and Life”, “Tools and Productivity”, “Shopping” and “Health and Fitness” were assigned to Utilitarian applications (128 responses).

As it was discussed previously, the only study in our literature review that used UTAUT2 model to research the user adoption of mobile applications revealed no significant moderating

effects from age, gender and education level (Hew et al., 2015). Moreover, other UTAUT extensions in our review revealed no significant moderating effects from age, gender and education level (e.g. Brown et al., 2010, Liang et al., 2010, Xiong, Qureshi & Najjar, 2013, Wong et al., 2014, Shen, 2015) revealed no significant moderating effects of age, gender and education level on the main direct effects in the model. Based on such results from previous research we decided not to test the moderating effects of age, gender and education in our study and we preferred to focus on targeting a specific sample represented by students in Norway. Targeting students, didn't allow us track different effects for age groups. Our sample also proved to be homogeneous in terms of education level of respondents (87,5% of respondents have higher education) and experience with using mobile applications (93,88% of respondents have average or higher than average level of experience with mobile applications).

## 5.2 Sample demographics

Table 5.1 presents the descriptive statistics of the sample for our research. The bigger part of respondents who completed the survey is female (65.6%). Such distribution is not representative for gender distribution at Norwegian School of Economics, where in between 37-40% of students are female (nhh.no, 2017). More than 87% of the respondents have higher education, what is relevant for our target sample and confirms the fit of the dataset with the targeted segment. The mean age in the sample is 26.02 years, where minimum age is 19 years and maximum age is 42 years. Such age distribution also corresponds to the sample that we targeted in our study and describes the traditional student sample.

We also collected the background information on the experience of respondents with usage of mobile applications. This was made for sample description. As a result, we saw that our respondents had the same and equally comparable level of experience with using mobile applications. More than 90% of respondents indicated that they are experienced with using mobile applications. With reference to 7-point Likert scale, where 1 stands for very little experienced and 7 – for very experienced, this means that 22,22% of respondents indicated that they are very experienced with using mobile applications and chose option 7 - "very experienced", 30,70% of respondents chose option 6 - "experienced" and 28,70% chose option 5 "somewhat experienced". 81,62% of respondents indicated that they have higher than average experience with using mobile applications and chose options 5, 6 and 7.

Table 5.1

*Sample demographics*

| | |
|---|---|
| **Gender** | |
| Male | 34.4% |
| Female | 65.5% |
| **Age** | |
| Minimum | 19 |
| Maximum | 42 |
| Mean | 26.02 |
| **Education** | |
| Secondary school | 1% |
| University/college < 3 years | 11.5% |
| University/college > 3 years | 87.5% |
| **Experience level** | |
| Very little experienced | 1,85% |
| Little experienced | 1,70% |
| Somewhat unexperienced | 2,56% |
| Average experience level | 12,26% |
| Somewhat experienced | 28,70% |
| Experienced | 30,70% |
| Very experienced | 22,22% |

## 5.3 Assumptions of structural equation modeling

The review of the dataset used for the test of our model confirms that our dataset meets the assumptions of multivariate analysis and allows drawing conclusions based on it. The observations during the survey conduction were collected independently among a wide range of individuals. The questionnaire was distributed among 700 students of Norwegian School of Economics out of which 277 participated in the survey. Due to limitations of the research setting it was impossible to fully control for the independence and quality of responses, the responses were collected anonymously through internet service. This did not allow for full control over collection of responses. At the same time such setting ensured that respondents don't have contact with each other, and are not influenced by external factors or people conducting the survey. In such cases the responses are collected independently and the quality of the responses to large extent depends on the engagement of the respondents into the survey.

The initial overview of the sample and the sample cleaning allows us expect a good quality of responses. The average time spent on the questionnaire was 10,5 minutes while the estimated response time was 7 minutes. This means that respondents took time to read the questions thoroughly and think about their choices. Moreover, even though it was not required by the survey setting, during the data collection process we received 143 confirmations from the respondents that they answered the survey. We also received 12 questions from the respondents with feedback on

their experience and with comments on what mobile app they were thinking about when answering the questions of the survey. Such engagement can be an indirect evidence of the quality and reliability of the data collected during the experiment. Even though the initial data collection process showed high level of engagement from the respondents, some careless responses were still indicated, and to ensure the better quality of the analysis 8 responses were removed as careless responses.

Table 5.2

*Descriptive Statistics*

| | Minimum | Maximum | Mean | Std. Deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| **PE** | 1.00 | 7.00 | 5.0712 | 1.34598 | -1.239 | 1.329 |
| **SI** | 1.00 | 7.00 | 4.6476 | 1.18365 | -0.439 | 0.396 |
| **EE** | 2.75 | 7.00 | 6.1302 | 0.80247 | -1.311 | 2.372 |
| **FC** | 3.00 | 7.00 | 6.2578 | 0.71076 | -1.154 | 2.393 |
| **HM** | 1.00 | 7.00 | 4.7396 | 1.24974 | -0.380 | -0.165 |
| **PV** | 1.00 | 7.00 | 5.5191 | 1.30942 | -0.920 | 0.867 |
| **HT** | 1.00 | 7.00 | 3.3611 | 1.38945 | 0.150 | -0.664 |
| **OW** | 1.00 | 7.00 | 3.2396 | 1.74613 | 0.334 | -1.092 |
| **IO** | 1.00 | 7.00 | 4.4010 | 1.50103 | -0.365 | -0.629 |
| **DI** | 1.00 | 7.00 | 3.8628 | 1.34906 | 0.071 | -0.684 |
| **BI** | 1.00 | 7.00 | 4.9653 | 1.26847 | -0.915 | 0.887 |

The sample size also meets the assumption necessary for conducting the structural equation modeling; our final sample includes 192 observations what corresponds to 12 times as many cases as we have in the research model. The descriptive statistic of the model showed that the data collected fits the normality requirements. More than half of the values fall within one standard deviation of the mean (Table 5.2). To test the normality of the dataset distribution we did the analysis of skewness and kurtosis. Referring to West et al. (1996) for or the variables that had skewness higher than 2 or lower than -2 we considered the data skewed. Thus, based on the data presented in the descriptive statistics (Table 5.2), we can see that for most of the variables the data is normally distributed. Only for Performance Expectancy, Effort Expectancy and Facilitating Conditions it is somewhat more skewed that for other variables, yet not critically. As a cut-off value for kurtosis we used proper value > 7, as described by West et al. (1996). As a result we can conclude that the data distribution for all the factors in our model is also normally distributed in terms of kurtosis. The values for Performance Expectancy, Effort Expectancy and Facilitating Conditions are somewhat peaked. To test our conclusions visually we also run the normality test with Q-Q plots (Appendix B). As a result, the Q-Q test showed the normal distribution for most of the tested variables. For Performance Expectancy, Effort Expectancy and Facilitating Conditions

the data was somewhat distributed not perfectly, but the residual line of the plots still closely followed the normal diagonal without significant outliers. To check that the independent variables are not highly correlated with each other we run the collinearity diagnosis. The diagnosis showed that Variance Inflation Factor (VIF) for all independent variables in our model is lower than 5 what shows that there is no multicollinearity problem in our dataset (Hocking & Pendelton, 1983).

## 5.4 Measures and measure validation

To test the fit of the measures and measurement model for our data analysis we used the confirmatory factor analysis in Mplus7 data analysis software. The confirmatory factor analysis of our measurement model showed a reasonably good fit of the variables in the model. The data analysis showed that for our model coefficients of fit are within norm and correspond to the general cutoff criteria for the model fit. To define the cutoff criteria for our model we used the guidelines described by Hair et al. (2006) indicating that more complex models with smaller samples should require less strict model fit cutoff criteria. In our case we have acceptable but still not ideal number of responses for the model with 11 variables. According to Hair et al. (2006) for the models with relatively big number of measured variables and small samples, chi-square index is not a representative indicator of goodness of fit. It is recommended to make evaluations based on other fit indexes. Following this guideline, we will report the chi-square values but will evaluate the goodness of fit based on the CFI and RMSEA indexes. As a cutoff criteria for this indexes we also used the guidelines from Hair et al. (2006, p. 753), and assumed that for the good fit of our model CFI value should not be below 0,95 and RMSEA value should be below 0,08. In our case the model showed acceptable fit with the following indexes: chi/*df* = 6.88, CFI = 0.96, RMSEA = 0.067.

Most of the measurement items in our model were adapted from the previously validated studies. For Performance Expectancy, Social Influence, Effort Expectancy, Facilitating Conditions, Hedonic Motivation, Price Value, Habit and Behavioral Intention the measurement items were adapted from UTAUT2 model (Venkatesh et al., 2012). For measuring Herd Behavior we used two dimensions – Imitating Others and Discounting Own Information and the items for these dimensions were adapted from the model developed by Sun (2013) in his research of influence of Herd Behavior on the adoption of new technology. Finally, the measurement items for Online Rankings and Reviews were developed by author. The questionnaire distributed among respondents consisted of two parts where the first one measured the dependent and independent variables in the model and second collected demographic and background information of the respondent.

*5.4.1 Convergent validity*

To test the how well the measurement items used in our model fit the factors they were assigned to measure, we run a confirmatory factor analysis for SEM using software Mplus7 (Table 5.3). As a reference values for evaluating the factor loadings, construct reliability and average variance extracted we referred to guidelines suggested by Hair et al., (2006), expecting that standardized factor loadings ideally should be higher than 0,7 with lowest acceptable level of 0,5. In good measurement model values for construct reliability (CR), according to Hair et al. (2006), should be higher than 0,7. The values for average variance extracted (AVE) should be higher than 0,5 (Fornell & Lacker, 1981).

To measure the *Performance Expectancy* we used the items from UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012) models. In our study only three items that were most relevant for our setting were selected. The measurement items were also modified with an aim to make them descriptive for a setting where consumers think about a specific mobile application they have recently downloaded on their mobile phone. The confirmatory factor analysis showed high loadings (>0,7) of all three items on the factor showing high convergent validity of the measurement items within factor Performance Expectancy (Hair et al., 2006 p. 779). The factor analysis also indicated the construct reliability of 0,825, what is higher than the threshold value of 0,7 indicated by Hair et al. (2006, p. 779). This means that the selected measurement items are commonly related to the factor and can be applied in our measurement model.

To measure the *Social Influence* we adapted the measurement items from the UTAUT2 (Venkatesh et al., 2012) model, which was developed specifically for consumer setting. All three items were reformulated to describe the respondent's experience with usage of concrete mobile application recently downloaded on the phone. All three items showed high loadings (>0,7) on Social Influence indicating that the measurement items are commonly related and representative for the factor that they measure (Hair et al., 2006 p. 779). The factor analysis also indicated the construct reliability of 0,887, what is higher than the threshold value of 0,7 indicated by Hair et al. (2006, p. 779). This allows us conclude that for Social Influence there is a consistency in relationship between measurement items and that they consistently represent the same latent variable.

*Effort Expectancy* was measured with the help of the items adapted from the UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012) models. All four measures were adopted from previously confirmed research (Venkatesh et al., 2003, Venkatesh et al., 2012) but were tailored for the mobile application adoption setting. All four measurement items showed high loadings on Effort Expectancy (>0.7) indicating that the measurement items are commonly related

and representative for the factor that they measure (Hair et al., 2006 p. 779). The factor analysis also indicated the construct reliability of 0,867, what is higher than the threshold value of 0,7 indicated by Hair et al. (2006, p. 779). This means that for Effort Expectancy there is a consistency in relationship between adapted measurement items.

Table 5.3

*Factor Analysis*

| | | Loadings | CR | AVE |
|---|---|---|---|---|
| **PE: Performance Expectancy** | PE1: I find this mobile application useful in my everyday life | 0.812 | 0,825 | 0,612 |
| | PE2: Using this mobile application increases my chance of achieving things that are important to me | 0.8 | | |
| | PE3: Using this mobile application helps me accomplish things more quickly | 0.733 | | |
| **SI: Social Influence** | SI1: People who are important to me think that I should use this mobile application | 0.835 | 0,887 | 0,723 |
| | SI2: People who influence my behavior think that I should use this mobile application | 0.88 | | |
| | SI3: People whose opinions I value prefer that I use this mobile application | 0.835 | | |
| **EE: Effort Expectancy** | EE1: Learning how to use this mobile application is easy for me | 0.783 | 0,867 | 0,621 |
| | EE2: My interaction with this mobile application is clear and understandable | 0.831 | | |
| | EE3: I find this application easy to use | 0.839 | | |
| | EE4: It is easy for me to become skillful at using this mobile application | 0.689 | | |
| **FC: Facilitating Conditions** | FC1: I have the resources necessary to use this mobile application | 0.763 | 0,416 | 0,526 |
| | FC2: I have the knowledge necessary to use this mobile application | 0.685 | | |
| **HM: Hedonic Motivation** | HM1: Using this mobile application is fun | 0.944 | 0,879 | 0,711 |
| | HM2: Using this mobile application is enjoyable | 0.843 | | |
| | HM3: Using this mobile application is very entertaining | 0.728 | | |
| **PV: Price Value** | PV1: This mobile application is reasonably priced | 0.763 | 0,905 | 0,762 |
| | PV2: This application is a good value for its price | 0.976 | | |
| | PV3: At the current price this mobile application provides good value | 0.867 | | |
| **HT: Habit** | HT1: The use of this mobile application has become a habit for me | 0.769 | 0,748 | 0,501 |
| | HT2: I am addicted to using this mobile application | 0.761 | | |
| | HT3: I must use this mobile application | 0.576 | | |
| **OW: Online rankings and reviews** | OW1: I checked the online ratings and reviews when I searched for this application | 0.802 | 0,902 | 0,697 |
| | OW2: I accepted this mobile application because it ranks high on the app store | 0.897 | | |
| | OW3: I accepted this mobile application because it had many positive online comments and reviews | 0.846 | | |
| | OW4: I accepted this mobile application because it was listed on mobile app top charts | 0.791 | | |
| **IO: Imitating others** | IO1: If this mobile application seems to be a dominant mobile app on the market I would like to use it as well | 0.502 | 0,818 | 0,614 |
| | IO2: I followed others in accepting this mobile application | 0.851 | | |
| | I choose to accept this mobile applications because I see that other people use it | 0.93 | | |
| **DI: Discounting own information** | DI1: My acceptance of this mobile application did not reflect my own preferences for mobile applications | 0.618 | 0,679 | 0,415 |
| | DI2: I did not make the decision based on my own research and information when choosing this mobile application | 0.718 | | |
| | DI3: If I didn't know that a lot of people have already accepted this mobile application, I could choose another one | 0.59 | | |
| **BI: Behavioral Intention** | BI1: I intend to continue using this mobile application in the future | 0.736 | 0,839 | 0,478 |
| | BI2: I will always try to use this mobile application in my daily life | 0.75 | | |
| | BI3: I plan to continue to use this mobile application frequently | 0.899 | | |

Only two out of four measures for *Facilitating Conditions* were included in our model. The main criterion for selection was the level of factor loadings described by Hair et al. (2006, p. 779). The items that had factor loadings <0.5 were not included into the model. The construct reliability for the facilitating conditions is also lower than the average acceptable level. According to Hair et al. (2006, p. 778) low construct reliability can be acceptable for the measurement items where factor loadings and average variance extracted are still within the required thresholds. Based on this we prefer to keep the Facilitating Conditions in the model and conclude that it has acceptable convergent validity. Another reason for retaining the Facilitating Conditions is that the items used for our research were adopted from the prior UTAUT research and we prefer to keep the construct to allow for comparability of the model with earlier UTAUT studies.

The measurement items for Hedonic *Motivation* and *Price Value* were also adopted from the UTAUT2 (Venkatesh et al., 2012) model and all three items suggested in the initial study were modified for the purpose of our measurement model. The respective measurement items showed high loadings (>0.7) on Hedonic Motivation and Price Value. Both items also confirmed to have high construct reliability; Hedonic Motivation had construct reliability of 0,879 and Price Value had construct reliability of 0,905. This indicates that the measurement items describing these constructs are commonly related and that they consistently represent the respective latent variables.

For the measurement of the variable that represents *Habit* we also used three measurement items confirmed in the UTAUT2 model (Venkatesh et al., 2012). Similarly to other items in our model, they were modified for the description of the experience with using a mobile application. Two measurement items showed high factor loadings (>0.7) and one was slightly lower (0,576) but still higher than the lowest acceptable level (>0.5) as described by Hair et al. (2006, p. 779). Taking into account that the construct reliability for the factor with these measurement items is high we find these factor loadings acceptable for our model and conclude that the items have good convergent validity. To allow for comparability of the study with previous UTAUT models, we keep the factor and all measurement items in the model.

The measurement items for the construct called *Online Rankings and Reviews* were developed by authors. Even though there are several studies that have already tested and confirmed the importance of online rankings and reviews, e-WOM or Online WOM for the mobile app adoption, none of these studies used measurement items that could be adopted for our survey setting. For example, Liang et al., (2016) used multifacet sentiment analysis and collected data from Apple Store to evaluate the influence of Online Rankings and Reviews. Similar approach was used by (Hyrynsalmi et al., 2014) where they examined the effects of e-WOM by gathering a set of

application data from Google Play. For this reason, the measurement items for Online Rankings and Reviews were developed by authors specifically for the purpose of this research. All four items showed high loadings on the factor (>0.7) and had the highest construct reliability among other factors in our model (0,902) and proved to have high convergent validity.

The measurement of *Herd Behavior* was based on items used by Sun (2013) in his research of influence of Herd behavior on the adoption of new technology. Similarly to items adopted from UTAUT 2 study, we rephrased the measurement items from the original study to measure the adoption of mobile applications. As it was presented in the initial study on the Herd Behavior and its influence on the technology adoption, herd behavior concept was measured with the help of two separate variables which are *Imitating Others* and *Discounting Own Information*. The measurement items for both constructs were adopted from the study by Sun (2013). On the Imitating others two items showed high loadings on the factor (>0,7), while one showed low but still acceptable factor loading (>0,5). This factor also showed high construct reliability of 0,818. On Discounting Own Information one measurement item had a high loading on the factor (>0,7) while other two had a lower, but still acceptable loading (>0,5). The construct validity for Discounting Own Information was slightly lower than the generally acceptable level (0,679). This means that the convergent validity for Imitating Others is lower than for other factors in our model and slightly lower than initially described thresholds (Hair et al., 2006). Yet, for the purpose of our study – to avoid loss of model fit as well as to allow for the measurement of Herd Behavior with the help of two dimensions as described by Sun (2013), we decided to retain the variable measuring the Discounting Own Information.

For *Behavioral Intention,* measurement items were adopted from the UTAUT2 model (Venkatesh et al., 2012) where initially they were framed for measuring the potential usage of a general technology. In our study we adapted the Behavioral Intention measurement items for measurement of the actual user experience with mobile applications they have recently installed on their phone. The confirmatory factor analysis showed high loadings (>0,7) for all three items on the factor showing high convergent validity of the measurement items within Behavior Intention (Hair et al., 2006 p. 779). The factor analysis also indicated the construct reliability of 0,839, what is higher than the threshold value of 0,7 indicated by Hair et al. (2006, p. 779). This means that the selected measurement items are commonly related to the factor and can be applied in our measurement model. The AVE for Behavioral Intention is slightly lower than the threshold value indicated by Fornell & Larcker, 1981) and equal 0,478 (<0,5). This indicates that on average more error remains in the item than the variance explained by the measure of the factor. Taking into account that Behavioral Intention is an important construct for our model and that the AVE is slightly lower than the indicated threshold value we will retain the construct in the model.

*5.4.2 Discriminant validity*

To validate our measurement model we also run the analysis of discriminant validity using the criteria described by Fornell & Larcker (1981). We tested the discriminant validity of the model to ensure that each of the latent variables in our model accounts for more variance than other observed constructs within our framework. Using the methodology described by Fornell & Larcker (1981) we compared the squared AVE of each construct with the shared variance of other constructs in the model and tested the hypothesis about discriminant validity of the construct.

Table 5.4

*Pearson Correlation*

| | PE | SI | EE | FC | HM | PV | HT | OW | IO | DI | BI |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **PE** | **0.782** | | | | | | | | | | |
| **SI** | 0.401** | **0.850** | | | | | | | | | |
| **EE** | 0.088 | 0.115 | **0.788** | | | | | | | | |
| **FC** | 0.188** | 0.164* | 0.525** | **0.725** | | | | | | | |
| **HM** | 0.100 | 0.198** | -0.053 | 0.095 | **0.843** | | | | | | |
| **PV** | 0.318** | 0.211** | 0.144* | 0.271** | 0.087 | **0.873** | | | | | |
| **HT** | 0.278** | 0.330** | 0.046 | 0.019 | 0.299** | 0.072 | **0.708** | | | | |
| **OW** | 0.047 | 0.092 | -0.084 | -0.106 | 0.097 | -0.010 | 0.205** | **0.835** | | | |
| **IO** | 0.060 | 0.277** | 0.093 | 0.128 | 0.026 | 0.035 | 0.101 | 0.295** | **0.783** | | |
| **DI** | -0.021 | 0.115 | 0.040 | -0.041 | -0.118 | -0.006 | -0.011 | -0.087 | 0.439** | **0.644** | |
| **BI** | 0.617** | 0.471** | 0.094 | 0.232** | 0.274** | 0.366** | 0.474** | 0.083 | 0.144 | -0.064 | **0.691** |

In the Table 5.4 we present the results of the correlation matrix. The correlation coefficients for each of the construct can be compared with the $AVE^2$. For the constructs that will have greater correlation coefficient than the value of the squared variance extracted we should expect discriminant validity problems. If we look in detail into each of the constructs we have in the model, we can see that for Performance Expectancy the correlation coefficients with all other constructs in the model are lower that the squared variance extracted. This means that there is no cross-loadings with other constructs for Performance Expectancy and that the measurement items for this construct represent only one latent variable. The correlation coefficients of Social Influence with other constructs in the model are in general quite low and significantly lower than the squared average variance extracted for Social Influence. This means that there is no discriminant validity problem for Social Influence in the model. Effort Expectancy has only one significantly high correlation coefficient with Facilitating conditions, but this coefficient is still lower than the squared average variance extracted for the Effort Expectancy. We find such relatively high correlation

between Effort Expectancy and Facilitating Conditions quite natural as these two variables are more interconnected than the other variables in our model. In the replication of UTAUT2 model for adoption of mobile applications Hew et al. (2015) also had the highest correlation coefficient between Effort Expectancy and Facilitating conditions. That is why we conclude that these high cross loadings between Effort expectancy and Facilitating Conditions are not critical since it is still lower than $AVE^2$. The same conclusion can be made for Hedonic Motivation, Price Value, Habit, Online Rankings and Reviews and Discounting Own Information. For all these constructs we can see that correlation coefficients with other constructs are quite low and significantly lower than their respective $AVE^2$ values. This indicates that each of these constructs is unique and captures phenomena that other measurement items in the model don't describe.

Finally, we would like to separately discuss the correlation of Behavioral Intention with all other constructs in the model. In general Behavioral Intention has the highest cross-loadings with other variables in the model, what is quite natural since it is the dependent variable in the model. The highest correlation coefficient for Behavioral Intention is with Performance Expectancy. Yet, it is still lower than the $AVE^2$, so we can conclude that there is no discriminant validity problem. Moreover, Behavioral Intention has high correlation coefficients with Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value and Habit. Such correlations can have a sign of the potential dependence relationship between these variables, what we will investigate in more detail with the help of Structure Equation Modeling.

The conclusion can be made that there is no discriminant validity problems in our measurement model. Using the AVE discriminant validity test described by Fornell & Larcker (1981) we confirmed that all constructs in the model are distinct from each other and represent unique latent variables.

### *5.4.3 Common Method bias*

To reduce the chance of occurrence of common method bias in our study we used some of the remedies described by MacKenzie & Podsakoff (2012). MacKenzie & Podsakoff (2012) identified the lack of ability to answer the questions in the survey as one of the causes for occurrence of common method bias in the study. In our research this should not be the cases since our study was conducted among the bachelor and master students of Norwegian School of Economics. Our respondents have high level of education and high ability to answer the questions in the survey. The questions were framed in a simple straightforward manner and the questionnaire format using Likert 7-point scale is familiar to the students. The lack of experience with the topic is also not the case in our survey sample. Statistics show that students and young people fall into the category of the most frequent users of mobile applications (Pedotto & Chen, 2016). The high

experience and knowledge of students about mobile applications was one of the reasons for choosing them as the sample for our survey. Moreover, we can also expect that the knowledge and awareness about their mobile app usage decisions was easily available for our respondents based in the fact that the topic of mobile application development and usage is widely discussed in the student environment. To avoid the abstract nature of the questions in the survey and to make it easier for the users to understand their motives and adoption behavior with mobile applications we reframed the measurement items adopted from previous research. Instead of asking about user behavior for a theoretic and abstract mobile application, we asked the user about their actual experience and intention to adopt the last mobile application they downloaded on their phone. To decrease the ambiguity of the items, the survey was tested several times for the presence of ambiguous and unfamiliar terms on 5 respondents of different age, with different background and native language. Based on their comments and feedbacks the questions in the survey were adjusted and the language was improved. No double-barreled questions were used in our survey. As it was already mentioned, to increase the relevance of the topic for the respondents we used the questions about their experience with a mobile application that they have recently downloaded on their phone. We expect that such approach created higher interest of respondents in the topic and increased their motivation to respond and share their real experience, rather than responding about something theoretical and obscure. There is evidence that users were interested in the topic and had high motivation to reply. During the survey we received 143 confirmations from the respondents confirming that they answered the survey and moreover, we received 12 feedbacks where users specified what kind of mobile application they were responding about and questions if this type of mobile application is a relevant one for our survey. To decrease the chance of occurrence of careless and impulsive responses in our survey we explicitly highlighted the purpose of the study and asked the respondents to respond carefully and attentively. To decrease the suspicions of the respondents and to allow them reveal their true opinions, we run the survey anonymously.

In addition to all the described above measures to prevent the occurrence of common method bias, we also used the Herman's one factor test to statistically test the presence of the common method variance in the model. The common method bias analysis showed that no factors in our model explain more than 50% variance extracted, what also confirms that no common method variance is present in the model. The first component in measurement model explains almost 20% of the variance extracted. The first ten components in the model have a value of more than 1 and explain almost 80% of total variance in the model. These results of the Common Method Bias test once again confirm the good fit of our model and the measurement items, what allows to continue the data analysis and test our hypotheses.

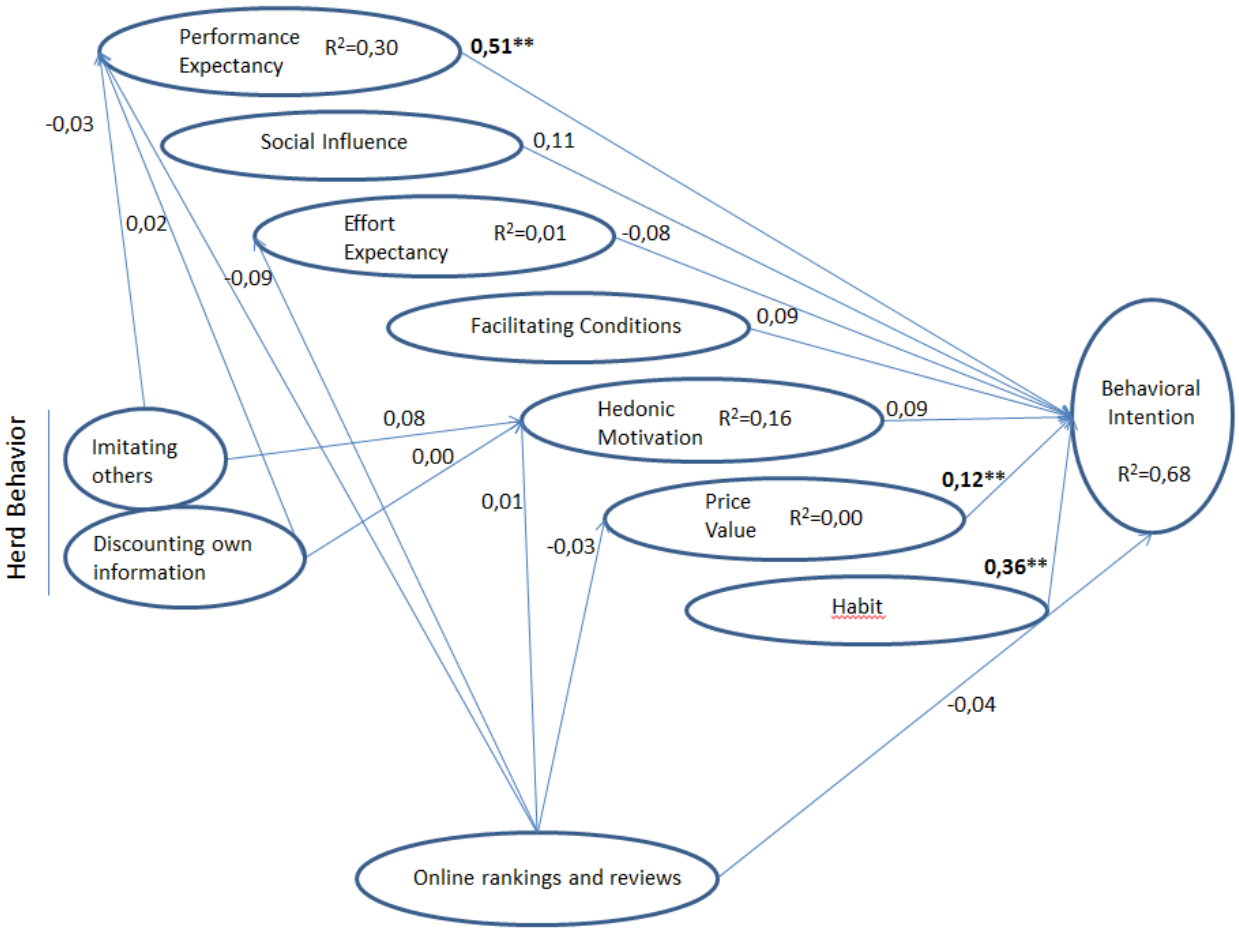
# 6. Results

## 6.1 Main model

To test the hypotheses in our research model we used the structural equation modelling in the Mplus7 software. The effects tested in the model described the influence of independent variables, which are Performance Expectancy, Social Influence, Effort Expectancy, Facilitating Conditions, Hedonic Motivation, Price Value, Habit and Online Rankings and Reviews on the dependent variable, which is Behavioral Intention. We also tested the indirect effect of Online rankings and reviews on the Behavioral Intention through Performance Expectancy, Effort Expectancy, Hedonic Motivation and Price Value and influence of Herd Behavior on Behavioral Intention through Performance Expectancy and Hedonic Motivation. Table 6.1 shows the results of analysis.

Figure 6.1

*Empirical results*



The structural model showed reasonably good fit results (chi/*df* = 3,84, CFI = 0,89, RMSEA = 0.061), what corresponds to results of the measurement model fit. As it is presented in the Table 6.1, not all hypotheses of the research model were confirmed. Only Performance expectancy, Price Value and Habit confirmed to have a positive significant influence on user Behavioral Intention to adopt mobile applications. The expected direct effect of Online Rankings and Reviews on the Behavioral Intention was not confirmed. The indirect effect of Herd Behavior on the Behavioral intention through Performance Expectancy and through Hedonic motivation was not confirmed. Effect of Online Rankings and Reviews on the Behavioral intention through Performance Expectancy, Effort Expectancy, Hedonic Motivation and Price Value were neither confirmed.

## 6.2 Direct effects versus mediating effects

The initially tested model in our research was based on assumption that the Performance Expectancy and Hedonic Motivation fully mediate the relationship between Herd behavior and Behavioral intention. Referring to Sun (2013) and his approach to the measurement of Herd Behavior with the help of two dimensions; Imitating Others and Discounting Own Information, in our model we suggested that indirect effects of Herd Behavior on Behavioral Intention will be represented by separate indirect effects of each of the measurement dimensions for the Herd Behavior. No direct effect from dimensions of Herd Behavior (Imitating Others and Discounting Own Information) on Behavioral intention was expected. Baron and Kenny (1986) described that the main conditions for presence of mediation effects in the model are: a) significant effects in the relationships between independent variable and presumed mediator, b) significant effects between the mediator and dependent variable, c) the direct relationship between independent and dependent variables is not significant. In our model this would mean that there is a significant effect of Imitating Others on Performance Expectancy and Hedonic Motivation and that there is a significant effect of Performance Expectancy and of Hedonic Motivation on Behavioral Intention. Out of these conditions only the effect of Performance Expectancy on Behavioral Intention proved to be significant. This indicates that there is no mediating effect of Performance Expectancy and Hedonic Motivation in the relationship between Imitating Others and Behavioral Intention. The same logic can be applied to the second dimension of Herd Behavior. The hypothesis about the mediating effect for the second dimension is confirmed if there is a significant effect of Discounting Own Information on Performance Expectancy and Hedonic Motivation and that there is a significant effect of Performance Expectancy and of Hedonic Motivation on Behavioral Intention. The test of our research model showed that out of these conditions only the significant effect of Performance Expectancy on the Behavioral Intention was confirmed. This means that there is no meditated effect

of Discounting Own Information on Behavioral Intention. The presence of mediated effect of Imitating Others and Discounting Own Information were not confirmed, what means that there is no mediated effect of Herd Behavior on Behavioral Intention.

### 6.3 Moderating influences of app type

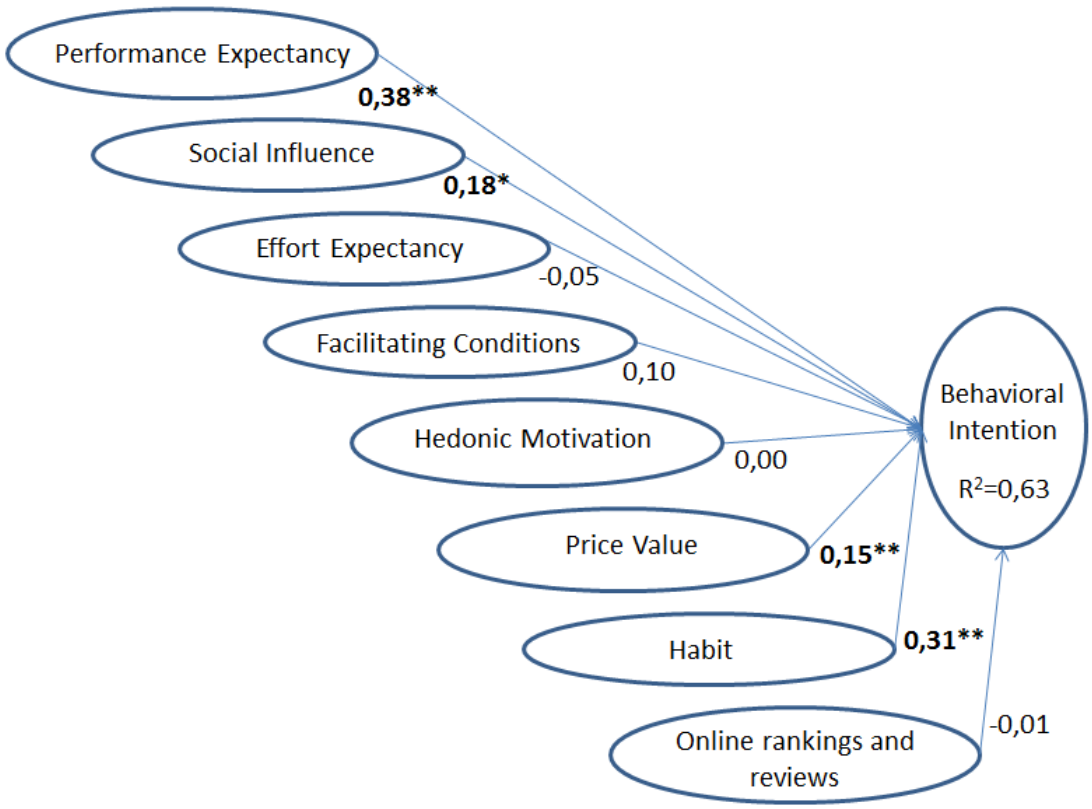
In addition to initially described model, in our research we also presented a proposition to test the model separately for two main types of mobile applications. The types of the applications were defined based on the value they create for users (utilitarian and hedonic). To confirm or reject this proposition we tested the initial model with only direct effects separately for Utilitarian apps and for Hedonic apps. In our model we proposed that Herd Behavior will have only mediated effect on the Behavioral Intention. This means that in case of Herd Behavior, to test the moderating effect of mobile app type we would need to test the hypothesis about moderated mediation of Performance Expectancy and Hedonic Motivation in the effect of Imitating Others and Discounting own Information on Behavioral Intention. Muller, Judd & Yzerbyt (2005) described that testing such effects with the help of SEM is possible, but in case of limited research setting this may result in loss of statistical power of the test. In our case, we have a relatively small for such test size of sample (192 responses). In this sample 128 responses are for Utilitarian mobile applications and 64 are for Hedonic mobile applications. Such number of responses is not sufficient for testing a sophisticated model with moderated mediation without losing statistical power of the test. That is why we limited our test of moderating influences to test of only direct effects with the help of multiple regression analysis in SPSS. These tests allowed us discover new direct effects for both Utilitarian and Hedonic apps, that were not presents in the initially tested model. The descriptive statistics, VIF and Tolerance analysis are presented in Appendix D.

The results of the model with only direct effects test for Utilitarian mobile applications are presented in Figure 6.2. The test confirmed the effects of Performance Expectancy, Price Value and Habit on the Behavioral Intention similarly to the results of the main model. In addition to this the test of the model for Utilitarian apps also revealed a significant effect of Social Influence on the Behavioral Intention to adopt mobile application. This indicates that when it comes to adoption of mobile applications in categories “Finance, banking and insurance”, “Travel and Life”, “Tools and Productivity”, “Shopping” and “Health and Fitness” consumers may value opinions of their significant others. Kim & Han (2011, p. 2312) described that “utilitarian value for mobile data service users is closely related to the effectiveness and efficiency that results from the use of the data service”. Users perceive utilitarian value as something concrete and task-related. The fact that Social Influence showed significant influence on the user attitude towards adopting utilitarian

mobile applications may indicate that for the services where the result and performance are value creators, users may be more influenced by opinions of their significant others. No significant effect of Effort Expectancy, Facilitating Conditions, Hedonic Motivation and Online Rankings and Reviews on Behavioral Intention was revealed.

Figure 6.2

*Moderating effects for Utilitarian mobile applications*

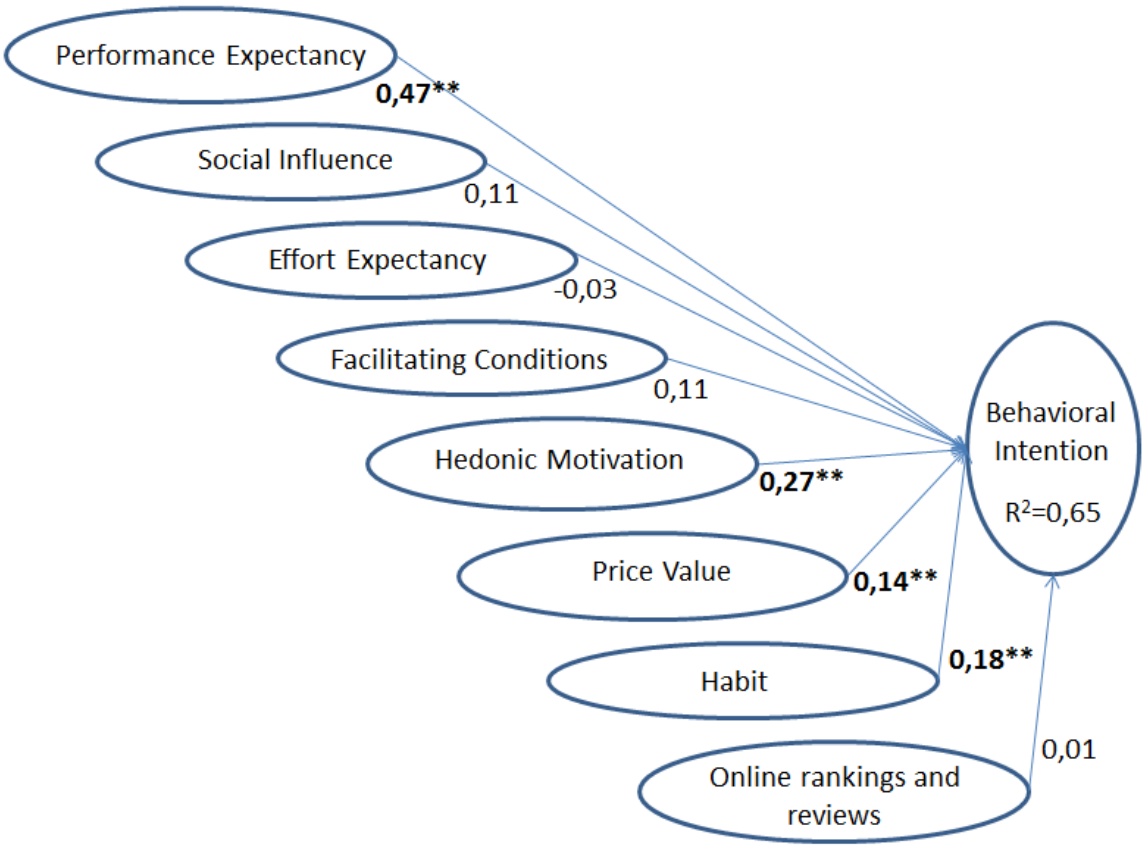



Following the same logic we run a test of the multiple regression model for only Hedonic mobile applications (in categories “Hobbies”, “Social and Communication”, “Causal Reading”, “Entertainment and Sports” and “Games and Music”). This test also confirmed a significant effect of Performance Expectancy, Price Value and Habit on the Behavioral Intention (Figure 6.3). This once again confirmed the effects revealed in the initial model and proves that there is no moderating effects in these relationships and these antecedents are valid and significant determinants of user intention to adopt mobile application for all types of mobile apps. Moreover, as it could be expected for hedonic mobile applications, Hedonic Motivation also confirmed to have significant influence on the Behavioral intention. Kim & Han (2011, p. 2312) described that “hedonic value is primary non-instrumental, experiential and affective”, while Venkatesh et al. (2012, p 161) explained

Hedonic motivation as “the fun or pleasure derived from using a technology”. Thus, the results revealed in our study fully comply with theoretical concepts. For Social Influence, Effort Expectancy, Facilitating Conditions and Online Rankings and Reviews no significant effects were found.

Figure 6.3

*Moderating effects for Hedonic mobile applications*




As a result of these two tests we can conclude that no moderating effect of app type in the influence of Performance Expectancy, Price Value and Habit on the Behavioral Intention was revealed and these antecedents have significant direct effects on Behavioral Intention for both utilitarian and hedonic mobile apps. Moreover, there is no moderating effect from app type in the influence of Effort Expectancy, Facilitating Conditions and Online Rankings and Reviews on Behavioral Intention. All these antecedents have no significant effect on Behavioral Intention for both utilitarian and hedonic mobile apps. There are differences between utilitarian and hedonic mobile applications in the influence of Social Influence and Hedonic Motivation on Behavioral Intention.

To evaluate the strength of these differences in the model for Utilitarian and Hedonic mobile applications we conducted a test on the significance of the differences in influence on the dependent variable for all antecedents that proved to be significant for at least one type of mobile applications The tests were done to investigate whether the influences of Performance Expectancy, Social Influence, Hedonic Motivation, Price Value and Habit on Behavioral Intention is significantly stronger for Utilitarian apps compared to Hedonic apps. The results of these tests are presented in Table 6.1. To calculate the t-value that was used to evaluate the significance of difference in the strength of influence for each of the antecedents we used the formula form Dillon & Goldstein (1984):

$$t < (B1 – B2) / (S.E1 + S.E2)$$

The results of this test showed that none of the antecedents that proved to have significant influence on Behavioral Intention for either Utilitarian or Hedonic mobile applications, had a significantly stronger influence on the Behavioral Intention compared to the influence from the same antecedent for the other type of mobile applications. Such findings lead to conclusion that even though the results of our regression analysis indicated that there are differences in antecedents that influence the Behavioral Intention for Utilitarian and Hedonic mobile applications, these differences are not significant.

Table 6.1

*Comparison of strength of influence on Behavioral Intention*

| | **Utilitarian apps** | | **Hedonic apps** | | **Significance** | |
|---|---|---|---|---|---|---|
| Relationship | Unst. B | Std. Error | Unst. B | Std. Error | Value (t) | Sig. |
| PE → BI | 0,396 | 0,075 | 0,374 | 0,079 | 0,143 | No |
| SI → BI | 0,188 | 0,078 | 0,118 | 0,099 | 0,395 | No |
| HM → BI | 0,001 | 0,08 | 0,229 | 0,073 | -1,490 | No |
| PV → BI | 0,145 | 0,066 | 0,137 | 0,09 | 0,051 | No |
| H → BI | 0,286 | 0,068 | 0,164 | 0,081 | 0,819 | No |

# 7. Discussion

## 7.1 Main Conclusions

The main results of our study are presented in Table 7.1. To discover the suggested effects in our extended UTAUT2 model for mobile applications we tested a structural equation model for our main model and run a multiple regression analysis separately for only utilitarian and only hedonic mobile applications. As a result of this study we enriched the UTAUT-related research base and build a technology acceptance model that explains the adoption mechanisms of mobile applications for voluntary market setting. In our study we build a research model, run a self-reported survey and conducted the data analysis of the sample in Mplus7 and SPSS. Based on the results obtained for our model we answered the three main research questions of our study.

Table 7.1

*Summary of main results*

| DV: Behavioral Intention | Main Model | Utilitarian apps | Hedonic apps |
|---|---|---|---|
| $R^2$ | 0,68 | 0,63 | 0,65 |
| Performance Expectancy (PE) | 0,51** | 0,38** | 0,47** |
| Effort Expectancy | | | |
| Social Influence (SI) | | 0,18** | |
| Facilitating Conditions (FC) | | | |
| Hedonic Motivation (HM) | | | 0,27** |
| Price Value (PV) | 0,12** | 0,15** | 0,14** |
| Habit (HT) | 0,36** | 0,31** | 0,18** |
| Online Rankings and Reviews (OW) | | | |
| Imitating Others (IO) | | | |
| Discounting Own Information (DOI) | | | |

The first research question in our study aimed at discovering whether the constructs from UTAUT2 model explain user acceptance of mobile applications. As a result of our research we discovered that some of the constructs in UTAUT2 model do explain the user acceptance of mobile application. Three main constructs that in our research proved to have significant influence on the user behavioral intention to adopt mobile applications are: Performance Expectancy, Price Value and Habit. The hypotheses about effect of Social Influence, Effort Expectancy, Facilitating Conditions and Hedonic Motivation on the Behavioral Intention were not confirmed for the main model.

The second research question in our study aimed at discovering the potential influences of Online Reviews and Rankings and Herd Behavior on Behavioral Intention in the extended UTAUT2 model for explaining acceptance of mobile applications. The results of our study showed no significant direct effect of Online Rankings and Reviews on Behavioral Intention. The mediated effects of Online Rankings and Reviews on Behavioral Intention through Performance Expectancy, Effort Expectancy, Hedonic Motivation and Price Value were neither confirmed. Similarly to the effects of Online Rankings and Reviews, the research model showed no mediated effect of Herd Behavior on Behavioral Intention through Performance Expectancy and Hedonic Motivation. Based on this we can conclude that Online Rankings and Reviews and Herd Behavior did not contribute to a better explanatory power of the model.

Finally, the third research question aimed at exploring moderating effects of the type of mobile application in the UTAUT2 model. The direct effects in the model were tested separately for utilitarian mobile applications and for hedonic mobile applications. The initial tests indicated that app type has a moderating effect in the UTAUT2 model for adoption of mobile applications. The tests indicated that for utilitarian mobile applications Social Influence has a significant influence on the Behavioral intention, while for hedonic apps, Hedonic Value has a significant influence on behavioral intention. Yet, the results of a more conservative test (Dillon & Goldstein, 1984) showed that the differences in the influences revealed for utilitarian and hedonic apps were not significantly different.

## 7.2 Theoretical Implications

The main theoretical interest of this study was to test the UTAUT2 model for the adoption of mobile applications and extend the model with regard to high-level contextual factors such as online rankings and reviews and herd behavior and with individual level contextual factors connected with task attributes such as utilitarian value focus and hedonic value focus. The literature review in our study showed that the research for mobile application adoption is quite new and is still limited to a narrow selection of studies. The research of mobile application adoption based on UTAUT model is even scarcer, despite the potential of UTAUT and UTAUT2 models to discover the effects and antecedents in the adoption process of information technologies. This study enriches both the UTAUT research baseline and adds new theoretical contributions to the mobile application adoption research.

This research also contributes to the line of theoretical research established by Hew et al. (2015) in their study of adoption of mobile applications on the Malaysian market. This is the only study in our literature review that applied the UTAUT2 model for the research of adoption of

mobile applications. Yet, this study was conducted on Malaysian market, which according to the authors is “underdeveloped in and not mature enough in terms of mobile applications development and adoption” (Hew et al., 2015, p. 1274). Our study enriches the results of this research by discovering the mobile application adoption process on a more developed market in Norway. As a result, some of the effects revealed in our study are different from the ones confirmed by Hew et al. (2015) for the Malaysian market. In contrast to our study, the UTAUT2 model confirmed the significant effect of Hedonic Motivation, Facilitating Conditions and Effort Expectancy for all types of mobile applications, while Price Value showed no significant effect in the model. This leads us to conclusion that there might be differences in the how users perceive the process of mobile application adoption based on the maturity and level of market development, and shows the need for further research in this area.

In the review of applications of UTAUT model Venkatesh et al. highlighted that “one of the directions for the future UTAUT research is to conceptualize technology use at the feature level and link it to individual outcomes” (2016, p. 347). Moreover, it was also mentioned that “there are few studies that test the moderation effects in their UTAUT applications” (Venkatesh et al., 2016, p. 332). In our model we tested new moderating effects that were not research in UTAUT research before. By differentiating between adoption effects for utilitarian mobile applications and hedonic mobile applications, we did a test of how task attributes of mobile applications moderate the effects of main antecedents of the UTAUT model on the behavioral intention to adopt mobile application. These findings go in line with the previous empirical research by Kim & Han, (2011) and Shen (2015) and indicate that users may perceive the adoption of mobile application differently depending on the type of mobile application and value that mobile application creates for them.

One of the declared contributions of this study was to extend the UTAUT2 model new high-level contextual factors. The expected effects from Online Rankings and Reviews and Herd Behavior on the user intention to adopt mobile application were not confirmed in our study. The reasoning behind extending the original UTAUT2 model with these two addition constructs was that the Social Influence construct that is included in the original UTAUT2 model is not representative enough for the modern environment. Social Influence in the original UTAUT2 model is limited to the influence of significant others representing family, friends etc. (Venkatesh et al., 2012). There are numerous confirmations of effects of Online Rankings and Reviews and Herd Behavior on the user intention to adopt new technology (Sun, 2013; Hyrynsalmi et al., 2015; Liang et al., 2015; Shen et al., 2015). Yet, in contrast to the previous findings, in our study we didn’t reveal the effects from Herd Behavior and Online Rankings and Reviews on the Behavioral intention. Moreover, the effect of Social Influence, proved to be significant for only utilitarian mobile applications.

## 7.3 Managerial Implications

The main contribution of this research for business is that it discovers the main motives and factors that influence the user intention to adopt mobile applications. The results of this research will be valuable for application in a business setting and will fill the knowledge gap on the adoption of mobile applications for business managers, developers and marketers. This study contributes to understanding of the mechanism of technology adoption on consumer markets and user acceptance of mobile applications.

Based on our findings we can make implications about the main factors that influence the user intention to adopt mobile application. Firstly, we see that user intention to adopt mobile application is influenced by the expectance of how the mobile application will perform on its main functions and tasks. This finding corresponds to the description of how mobile applications create value for businesses (Nah et al., 2005). Kim, Wang, & Malthouse (2015) mentioned convenience among the main features that draw consumers to mobile applications and differentiate mobile applications from other competing technologies. Oghuma et al. (2015) confirmed the crucial role of benefit seeking for the adoption of mobile instant messaging applications. In our study we confirmed that performance expectancy is one of the decisive factors that influence the mobile application adoption process for both utilitarian and hedonic mobile applications. This means that when making a decision to build a mobile application businesses and developers should with scrutiny evaluate performance, usefulness and task-fit of the mobile application. Such finding is especially useful for promotional and marketing purposes showing that users are ready to adopt mobile applications that they believe will create value and perform well for them. Clear communication of potential performance of mobile application will help increase the adoption rate of the app.

The research on the influence of price and price value on the user intention to adopt mobile application is rather scarce. Since it is quite common for mobile applications to be offered on the market for free or for a not significant price, it is important to develop understanding of how the price of mobile application influences the user intention to adopt it. In previous research the importance of app price and price value was not presented extensively. Shen (2015) confirmed that in the process of adoption of free mobile applications users tend to base their decisions on the top charts and ranking for mobile applications. Liang et al. (2015) described the moderating effect of app price for how consumers perceive the service and product quality for mobile application. The only study that extensively researched the importance of Price Value for the adoption of mobile applications is done by Hew et al. (2015) and in this study Price Value did not have a significant

influence on the Behavioral Intention. In contrast to these results, our study focusing on Norwegian market confirmed that price value is an important factor that has influence on the behavioral intention to adopt mobile applications. Mobile app users are cautious about the price of mobile apps. But at the same time, the results of our study shows that users are ready to pay for mobile applications that they believe will be useful for them. This finding can be useful for developers in the decision of choosing the pricing strategy for their mobile application. Our recommendation here will be to conduct early user tests and see how consumers evaluate the potential usefulness of the app and to develop a pricing strategy based on these findings.

Another factor that confirmed to have influence of the behavioral intention to adopt mobile applications is habit. Here our finding is similar to the results described by Hew et al. (2015), where they described that habit is the most significant factor that influences the user intention to adopt mobile applications. Habit is an important factor for the technology adoption process and there are examples of businesses that managed to successfully utilize the power of Habit to increase the adoption rate of their mobile applications (com.score, 2015). In the empirical research habit proved to be a significant factor for adoption of mobile TV (Wong et al., 2014) and social networking sites (Nikou & Bouwman, 2014). The results of our study correspond to these findings and we can indicate several directions for businesses, developers and marketers on how they could increase the user adoption rate for mobile applications. For businesses, developers and marketers importance of habit for mobile application adoption process means that when launching a new mobile application they should provide for mechanisms and activities that will quickly make users used to this mobile application on a daily basis. This finding is also useful for business managers who consider launching a mobile app that will support their main service or market solution. If there is evidence that users have a habit for using this service, or that they use it often and there is a potential to develop a habit, it is very likely that users will be willing to adopt the newly launched mobile app. Finally, such finding can be also useful for business when evaluating competitors on the market for mobile applications; is there is a similar solutions on the market for which users have already developed a habit, it may be difficult to outcompete this solution.

More managerial implications can be made from the fact that expected effects from online rankings and reviews didn’t confirm. Online rankings and reviews for mobile applications are wide spread and easily available and it is not possible to download mobile app without being exposed to its rating on the app store and some comments from the users. There is several evidence in the empirical research confirming the significant influence of online WOM, feedbacks, ratings and reviews for the sales and attitudes towards mobile applications (e.g. Hyrynsalmi et al., 2015, Liang et al., 2015, Shen, 2015, Huang & Korfiatis, 2015, etc.). In contrast to this, our tests show that these rankings and reviews have no significant influence on the user intention to adopt mobile

application. Based on this we suggest businesses and marketers not to invest into promoting their mobile application through online rankings and reviews.

Interesting findings are made with regard to specific types of mobile applications. In the research of mobile application adoption it is more common to research mobile applications based on the specific functional category they fit in (e.g. mobile banking apps (Verossimo, 2015), messaging apps (Oghuma et al., 2015), security apps (Han, Wu & Winsdor, 2014), shopping apps (Taylor & Levin, 2014), hotel mobile services (Morosan & DeFranco, 2016) etc). The research that distinguishes among utilitarian and hedonic mobile applications is scarcer (e.g. Sohn, Schulte & Seegebarth, 2014, Shen, 2015). Yet, there are evidences that users distinguish mobile services based on the value they provide them with, and mobile applications are included into these services (Kim & Han, 2011). Managers should be aware of that users may perceive utilitarian and hedonic mobile applications differently and have different adoption patterns for these types of mobile applications. For example, even though the social influence did not confirm to be significant for all categories of mobile applications, the results of our tests indicated that for mobile apps in categories finance, banking and insurance, travel and life, tools and productivity, shopping and health, fitness (utilitarian mobile apps), the opinion of significant others, such as friends and family may have significant influence on the behavioral intention. It is quite natural that hedonic motivation indicated to have a significant influence of the behavioral intention only for hedonic mobile apps. This finding can be useful rather for developers of utilitarian mobile applications than for developers of hedonic apps. Kim, Wang & Malthouse (2015) described vividness, novelty and interactivity as mobile app attributes that attract consumers to use mobile applications. Morosan & DeFranco also (2016) reported that consumer mobile app adoption process can be significantly enhanced by gamification of mobile app. Hew et al. (2015) also confirmed that hedonic motivation is a strong factor that positively affect behavioral intention to adopt mobile application. Our findings suggest that for utilitarian mobile applications adding fun and experiential part to attract users may not have influence on the user intention to adopt mobile application. Referring to this, we recommend managers and developers of utilitarian mobile applications to be aware of the potential differences in how users adopt different types of mobile applications.

## 7.4 Future Research

As was already described in the introduction and literature review, the area of mobile application adoption process research is a relatively fresh and there is a big potential for the future research and more findings. Mobile applications technology is a complex, highly flexible and the development of this technology is highly dependent on the market. If we compare mobile

applications with mobile internet service, which was the first technology that UTAUT2 model was used to discover, we can see that while mobile internet is a rigid and established technology controlled solely by the owners of technology, mobile applications technology is extremely flexible and readily available for many developers. Such flexibility significantly differentiates mobile applications form other technologies and adds new factors that may influence how users perceive and adopt mobile applications. For the future research in this area we would suggest investigating the mobile app adoption model for different types of mobile applications, discovering the influence of negative Online WOM on the behavioral intention to adopt mobile apps, testing the model on other groups of respondents and in another setting.

The aim of this research was to investigate the adoption mechanism of mobile technologies without a regard for specific categories of mobile applications, but with consideration for utilitarian and hedonic value that mobile application creates. Having an overview of such model for all types of mobile applications adds to understanding of how users perceive mobile applications and what are the main factors that influence their decisions. Yet, there is a bigger research potential for discovering adoption mechanisms for specific categories of mobile applications, such as social, banking, shopping, lifestyle, games etc. Previous research discovered some adoption patterns for different categories of mobile apps: mobile banking apps (Verissimo, 2015), messaging apps (Oghuma et al., 2015), security apps (Han, Wu & Winsdor, 2014), shopping apps (Taylor & Levin, 2014), hotel mobile services (Morosan & DeFranco, 2016), but none of these studies used UTAUT2 model even though it is confirmed that UTAUT2 model has many strong benefits compared to other technology adoption models. We suppose that one of the reasons why some of the hypotheses in the initial research model were not confirmed is that some of antecedents that are insignificant in the overall model may have a stronger effect for specific categories of mobile applications. For example, Hong, Cao & Wang (2016) reported significant effect of herd behavior for social mobile applications. While in our study herd behavior didn't confirm to be significant for all types of mobile applications, the importance of this factor for social mobile apps still needs to be researched more extensively. Similarly to this, we would suggest that effort expectancy, which did not confirm to be significant for all types of mobile applications, may still have an influence on adoption of finance and banking or shopping mobile apps, as it was confirmed in the study by Verissimo (2015). Such development of the UTAUT2 research base would allow for deeper understanding of how consumers perceive mobile applications and would test and generalize our findings on the different antecedents for utilitarian and hedonic mobile applications.

In our study we took into consideration only the general influence of Online Rankings and Reviews. In the questionnaire we asked our respondents if they checked the online rankings and reviews of their mobile application and if they wanted to adopted the mobile application because it

ranked high and had good reviews. For the future research a recommendation would be to look into the influence of negative Online WOM on the user intention to adopt mobile applications (Liang et al., 2016). Moreover, Huang & Korfiatis (2015) run a test that showed how online reviews of mobile applications influence user judgments about app experience during trial period. Among other attributes that influence the app sales, researchers also reported the *price (paid/free subscription basis)*, that also moderates the importance of online reviews for the purchase (Huang & Korfiatis , 2015). This can be another potential area for future research and extension of UTAUT2 model for mobile applications.

For the purpose of our study we wanted to focus on more mature group of mobile application users and that is why we targeted students in our research. Such approach allowed us to test the model on a more experienced and mature group of users. Yet, focusing only on young people limits the generalizability of the study. Young people and students in terms of technology adoption are recognized to fit into the "Innovators" segment. Users in this segment look mainly for low cost and convenience (Pagani, 2004). Such characteristics of this group correspond to our findings, where we confirmed that Performance Expectancy, Price Value and Habit are main determinants of mobile application adoption among Norwegian students. Hew et al. (2015) in their UTAUT2 adoption study by for the less mature mobile application market in Malaysia, revealed different results where Effort Expectancy and Hedonic Motivation were also important antecedents for mobile app adoption. Such contrasting results show that the same factors may have different power for the users depending on their level of experience with mobile applications and depending on the maturity of the market. It makes sense that on the market where mobile applications are just introduced, users have more interest in entertaining and fun part of mobile apps and it also requires them more effort to adopt mobile applications. At the same time, once he market becomes more experienced – users focus more on the potential performance and benefits that mobile application offers them. That is why, for the future research we suggest testing the model for new groups of users and on new markets, differentiating between different level of experience with mobile applications and different age groups.

Another suggestion for the future research would be to test the model in the experiment setting instead of a survey setting. This will allow observing the actual user reactions on different factors and how these reactions influence the attitude towards adoption of mobile application. One of potential reasons for why the hypotheses about positive influence of Herd Behavior and Online Rankings and Reviews on the Behavioral Intention didn't confirm is that the measurement items for these variables were self-reported. The measurement items were framed in the way that can be not consistent with the respondent's self-esteem. Specifically, to measure Herd Behavior we used items where respondents had to admit that they followed others in making their decision and that they

didn't make their decision based on their own preferences and knowledge. These are quite strong negative statements that may not be consistent with the respondent's personal self-esteem and perceptions of their independence and freedom to make decisions. The method of self-reported questionnaires is widely criticized in the research literature for a number of reasons that are hard to control even in the structural equation modeling (Spector, 1994). Earlier research that confirmed the positive influence of Online Rankings and Reviews on the Behavioral Intention measured the relationships and results with the help of analysis of downloads on the app stores such as multifacet sentiment analysis of the data from Apple Store (Liang et al., 2016) and Google Play (Hyrynsalmi et al., 2014). This means that Online Rankings and Reviews may still have a positive influence on the Behavioral Intention to adopt mobile applications, but the users may not be completely aware of these influences.

Finally, we would like to emphasize that our review of mobile app adoption studies indicated that there are more variables that may have potential influence on the adoption process of mobile applications and can be used for the extended UTAUT2 model. They were not tested in our model but are recommended for exploration in the future research. Among these variables we would like to pinpoint privacy and perceived risk described by Han, Wu & Winsdor (2014), personalization and customization (Morosan, & DeFranco, 2016), personal innovativeness (Morosan, & DeFranco, 2016), personal technology traits (Yang, 2012), comparison of paid and free mobile applications (Liang et al., 2015), technological features of mobile applications such as storage capacity and compatibility (Oghuma et al., 2015) etc. There are also several suggestions that may help the researcher deal with a complex nature of mobile applications. For example, following the logic established by Liang et al. (2015) and differentiating between the product and the service nature of mobile application could help the researchers understand what features of mobile applications are important for all types of mobile apps and what features are connected with specific service that mobile app provides to the user. Zhao & Balague (2015) suggested three main building blocks of mobile application features: mobile features, social features and brand features. In our study we partially covered mobile and social features, but we didn't not research the brand features. Thus, one of the directions for future research would be also to group the features described as suggested by Zhao & Balague (2015) and test the influences of these features according to the groups.

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# Appendix A

*Questionnaire*

**Page 1.**
Introduction

Dear respondent, thank you for your participation!
The following survey was prepared by Viktoriia Vinnik, master student at Norwegian School of Economics (NHH).
The survey is part of my master thesis work.

It will take you approximately 7 minutes to complete the survey. Your response is anonymous. It is voluntary to answer the questionnaire and you can drop out from the survey at any point.
For questions and comments feel free to send an email to Viktoriia.Vinnik@student.nhh.no .

The topic of my master thesis is mobile applications.
Some of the questions may look a bit similar. This is done on purpose to ensure valid results. To make your response valuable for the research, please answer all the questions as carefully as possible.

**Page 2.**
Control Variables

Please, think about and choose for this survey a mobile app you have recently downloaded on your phone. Answer the following questions related to this app.

What is the category of this app?

| Finance, banking and insurance | Travel and Life | Hobbies | Social and Communication | Tools and productivity | Shopping | Casual reading | Entertainment and Sports | Games and Music | Health and Fitness |
|---|---|---|---|---|---|---|---|---|---|
| ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

**Page 3.**
Please think about the app you have chosen and answer the following questions. Feel free to use the whole scale.

Performance Expectancy

How would you describe the performance of this mobile application?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| I find this mobile application useful in my everyday life | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Using this mobile application increases my chance of achieving things that are important to me | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Using this mobile application helps me accomplish things more quickly | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

Social Influence

What do people who are important to you think about this mobile application?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| People who are important to me think that I should use this mobile application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| People who influence my behavior think that I should use this mobile application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| People whose opinions I value prefer that I use this mobile application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

**Page 4.**
Keep thinking about the app you have chosen and answer the questions below. Feel free to use the whole scale.

Effort Expectancy

How much effort does it take you to use this application?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| Learning how to use this mobile application is easy for me | | | | | | | |
| My interaction with this mobile application is clear and understandable | | | | | | | |
| I find this application easy to use | | | | | | | |
| It is easy for me to become skillful at using this mobile application | | | | | | | |

Facilitating Conditions

Do you feel like you have the necessary conditions and infrastructure to use this app?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| I have the resources necessary to use this mobile application | | | | | | | |
| I have the knowledge necessary to use this mobile application | | | | | | | |
| This mobile application is compatible with other technologies I use | | | | | | | |
| I can get help from others when I have difficulties with using this mobile application | | | | | | | |

**Page 5.**
Please think about the app you have chosen and answer the following questions. Feel free to use the whole scale.

Hedonic Motivation

How would you describe the pleasure of using this mobile application?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| Using this mobile application is fun | | | | | | | |
| Using this mobile application is enjoyable | | | | | | | |
| Using this mobile application is very entertaining | | | | | | | |

Price Value

Does this application deliver value for money?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| This mobile application is reasonably priced | | | | | | | |
| This application is a good value for its price | | | | | | | |
| At the current price this mobile application provides good value | | | | | | | |

**Page 6.**
Please think about the app you have chosen and answer the following questions. Feel free to use the whole scale.

Habit

Is using this app a habit for you?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| The use of this mobile application has become a habit for me | | | | | | | |
| I am addicted to using this mobile application | | | | | | | |
| I must use this mobile application | | | | | | | |

Online rankings and reviews

Do you know what ratings and feedbacks this app has online?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| I checked the online ratings and reviews when I searched for this application | | | | | | | |
| I accepted this mobile application because it ranks high on the app store | | | | | | | |
| I accepted this mobile application because it had many positive online comments and reviews | | | | | | | |
| I accepted this mobile application because it was listed on mobile app top charts | | | | | | | |

**Page 7.**
Please think about the app you have chosen and answer the following questions. Feel free to use the whole scale.

Herd behavior

When making your choice, do you consider how popular this app is on the market?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| If this mobile application seems to be a dominant mobile app on the market I would like to use it as well | | | | | | | |
| I followed others in accepting this mobile application | | | | | | | |
| I choose to accept this mobile applications because I see that other people use it | | | | | | | |

When making your choice to use this mobile application, to what extent do you rely on your own knowledge and information?

| | Strongly disagree | Disagree | Somewhat disagree | Niether agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| My acceptance of this mobile application did not reflect my own preferences for mobile applications | | | | | | | |
| I did not make the decision based on my own research and information when choosing this mobile application | | | | | | | |
| If I didn't know that a lot of people have already accepted this mobile application, I could choose another one | | | | | | | |

**Page 8.**
Please think about the app you have chosen and answer the following questions. Feel free to use the whole scale.

Behavioral Intention

Do you intend to continue using this app?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| I intend to continue using this mobile application in the future | | | | | | | |
| I will always try to use this mobile application in my daily life | | | | | | | |
| I plan to continue to use this mobile application frequently | | | | | | | |

**Page 9.**
Demographics

Please, indicate your age

What is your gender?

- Male
- Female

What is your highest education level?

- Primary school
- Secondary school
- University/college ≤ 3 years
- University/college > 3 years

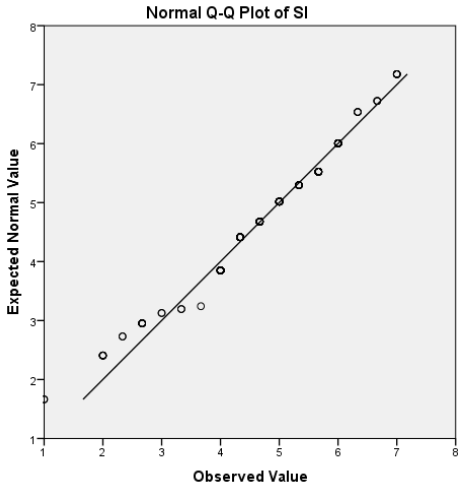
How would you describe your experience with using mobile apps?

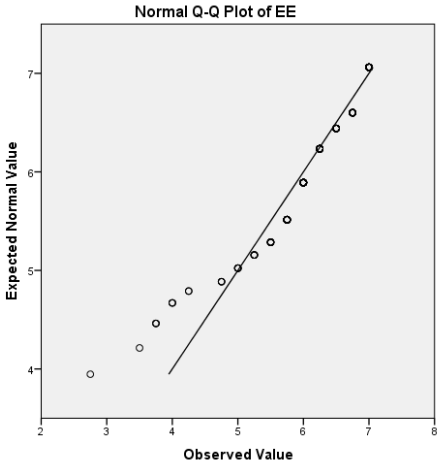
| 1. Very little experienced | 2 | 3 | 4 | 5 | 6 | 7. Very experienced |
|---|---|---|---|---|---|---|

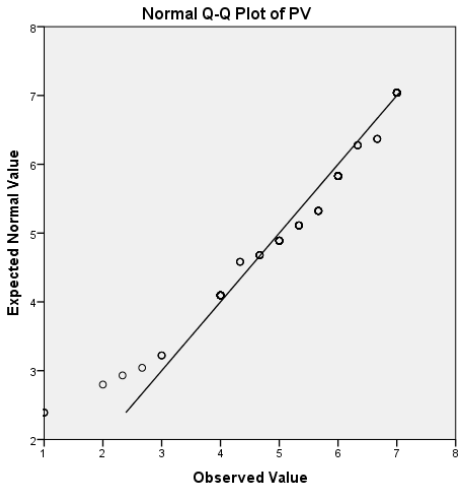
Your response has been recorded. Thank you!

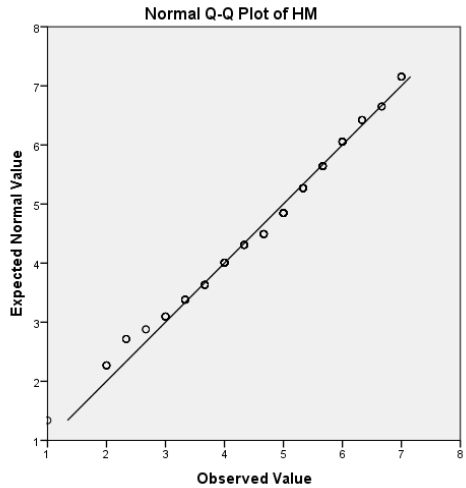
# Appendix B

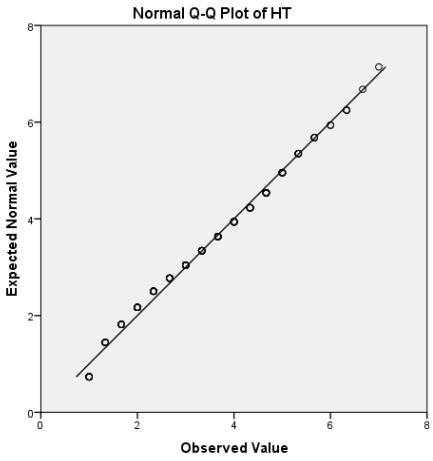
*Normality test*

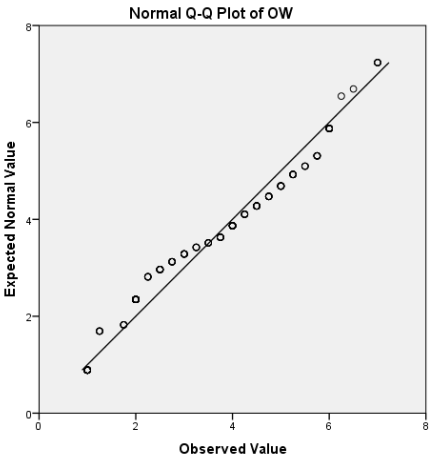


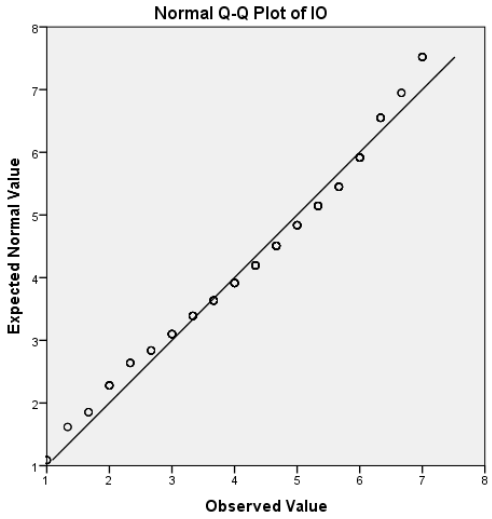



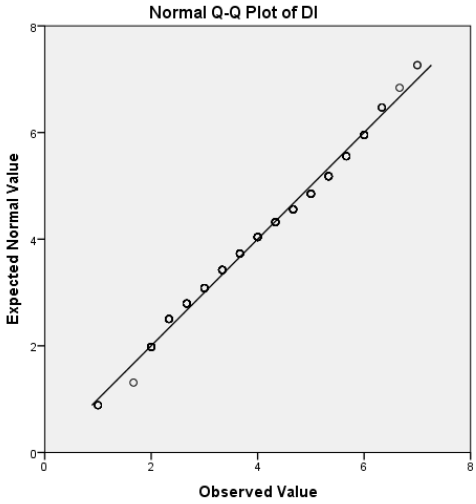



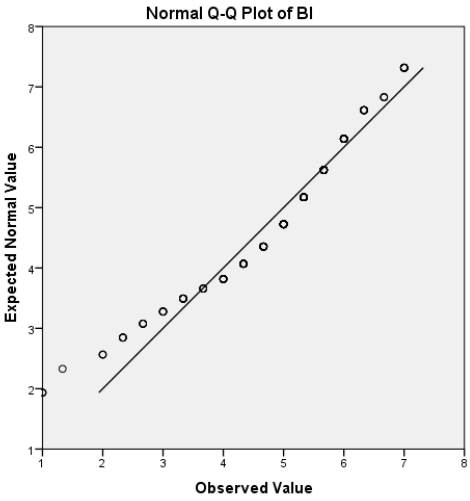



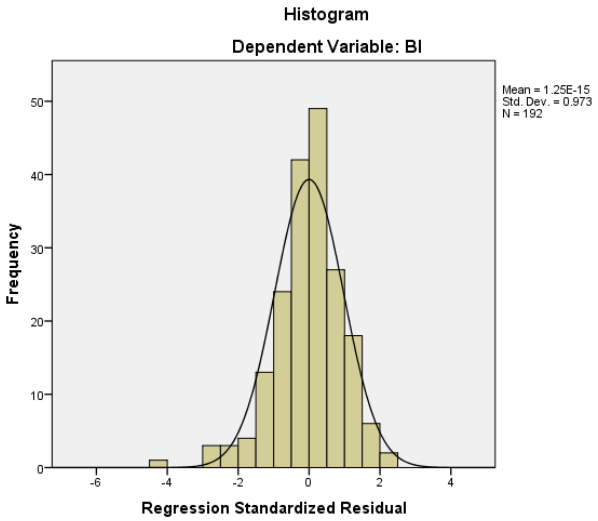




Normal Q-Q Plot of IO
Expected Normal Value
Observed Value


Normal Q-Q Plot of DI
Expected Normal Value
Observed Value


Normal Q-Q Plot of BI
Expected Normal Value
Observed Value


Histogram
Dependent Variable: BI
Mean = 1.25E-15
Std. Dev. = 0.973
N = 192
Frequency
Regression Standardized Residual

# Appendix C

*Collinearity diagnosis*

| | Collinearity Statistics | |
|---|---|---|
| **Model** | **Tolerance** | **VIF** |
| PE | .747 | 1.339 |
| SI | .711 | 1.407 |
| EE | .704 | 1.420 |
| FC | .636 | 1.572 |
| HM | .859 | 1.164 |
| PV | .844 | 1.184 |
| HT | .777 | 1.287 |
| OW | .797 | 1.255 |
| IO | .631 | 1.585 |
| DI | .725 | 1.378 |

a. Dependent Variable: BI

# Appendix D

Table 1
*Collinearity diagnosis for Utilitarian mobile apps*

| Model | Tolerance | VIF |
|---|---|---|
| PE | .775 | 1.291 |
| SI | .750 | 1.333 |
| EE | .591 | 1.692 |
| FC | .548 | 1.825 |
| HM | .840 | 1.190 |
| PV | .876 | 1.142 |
| HT | .732 | 1.365 |
| OW | .941 | 1.063 |

Table 2
*Descriptive statistics for Utilitarian mobile apps*

| | | PE | SI | EE | FC | HM | HT | PV | OW | BI |
|---|---|---|---|---|---|---|---|---|---|---|
| N | Valid | 128 | 128 | 128 | 128 | 128 | 128 | 128 | 128 | 128 |
| | Missing | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Mean | | 5.1589 | 4.6536 | 6.1738 | 6.2383 | 4.5833 | 3.4844 | 5.5130 | 3.3691 | 5.0260 |
| Std. Error of Mean | | .10930 | .10648 | .06880 | .06538 | .09803 | .12317 | .11715 | .15701 | .11424 |
| Median | | 5.3333 | 4.6667 | 6.2500 | 6.0000 | 5.0000 | 3.3333 | 6.0000 | 3.0000 | 5.3333 |
| Std. Deviation | | 1.2366 | 1.20469 | .77837 | .73967 | 1.1091 | 1.39356 | 1.32537 | 1.77637 | 1.29242 |
| Variance | | 1.529 | 1.451 | .606 | .547 | 1.230 | 1.942 | 1.757 | 3.155 | 1.670 |
| Skewness | | -1.088 | -.435 | -1.440 | -1.340 | -.447 | .121 | -.938 | .261 | -.824 |
| Kurtosis | | 1.051 | .220 | 3.208 | 3.083 | -.246 | -.558 | .840 | -1.187 | .459 |
| Minimum | | 1.33 | 1.00 | 2.75 | 3.00 | 2.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Maximum | | 7.00 | 7.00 | 7.00 | 7.00 | 7.00 | 7.00 | 7.00 | 7.00 | 7.00 |

Table 3
*Collinearity diagnosis for Hedonic mobile applications*

| Model | Tolerance | VIF |
|---|---|---|
| PE | .651 | 1.535 |
| SI | .743 | 1.346 |
| EE | .853 | 1.172 |
| FC | .814 | 1.229 |
| HM | .855 | 1.170 |
| PV | .714 | 1.400 |
| HT | .786 | 1.272 |
| OW | .889 | 1.125 |

Table 4
*Descriptive statistics for Hedonic mobile applications*

| | | PE | SI | EE | FC | HM | PV | HT | OW | BI |
|---|---|---|---|---|---|---|---|---|---|---|
| N | Valid | 64 | 64 | 64 | 64 | 64 | 64 | 64 | 64 | 64 |
| | Missing | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Mean | | 4.8958 | 4.6354 | 6.0430 | 6.2969 | 5.0521 | 5.5313 | 3.1146 | 2.9805 | 4.8438 |
| Std. Error of Mean | | .19215 | .14371 | .10602 | .08162 | .18143 | .16090 | .16981 | .20843 | .15250 |
| Median | | 5.3333 | 4.5000 | 6.0000 | 6.0000 | 5.3333 | 5.8333 | 3.0000 | 2.7500 | 5.0000 |
| Std. Deviation | | 1.53716 | 1.14968 | .84815 | .65295 | 1.45141 | 1.28719 | 1.3585 | 1.66744 | 1.22001 |
| Variance | | 2.363 | 1.322 | .719 | .426 | 2.107 | 1.657 | 1.846 | 2.780 | 1.488 |
| Skewness | | -1.292 | -.462 | -1.109 | -.565 | -.625 | -.898 | .202 | .476 | -1.217 |
| Kurtosis | | 1.053 | .962 | 1.377 | -.308 | -.078 | 1.091 | -.888 | -.832 | 2.111 |
| Minimum | | 1.00 | 1.00 | 3.50 | 4.50 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Maximum | | 7.00 | 7.00 | 7.00 | 7.00 | 7.00 | 7.00 | 6.33 | 7.00 | 7.00 |