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DELIVERY ROBOTS FROM UTAUT2 PERSPECTIVE IN FINLAND

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UNIVERSITY OF OULU ABSTRACT OF THE MASTER'S THESIS
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Abstract

The purpose of this thesis is to enhance knowledge of peoples' intentions to use delivery robots. Significant growth in e-commerce, high costs of last mile deliveries, and rising customer expectations of delivery conditions are pushing companies to find new solutions for last mile deliveries. Innovation can be more efficient and more sustainable, but it will only be a success if the audience accepts it. Therefore, it is important for logistics, retail, and marketing professionals to understand the factors that influence on consumers' intentions to use delivery robots to be able to design, develop, and promote delivery robots properly. To fulfill the purpose of the study a main research question "Which factors influence on consumers' intentions to use delivery robots in Finland?" will be answered.

The research was limited to Finland to keep the study manageable and to enhance the knowledge of Finnish professionals in the field of delivery robots. The topic is also very current as the first delivery robots in Finland have been in use only a short time and only in a limited area of certain cities. Existing studies have suggested that behavioral intention is the main predictor of use behavior, and due to the novelty of delivery robots in Finland behavioral intention is the main dependent construct in this study.

The theoretical framework of this study is based on Autonomous Delivery Vehicle Acceptance Model (ADVAM) that has a strong basis in Unified Theory of Acceptance and Use of Technology (UTAUT2) model in consumer context. This technology acceptance model is applicable in quantitative research which is why the quantitative research method for this study was chosen. Based on the theoretical model eight hypotheses were formed to answer the research question. To perform the empirical study a survey was conducted using Webropol's survey tool. The data was gathered for one week period with anonymous survey where the survey link was sent through different social media channels. Total of 115 responses were collected and analysed with SPSS Statistics and SPSS Amos software using confirmatory factor analysis.

Based on the analysis performed social influence and price sensitivity revealed to have the strongest influence on intentions to use delivery robots among respondents. Additionally, effort expectancy was proven to have slight positive influence on the behavioral intention. However, facilitating conditions and perceived risk did not have significant influence on the intentions to use delivery robots. Similarly, age, gender and earlier use of delivery robots did not have significant effect on behavioral intention. The constructs of hedonic motivation and performance expectance needed to be removed from the model as first the model yielded a poor fit. Meaning, the original theory-based model did not have good reliability in this study. The results can't be directly generalized to Finnish population as the respondent sample did not fully represent Finnish demographics. Overall, the results of this study provide more information and knowledge about relatively new delivery concept, supplementing the existing knowledge gap of peoples' acceptance of delivery robots.

Keywords
Delivery robot, consumer acceptance, last mile, autonomous delivery vehicles, UTAUT2

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1 INTRODUCTION

This chapter introduces the thesis topic. Following, the purpose of the study as well as research question is addressed. In addition, the research process is determined. The chapter ends with introducing the structure of this thesis.

1.1 Review to thesis topic

E-commerce is one of the most remarkable outcomes in the era of internet and is seen as a major factor in the 21st century. E-commerce entails buying and selling of goods and services, with an enormous growth during the last 10 years. The growth in the use of smartphones and extended use of internet have enabled e-commerce to go mobile. Resulting quicker purchase decisions due to ease access, as smartphones are with the users all the time. One of the most emerging e-commerce trends during pandemic was the growth of grocery e-commerce as people started to order food home. Resulting, many retail stores introduced delivery services to response to the needs of people. (Techblocks, 2022.) In Finland, e-commerce has increased notably as well and continues to grow. It is recognized that many industries are still unfinished with their development of digitalization, for instance grocery stores are seen to have lot of potential to grow still. (Marttila, 2023.) Rapidly expanding e-commerce has shown a challenge for logistic service providers in last mile delivery (Ouyang, 2023). Resulting, new solutions for last mile delivery services are sought, such as delivery robots (Kapser & Abdelrahman, 2020).

In the beginning of 20th century, the concept of robotics entered the popular consciousness through a story written by the Czech brothers. In literary, robots have often been depicted as man's enemy. The transition from science fiction to reality occurred in 1950s when General Motors introduced a robot to assist in automobile production. (Hockstein et al., 2007.) Since then, robots have created worries for workers in a sense that robots are feared to replace human work and lead to shortened working hours (Calfas, 2019). However, robots are also generally seen to improve efficiency, accuracy, and customer satisfaction (Hockstein et al., 2007; Kapser & Abdelrahman, 2020). Citizens of developed countries already benefit from the advances of robotics in everyday life. Manufacturing, service, logistics and healthcare industries have all incorporated robotics to improve efficiency and accuracy. Robots help to, for instance, build machines, package foods, perform surgeries and deliver goods. (Hockstein et al., 2007; Starship 2023.)

As mentioned, retail and logistics industries have been motivated to develop their activities due to dramatic growth in e-commerce (Vakulenko et al., 2019). The final stage of transportation, last mile delivery, has been a key success factor to achieve customer satisfaction and increased market share for logistics providers (Chen et al., 2021). However, last mile delivery is the most cost-intensive part of supply chain due to high labor costs (Gevaers et al., 2011; Zofkie, 2023). Additionally, customers are looking for flexible options for the time and place of delivery, conditions of purchase and more convenient methods of collecting and returning their shipments (Michałowska et al., 2015). In response to growing e-commerce, last mile challenges and customer demands new solutions for delivery services are needed. New trends are rising such as drones and autonomous delivery vehicles (Joerss et al., 2016), which are believed to have potential to revolutionize the market of last mile delivery, and as such make the delivery more sustainable, more efficient, and perhaps even more customer focused (Kapser & Abdelrahman, 2020). Additionally, many researchers expect the increasing use of robots to be one of the most important trends in marketing in the coming years (Li & Wang, 2022).

Globally the first commercial delivery robots in last mile deliveries were taken into use in 2018 by Starship Technologies (Starship, 2023a). In Finland the first Starship delivery robots were taken into use in 2022. Starship delivery robots were first launched in Espoo in Finland and have now been launched in other cities as well, Oulu being the northernmost one (S-kaupat, 2023). In addition to Starship Technologies, there are also other companies providing delivery robot services. For instance, Robomart (2023) is providing self-driving stores where they have offering for cafes, shops, restaurants, and grocery stores. However, these self-driving stores are yet not operating in Finland.

In Finland, as well as globally, delivery robots have been in use relatively short time. And in general, there is very little research on consumer acceptance of new service innovations in the field of last mile deliveries (Kapser & Abdelrahman, 2020). To examine this matter in Finland the Autonomous Delivery Vehicle Acceptance Model (ADVAM) by Kapser and Abdelrahman (2020) is used. ADVAM is a modified version of widely used extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model by Venkatesh et al. (2012).

1.2 Purpose of the study and research question

Significant growth in e-commerce, high costs of last mile deliveries, and rising customer expectations of delivery conditions are pushing companies to find new solutions for last mile deliveries (Vakulenko et al., 2019; Gevaers et al., 2011; Michałowska et al., 2015). Especially, in the matter of finding more sustainable, more customer focused and less expensive solutions (Kapser & Abdelrahman, 2020; Zofkie, 2023). In general, acceptance is an important aspect of technological innovation. Even though an innovation can be more efficient and more sustainable, the innovation will be a success only if the audience accepts it. (Arntz et al., 2023.) The user acceptance in this study is represented by the behavioral intention to use delivery robots as done also in previous studies (Kapser & Abdelrahman, 2020; Väisänen, 2015). Existing studies have suggested that behavioral intention is the main predictor of use behavior (Venkatesh & David, 2000; Kapser & Abdelrahman, 2020), and is therefore used as a main dependent construct in this study due to the novelty of delivery robots in Finland.

As outlined, it is important to understand the factors that influence on consumers' intentions to use delivery robots to be able to design, develop, and promote delivery robots properly. However, the existing knowledge of delivery robots among consumers is very limited. (Kapser & Abdelrahman, 2020.) Therefore, to enhance the knowledge of peoples' intentions to use delivery robots and to response to the needs in the field of last mile deliveries, this thesis examines the factors that are affecting on consumers' intentions to use delivery robots in Finland. Therefore, the main research question for the thesis is represented as following.

Which factors influence on consumers' intentions to use delivery robots in Finland?

With this research question this study aims to supplement the knowledge of delivery robots and consumers. The scope of the study is limited to Finland to keep the study manageable, and to enhance the knowledge of Finnish retail, logistic and marketing professionals in the field of delivery robots. The topic is also very current in Finland as the first delivery robots in Finland have been in use only a short time and only in a limited area of certain cities. The study proposes a theoretical framework, in addition to which empirical research will be done to answer above research question. The research will assist logistics and retail professionals in research and planning as well as marketing professionals in gaining consumers' acceptance. As outlined earlier, delivery robot in last mile delivery is relatively new concept and is yet relatively little researched. Therefore, the purpose of this study is to enhance understanding around these relatively new last mile solutions.

1.3 Introduction of delivery robots

As outlined before, there are different companies that are providing delivery robot services in last mile deliveries. In this subchapter Starship delivery robots and Robomart self-driving stores are introduced to demonstrate what kind of delivery robots are the robots that this study concentrates on.

1.3.1 Starship delivery robots

Starship Technologies was launched in 2014 and the company is using autonomous delivery robots for local deliveries (Figure 1). Delivery robots are delivering food and package deliveries in short distances, and already millions of autonomous deliveries have been completed. The company has its headquarters in San Francisco, and engineering offices in Estonia, United Kingdom, and Finland. The first Starship delivery robots in Finland were launched in Espoo in April 2022. Additionally, in May 2023 Starship Technologies announced partnership with Finnish S-Group. (Starship, 2023a.) The use of Starship robots has expanded in Finland during 2023 and are now operating in the cities of Helsinki, Espoo, Vantaa, Tampere, Turku, Pori, Rauma, Jyväskylä and Oulu, Oulu being the northernmost city (S-kaupat, 2023).

Figure 1. Starship delivery robot (Starship, 2023b)

Starship robots have sensors and cameras to enable each one to see where it is going. The traveling speed is equivalent to pedestrian walking speed, and the created technology enables them to navigate around objects and people. The robots are battery-powered, which provide an energy-efficient and environmentally friendly solution to last mile delivery. In case of vandalism, a loud alarm will sound. Robots are also GPS tracked and it can only be unlocked by the customer at the delivery destination. Placing a robot food delivery order, customer needs to download the Starship food delivery application, which is available on iOS and Android. Or alternatively, to download the retailer's application such as S-kaupat in Finland and choose delivery robot as a delivery method (S-kaupat, 2023). After that the delivery address needs to be addressed and purchases browsed, after which the order can be placed. The customer can track Starship robot's journey and if wanted, also add a song for the robot to sing upon arrival. (Starship, 2023a.)

1.3.2 Robomart self-driving stores

Robomart was found in 2018 by professionals of robotics, retail, and deliveries. The company launched the world's first store-hailing service in 2020, and now they have two different solutions: Oasis and Haven. Oasis has a nimble offering for cafes, shops, and restaurants. Haven was recently introduced, and it has a larger format offering for grocery chains. These solutions are customizable for different kind of products such as heated, frozen, and refrigerated food. (Robomart, 2023a.)

To use Robomart customer needs to download the Robomart application, browse the purchases and order Robomart to wanted address. When the Robomart arrives, customer can open the door with the application and pick the purchased products. All removed products are tracked, and cameras used to secure the process. Once shopping is completed, purchases will be charged from customer from the credit card added in the Robomart application. (Robomart, 2023b.)

1.4 Research process

The research process started with choosing a research topic. Working in the field of logistics and robotics in last mile deliveries being relatively new concept, I chose to study delivery robots among consumers in Finland. After the topic was chosen and research question addressed, the literature review was conducted to establish the theoretical framework. The literature for the theoretical research was searched from Google Scholar, Oula-Finna, and other databases such as ProQuest. The literature used consists of academic journals, papers, articles, e-books, videos, and websites. The research started first broadly and quite quickly narrowed to focus on relevant information. Based on the literature review the theoretical framework was decided to build on widely used Venkatesh's et al. (2012) extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model, with certain modifications by Kapser & Abdelrahman (2020), to make it suitable for this study. The modified model ADVAM by Kapser and Abdelrahman (2020) is specifically suggested to use in the field of technology acceptance of autonomous delivery options. Throughout the above-described literature research the research question became more accurate.

The ADVAM, that was decided to use in this study, is applicable in quantitative research. As common for quantitative study, the hypotheses were determined based on existing studies and theories, which are then tested by the experiment (Swanson & Holton, 2005). Therefore, to be able to answer to the research question of this study, quantitative research is conducted by collecting data with a survey. Surveys are widely used by many scholars due to their lower costs, ability to reach masses and ease of adaptation (Gürbüz, 2017). The survey of this study consists of cover letter, respondent's profile, information sheet and survey questions. Questions are based on ADVAM model, that has a strong base in UTAUT2 model, to make the study convenient for examining delivery robots that are not yet widely used. In the survey 7-point Likert scale is used ranging from 1 = 'Strongly disagree' to 7 = 'Strongly agree'. The survey is conducted in Finnish and shared through an anonymous link in social media channels: WhatsApp, Instagram, and Facebook. The empirical data is collected for one week after which the survey will be closed. The results of the survey are analyzed in SPSS Amos software using confirmatory factor analysis and presented in more detail in the third chapter of this thesis.

1.5 Structure of the study

This thesis consists of four main chapters, which are divided into subchapters. The first chapter is introducing reader to the thesis topic, the purpose of research is addressed, and research process determined. The second chapter forms a theoretical framework for this study. In the second chapter the history of chosen theoretical model is introduced and the main constructs of this in question theoretical model explained. Theory chapter justifies the use of chosen theoretical model within this study and refers to previous related studies, as well as presents the hypotheses of the study. The empirical part of the study is covered in third chapter where detailed description of research methods used in this study are explained, and the chosen data collection method, in this case survey, is further explained. Additionally, research analysis and findings are presented in the third chapter. Following, the fourth chapter concludes the study by presenting key results, managerial implications, and limitations. Lastly, future research possibilities are proposed.

2 TECHNOLOGY ACCEPTANCE THEORIES

This chapter covers the theoretical framework of this study. First, related earlier theoretical models, Technology Acceptance Model (TAM) and the extended Unified Theory of Acceptance and Use of Technology Model (UTAUT), are introduced. After that, the chosen theoretical model for this study, Autonomous Delivery Vehicle Acceptance Model (ADVAM), is presented and justified. Lastly, the eight hypotheses for the study are addressed.

2.1 Technology Acceptance Model

In the very beginning when technology entered in people's everyday life, there was a growing need to understand, and there still is, why new technology was accepted or rejected. First theories were grounded in the field of psychology concentrating on peoples' intentions and attitudes. (Marangunic & Granic, 2015.) However, these theories were based on assumption that people are rational and make systematic decisions, but the theories were leaving out the unconscious motives, personality and demographic variables, and the fact that perceived behavior does not always predict actual behavior. These theories could not explain for instance user acceptance or rejection of information systems. (Mathieson, 1991.) Therefore, Davis (1986) refined previous theories and created TAM to predict actual use of any specific technology in organizational context. In TAM the perceived usefulness and perceived ease of use directly influence the intention to use technology. *Perceived usefulness* means how much person recognizes that new technology will help to improve the performance. *Perceived ease of use* is the degree to which the person believes he will use new technology without difficulty. (Davis, 1989.) *Intention to use technology* can be defined as the degree to which the person would like to use the technology in the future (Joo et al., 2018).

Through some years of research, original TAM was extended by Venkatesh and Davis (2000) to include also external variables that effect on usefulness, and therefore also on the intention to use the technology (Figure 2).

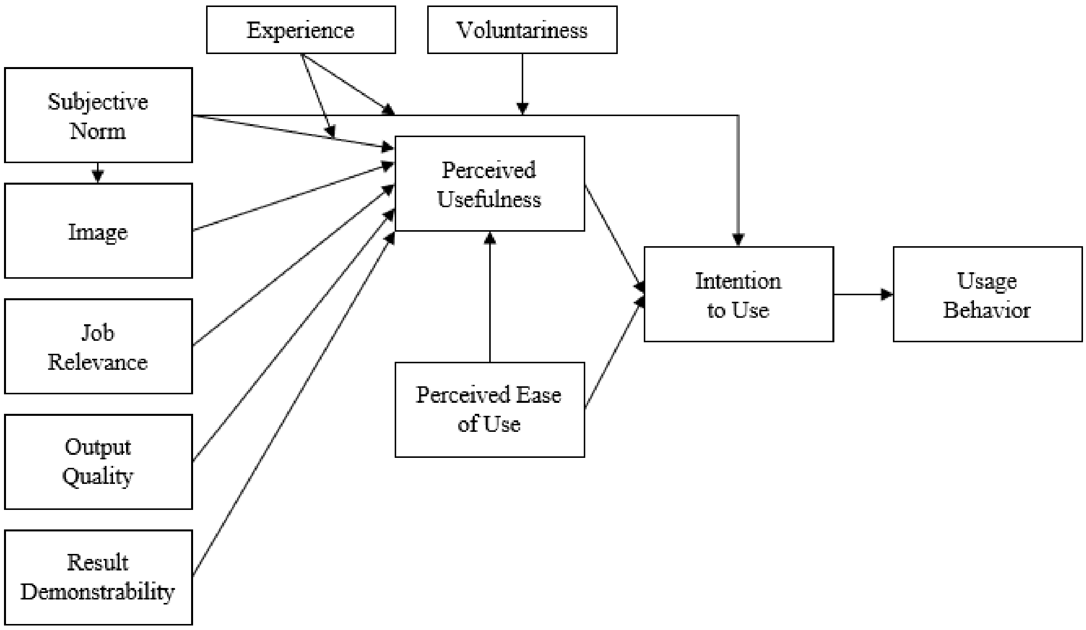


Figure 2. Extended Technology Acceptance Model (TAM2)
(Adapted from the TAM2 model of Venkatesh and Davis, 2000)

This proposed extended model of TAM was named as TAM2 (Venkatesh & Davis, 2000). In TAM2 external variables affecting on usefulness of technology were determined as *subjective norm*; the influence of others on the user's decision to use the technology, *image*; to maintain a favorable standing among others, *job relevance*; the degree to which the technology was applicable, *output quality*; the extent to which the technology adequately performed the required tasks, and *the result*; the production of results. In addition, *experience* and *voluntariness* were included, as the amount of experience influences person's intention to use the technology as well as whether the usage is compulsory or voluntariness. (Venkatesh & Davis, 2000.) Venkatesh and Bala (2008) have also introduced TAM3 where external variables affecting ease of use were discussed. Such as computer self-efficacy, perceptions of external control, computer anxiety, perceived enjoyment, and objective usability.

2.2 The extended Unified Theory of Acceptance and Use of Technology

Over the years of research many competing technology acceptance models have been created. By integrating these competing models, Venkatesh et al. (2003) have formulated a unified model UTAUT to combine technology acceptance literature and to form a unified theory to explain the use and acceptance of technology of individual in organizational context. Earlier created eight models, that UTAUT unifies, are TAM, theory of reasoned action, motivational model, the theory of planned behavior, a model combining the theory of reasoned action and theory of planned behavior, the model of PC utilization, the innovation diffusion theory, and the social cognitive theory. (Venkatesh et al., 2003.)

UTAUT incorporates four constructs that have significant role in user acceptance and usage behavior: *performance expectancy, effort expectancy, social influence and facilitating conditions*. First three constructs are similar with determinants in TAM; performance expectancy is similar to perceived usefulness, effort expectancy is similar to perceived ease of use and social influence is similar to subjective norm. *Facilitating conditions* are defined as the degree to which a person believes that an organizational and technical infrastructure exists to support use of the system, for instance, adequate guidance and instructions. (Venkatesh et al., 2003.) In addition, Venkatesh et al. (2003) confirmed four significant influences of *experience, voluntariness, gender*, and *age* as integral features of UTAUT. It was confirmed that UTAUT was able to account for 70 percent of the variance in usage intention – which was notable improvement compared to any other original eight models. UTAUT has been widely used in different fields of research such as banking (Rahi et al., 2019), health services (Cimperman et al., 2016), and e-learning (Muneer, 2021).

However, UTAUT has also been criticized because it is only discussing technology acceptance in organizational context to explain employee technology acceptance and use (Bouwman et al., 2007). Therefore, Venkatesh et al. (2012) extended the original UTAUT to examine the technology acceptance in consumer technology context and proposed UTAUT2 (Figure 3). The expanded model introduces three new constructs: hedonic motivation, price value and habit. *Hedonic motivation* is defined as the enjoyment and pleasure derived from using the technology. *Price value* is about cost and pricing structure that may have a significant impact on consumer's technology use. Price value has an important difference between UTAUT and UTAUT2 as consumers usually bear the monetary cost of such use whereas employees do not. *Habit* is defined as the extent to which individual will perform a behavior automatically because of learning. Additional difference to UTAUT is leaving out voluntariness from UTAUT2 as it was seen unnecessary in consumer context. (Venkatesh et al., 2012.)

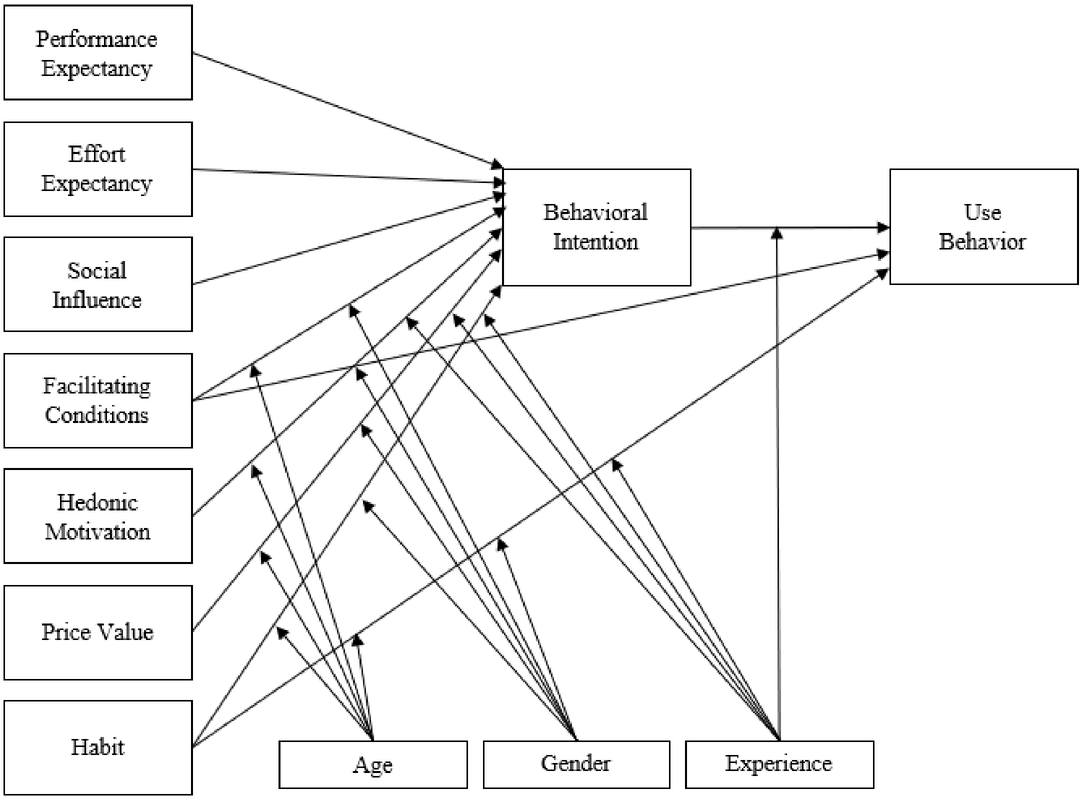


Figure 3. Extended Unified Theory of Acceptance and Use of Technology Model
(Adapted from the UTAUT2 model of Venkatesh's et al., 2012)

Venkatesh et al. (2012) found that hedonic motivation is a critical determinant of behavioral intention and is more important driver than performance expectancy, which was the main driver in employees' technology use in organizational context. In addition, gender, age, and experience, were found to effect on hedonic motivation; motivation on behavioral intention was stronger for younger men with less experience with technology, while older women experienced price value more important. It was also found that facilitating conditions, such as guidance and instructions, was more emphasized within older women. In addition, in consumer context (UTAUT2) the effect of behavioral intention on technology use was moderated by experience with the technology whereas in organizational context (UTAUT) intention had a positive direct effect on use. In UTAUT2 age, gender and experience were moderating the effects of performance expectancy, effort expectancy and social influence on behavioral intention. (Venkatesh et al., 2012.)

2.3 Autonomous Delivery Vehicle Acceptance Model

The knowledge of users' intention to use delivery robots is still very limited. Namely, from the outside vehicle perspective where delivery robots are designed to carry goods only. (Kapser & Abdelrahman, 2020.) Even though UTAUT2 model is applicable to consumer context within technology acceptance, it is not the most convenient model in this study due to the novelty of delivery robots in Finland. Additionally, it does not take into account the risk perception that is suggested to effect on technology acceptance (Zhu & Xie, 2015). Kapser and Abdelrahman (2020) have investigated the acceptance of delivery robots in Germany by modifying the UTAUT2 model to the context of last mile delivery robots. ADVAM by Kapser and Abdelrahman (2020) includes constructs predicting behavioral intention to use delivery robots (Figure 4).

To my best knowledge, Kapser and Abdelrahman (2020) are the first ones to examine acceptance of delivery robots from an outside vehicle perspective where the user is recipient of goods, not the passenger. In their study, the constructs of use behavior and habit were left out as the study was conducted in Germany where delivery robots were not available that time. Therefore, Kapser and Abdelrahman (2020) proposed that behavioral intention is the main dependent construct and is representing the user acceptance of delivery robots. In addition to mentioned practical reason, existing studies suggest that behavioral intention is the main predictor of use behavior (Venkatesh & David, 2000; Kapser & Abdelrahman, 2020). Therefore, behavioral intention will also be applied as a main dependent construct in this study.

Even when delivery robots were not available in Germany, price construct was kept in the study but modified to price sensitivity. Price construct was not wanted to be left out because price in general is considered as an important factor in the competitive market of last mile delivery. (Kapser & Abdelrahman, 2020.) *Price sensitivity*, compared to price value, is more related to consumers' willingness to pay for a product or service (Tsai & LaRose, 2015). In addition, *perceived risk* was included as additional construct as previous studies have found that delivery robots are seen as risky delivery method (Marsden et al., 2018; Braun & Buckstegen, 2017). All these constructs with their validated measuring items are presented in Table 1. Additionally, Kapser and Abdelrahman (2020) examined the effect of demographic characteristics, such as age and gender, on behavioral intentions to use delivery robots.

Even though delivery robots are available in Finland, they have been in use for a very short time and only in a limited area of certain cities (S-kaupat, 2023). Therefore, it is convenient for this study to leave out the constructs of habit and use behavior – as done in the study of Kapser and Abdelrahman (2020). For the same reasons the price sensitivity construct is kept in this study rather than price value construct. And as outlined above, the perceived risk is seen as relevant construct in the field of delivery robots in last mile deliveries, which is why it is included in this study as well. Leading to that, that the ADVAM by Kapser and Abdelrahman (2020) will be used in this study to examine consumers' intentions to use delivery robots in Finland. Additionally, the effect of age and gender on behavioral intentions to use delivery robots in Finland will be examined as done in existing studies (Kapser & Abdelrahman, 2020; Venkatesh et. al., 2012). As discussed earlier, delivery robots are already used in Finland at some level, which is why the effect of earlier use of delivery robots '*Have you used delivery robots before*' will be included in the model similarly as Kapser and Abdelrahman (2020) included the familiarity of delivery robots '*Have you heard about delivery robots before'* to their study. Age, gender, and earlier use of delivery robots are presented as 'characteristics' construct in the adapted model in Figure 4.

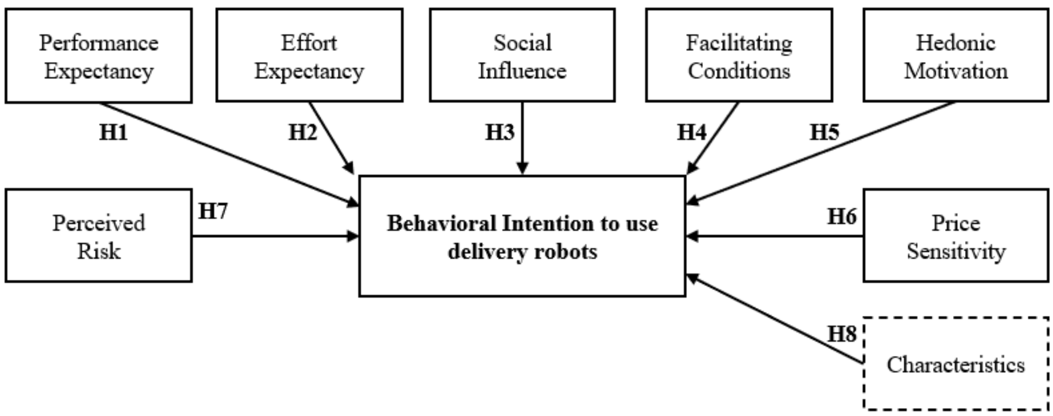


Figure 4. Autonomous Delivery Vehicle Acceptance Model
(Adapted from Kapser & Abdelrahman's model, 2020)

Kapser and Abdelrahman (2020) found that German population has quite neutral acceptance towards the use of delivery robots, which was considered understandable as it is alleged to be common that people have a neutral opinion towards new technologies as they might need some time to form an opinion about the invention (Liu et al., 2019). In the study price sensitivity was the most important construct in acceptance of delivery robots. Additionally, performance expectancy, facilitating conditions, hedonic motivation and social acceptance were proven to influence positively on intentions to use delivery robots. Differing from the study's hypothesis, there was no significant effect of effort expectancy on behavioral intention to use delivery robots found. This result was reasoned to be caused by the familiarity with e.g., mobile applications that are also needed when using delivery robots. Additionally, in that study perceived risk was proven to be an important determinant of users' acceptance of delivery robots, whereas some other studies have found insignificant effect of perceived risk. (Kapser and Abdelrahman, 2020; Liu et al., 2019.) Therefore, the empirical findings of perceived risk can be said to be mixed. In addition to other existing studies and literature, these described findings will be utilized when forming the hypotheses for this study in next subchapter.

Table 1 Constructs and their items

Construct	Items/Questions	Source adapted
Performance Expectancy (PE)	PE1: I find/would find delivery robots useful in my daily life	(Venkatesh et.al., 2012)
	PE2: Using delivery robots increases/would increase my flexibility in my daily life	
	PE3: Using delivery robots helps/would help me accomplish things more quickly	
	PE4: Using delivery robots increases/would increase my productivity	
Effort Expectancy (EE)	EE1: Learning how to use delivery robots is/would be easy for me	(Venkatesh et.al., 2012)
	EE2: It is/would be easy for me to become skillful at using delivery robots	
	EE3: My interaction with the delivery robots via the mobile app is/would be clear and understandable	
	EE4: I find/would find delivery robots easy to use	
Social Influence (SI)	SI1: People who influence my behavior think/would think that I should use delivery robots	(Venkatesh et.al., 2012)
	SI2: People who are important to me think/would think that I should use delivery robots	
	SI3: People whose opinion I value prefer/would prefer that I use delivery robots	
Facilitating Conditions (FC)	FC1: I have the resources necessary to use delivery robots (i.e., smartphone)	(Venkatesh et.al., 2012)
	FC2: I have the knowledge necessary to use delivery robots	
	FC3: Delivery robots are compatible with other technologies I use (e.g., smartphone)	
	FC4: I can get help from others when I have difficulties using delivery robots	
Hedonic Motivation (HM)	HM1: Using delivery robots would be fun	(Venkatesh et.al., 2012)
	HM2: Using delivery robots would be enjoyable	
	HM3: Using delivery robots would be very entertaining	
Perceived Risk (PR)	PR1: Overall, using delivery robots is risky	(Featherman and Pavlou, 2003;

	PR2: Overall, using delivery robots is dangerous	Kapser & Abdelrahman, 2020)
	PR3: Using delivery robots exposes me to an overall risk	
Price Sensitivity (PS)	PS1: I would not mind spending a lot of money for getting my orders delivered by delivery robots	(Goldsmith et al., 2005; Kapser & Abdelrahman, 2020)
	PS2: If I knew that delivery robots as a delivery option were likely to be more expensive than conventional delivery options, that would not matter to me	
	PS3: I could pay a lot money for a really great delivery option	
Behavioral Intention (BI)	BI1: I intend to use delivery robots in the future	(Venkatesh et.al., 2012)
	BI2: I will always try to use delivery robots in my daily life, if possible	
	BI3: I intend to use delivery robots frequently, if possible	

2.4 Research hypotheses

In quantitative study hypotheses are statements that are assumed to answer to the research question of the study. Hypothesis should always be testable with scientific research, and it should be based on previous theories and knowledge. (McCombes, 2023.) Based on the presented theoretical models, existing studies and literature, the hypotheses for this study are formed. The eight hypotheses of this study are built around the nine constructs presented in ADVAM (Figure 4). Hypotheses are also addressed in the Figure 4 from 'H1" to "H8".

Performance expectancy is defined as how much a consumer recognizes that using delivery robots will provide benefits to him (Davis, 1989; Kapser & Abdelrahman, 2020). Performance expectancy has been studied to be one of the biggest influencing factors for predicting behavioral intention in multiple studies. This is the case also in the context of autonomous vehicles acceptance, where it has been studied to be a significant predictor of user acceptance. (Madigan et al., 2017; Rahman et al., 2017; Kapser & Abdelrahman, 2020.) In organizational context Venkatesh et al. (2012) found that performance expectancy was a main driver for technology use. Additionally, in Kapser and Abdelrahman's (2020) study the performance expectancy was a second strongest predictor of behavioral intention to use delivery robots. Therefore, the following hypothesis is proposed:

H1: *Performance expectancy positively influences behavioral intention to use delivery robots.*

Effort expectancy is defined as a degree to which a consumer thinks the use of delivery robots is easy (Davis, 1989). In general, the ease of use has been studied to be influential in many autonomous vehicle acceptance studies (Rahman et al., 2017; Leicht et al., 2018; Choi & Ji, 2015). However, Kapser and Abdelrahman (2020) found in their study that effort expectancy did not have significant effect on consumers' intention to use delivery robots. Additionally, technology has spread everywhere, and it has become a part of peoples' everyday lives. People are adapting technology faster and faster. (MinnaLearn, 2023.) Therefore, the following hypothesis is proposed:

H2: *Effort expectancy does not have a significant influence on behavioral intention to use delivery robots.*

Social influence is defined as to what extend the user perceives that other important people believe he should use the delivery robots (Venkatesh & Davis, 2000; Venkatesh et al., 2012). Social Influence has been proven to be a significant predictor in other autonomous vehicle acceptance studies (Madigan et al., 2017; Rahman et al., 2017; Leicht et al., 2018), and it has been proven to be likely that consumers are influenced by their peers in the context of autonomous vehicles (Kapser & Abdelrahman, 2020). Additionally, Kapser and Abdelrahman (2020) found that social influence had a positive influence on German's intentions to use delivery robots. Therefore, the following hypothesis is proposed:

H3: *Social influence positively influences behavioral intention to use delivery robots.*

Facilitating conditions is defined as the degree to which consumers believe that resources and support is available to use the delivery robots (Venkatesh et al., 2003; Venkatesh et al., 2012). It is stated that users have different levels of access to information and resources that eases their use of delivery robots, and that consumers with poorer facilitating conditions have lower intentions to use delivery robots. Additionally, within Germans facilitating conditions had a significant influence on intentions to use delivery robots. (Kapser and Abdelrahman, 2020.) Therefore, the following hypothesis is proposed:

H4: *Facilitating conditions positively influence behavioral intention to use delivery robots.*

Hedonic motivation is defined as the enjoyment and pleasure gained from using the delivery robots. It has been found that hedonic motivation is a critical determinant of behavioral intention, even more critical than performance expectancy in consumer context. (Venkatesh et al., 2012). Additionally, Kapser and Abdelrahman (2020) found that hedonic motivation is an important factor in the acceptance of delivery robots. Therefore, the following hypothesis is proposed:

H5: *Hedonic motivation positively influences behavioral intention to use delivery robots.*

Price sensitivity is defined as consumers' willingness to pay for a product or service (Tsai & LaRose, 2015), or as consumers' reactions to price and price changes (Goldsmith et al., 2005). The construct of price value was modified to price sensitivity by Kapser and Abdelrahman (2020) because delivery robots were not yet in use in Germany. It was found that price sensitivity had the most significant, negative, effect on the intentions to use delivery robots in Germany. (Kapser and Abdelrahman, 2020.) Additionally, price sensitivity has been proven influential in previous acceptance studies as well (Goldsmith et al., 2005). Therefore, the following hypothesis is proposed:

H6: *Price sensitivity negatively influences behavioral intention to use delivery robots.*

Perceived risk can be defined as overall "potential for loss in the pursuit of a desired outcome" of using delivery robots (Featherman & Pavlou, 2003). Delivery robots are seen as potential safety risks while self-driving on public roads or while dropping of the delivery (Kapser & Abdelrahman, 2020). The studies of perceived risk in the context of autonomous vehicles are mixed. In some studies, the perceived risk has been proven to have significant effect on user's acceptance, whereas some studies have found insignificant effect. In Germany the perceived risk had a significant negative effect on peoples' intention to use delivery robots. (Kapser & Abdelrahman, 2020.) Therefore, the following hypothesis is proposed:

H7: *Perceived risk negatively influences behavioral intention to use delivery robots.*

Characteristics in this study consists of age, gender, and earlier use of delivery robots. Kapser and Abdelrahman (2020) found that demographic characteristics did not have significant influence on Germans' intention to use delivery robots. Only the familiarity of delivery robots had influence on Germans' intentions to use delivery robots. However, delivery robots in Finland have been in use since 2022 and have been widely discussed for instance in media (S-kaupat, 2023; Tuominen & Tommola, 2022). Therefore, the assumption is that majority of Finnish people have heard about delivery robots, and that to some extend Finnish people have also used them. Therefore, it is assumed that these characteristics do not significantly influence on intentions to use delivery robots.

H8: *Respondents' characteristics do not have significant influence on behavioral intention to use delivery robots.*

3 METHODOLOGY

The focus in this chapter is to describe and discuss the research methodology of this study. First, the chosen research method of quantitative survey is explained. After which the data collection process and representativeness of survey sample is described, and the chosen method of data analysis is explained and justified. Lastly, empirical findings and data analysis are discussed.

3.1 Research method: quantitative survey

As outlined before, the theoretical framework of this study is based on widely used technology acceptance model that is applicable in quantitative research. Quantitative research enables to i.a., quantify consumers' behaviours, perceptions, and attitudes. With quantitative survey a much broader study can be done, which enables to generalize the results to wider group of people. Additionally, quantitative research model is fast, cost-effective, and accurate. (Mander, 2022.)

Therefore, the quantitative research method for this study was chosen. To perform the empirical study the method of a survey was chosen due to its convenient implementation, reachability, and scalability (Gürbüz, 2017; Mander, 2022). In the era of technology acceptance studies, the survey based quantitative research are widely used (Kapser & Abdelrahman, 2020; Rahi et al., 2019; Cimperman et al., 2016; Tarhini et al., 2016). As discussed earlier, the theoretical model ADVAM (Kapser & Abdelrahman, 2020), that has strong basis in UTAUT2 model, is used in this study. Therefore, the content of the survey was built on the nine constructs examined in Kapser and Abdelrahman's model (Figure 4). Each construct consisted of three to four items that measure the answers of respondents (Table 1). In price sensitivity construct three items were addressed instead of original five, as done in Kapser and Abdelrahman's (2020) study due to inconvenience of the other two ones. The items of different constructs were adapted from previous technology acceptance studies where the questions have been validated. Additionally, two questions were addressed of whether the respondent had heard about delivery robots or not or used one.

In addition to the question part of the survey, the survey included cover letter, respondent's profile, and information sheet of delivery robots. The cover letter shortly introduced the aim of the study as well as the structure of the survey. In respondent's profile the age, gender, citizenship, income, degree of education and employment status were asked to validate the representativeness of the sample, and to see if age and gender influence on the intentions to use delivery robots. In the information sheet basic information of delivery robots were told, including illustrative picture. The aim of the information sheet was to make respondent familiar with delivery robots in case the respondent has not heard of them before.

Before the survey was shared more widely, it was pre-tested with three participants. Due to pre-testing two grammar mistakes were noticed and corrected. Otherwise, other surveys of existing technology acceptance studies were used as a benchmark to build enough informative and usable survey. The survey was conducted in Finnish and shared through an anonymous link in social media channels to people living in Finland. The survey was created using Webropol's survey tool, and it took on average 8 minutes for respondents to answer. The survey was compatible with smartphones, tablets, and laptops. The survey in its entirety can be found as attached in this study (Appendix). The attached survey is translated into English.

The survey did not include personal data and the data was collected and analysed completely anonymously. In the survey 7-point Likert scale was used ranging from 1= 'Strongly disagree' to 7 = 'Strongly agree'. The aim of the survey was to get answers to the research question and hypotheses addressed in this study. Hypotheses are all based on existing technology acceptance studies and presented more detailed in the previous chapter of theoretical framework.

3.2 Data collection and analysis

As outlined, the data was collected using a survey. The survey data was collected through an anonymous link in social media channels: WhatsApp, Instagram, and Facebook. The data was collected for one week in October 2023, and total of 115 answers were received. For generalizability the aim was to get as representative sample of Finnish population as possible. Therefore, the respondent sample was aimed to include people from different age groups, genders, and paygrades with different education degrees and employment statuses. The sample of respondents are presented in Table 2.

After data collection the survey results were examined and analyzed in SPSS Statistics and SPSS Amos software. The data was first exported from Webropol tool into Excel and modified into suitable form. Unnecessary titles and descriptives were removed and ensured that no values were missing. After this the data was divided into two Excel; one data set included data of eight different constructs, described in Figure 4, and the other data set included the data of respondent's profile; age, gender, and earlier use of delivery robots. The division was made to ease the analysis as respondent's profile is measured with different measure scale. Following, both data sets were separately imported and saved into SPSS Statistics. Few modifications were made to the data sets regarding the type and role of measurements.

After the data was modified and saved in SPSS Statistics, the analysis was done in SPSS Amos software using confirmatory factor analysis (CFA). CFA is widely used analysis tool for social and behavioral sciences. CFA allows to assess the fit between observed data and theoretical model that specifies the hypothesis of relations between latent factors and their observed variables. The main advantage of CFA is the ability to examine the gap between theory and observation. (Mueller & Hancock, 2001.) Therefore, CFA was chosen for as an analysis method for this study, as there is a need to understand the relationship between the construct of behavioral intention and other constructs that are determined based on existing theoretical model.

The data analysis was phased in two. First, the effect of earlier validated constructs to behavioral intention to use delivery robots was analyzed. This first phase of analysis started by creating a graph in SPSS Amos that was constructed from earlier presented eight constructs. After this the above-described data saved in SPSS Statistics was imported and saved to SPSS Amos. Following, the data of different constructs was inserted into earlier drawn graph. Before making any calculations the properties of analysis were determined. Maximum likelihood estimation was chosen as a default and the output selection for analysis was chosen. After this the analysis was run, resulting standardized factor loadings and correlations were now illustrated in the earlier drawn graph. The output was created in text as well including model fit indices that determine the acceptance of the model. The poor model fit required modifications to the model which were done by drawing covariance between error terms as well as by deleting items with high residual covariances.

Second, the analysis of the effect of respondents' characteristics on behavioral intention to use delivery robots was done. The methodology was identical to the first analysis described above. The effect of gender and age were analyzed as well as the earlier use of delivery robots. The output of this second analysis was provided similarly to above described. Based on these two-phased analysis the results for answering research questions and hypotheses were analyzed and are discussed in detail in following subchapters.

3.3 Empirical findings and data analysis

In this subchapter the results of this study are described and analysed. First the respondents' characteristics and the overall sample data are described. After which the results of performed analyses are presented and discussed.

3.3.1 Description of respondents and generalizability

As outlined in the previous chapter, total of 115 answers were collected through a quantitative survey. The respondents of the survey were representing different characteristics that are presented in Table 2. In Finland the percentage of men is 49% whereas the percentage of women is 51% (Statistics Finland, 2023a). Meaning, females were overrepresented in the survey with 68% of female respondents whereas males were underrepresented. The ages of respondents between 35-49 and 50-64 years were representing Finnish population quite well with only ± 2% difference to Finland's demographics. However, the respondents' age group of 25-34 years was overrepresented covering 46% of respondents. Additionally, the age groups of 15-24 and 65+ years were underrepresented in the survey. (Statistics Finland, 2023a.) Respondents' median incomes were higher than current median gross income in Finland, that is around 3000 euros (Statistics Finland, 2023b).

The employment status of respondents was partly representing Finland's demographics. Employment rate for people in the working age in Finland is 74% (Statistics Finland, 2023c) whereas 74% of respondents were working full-time and 4% were part-time workers. The unemployment rate among respondents was 3% whereas the unemployment rate in Finland is around 6%. Also, retired and disabled to work were underrepresented in the survey (Statistical Database, 2022; Statistics Finland, 2023c). The education level within respondents is higher than the education level among Finnish citizens. The undergraduate and graduate degree in Finland is around 40% (Opetus- ja kulttuuriministeriö, 2022), whereas 64% of respondents had either graduate or undergraduate degree.

Respondents' nationality was 99% Finland with only one exception where nationality was something else. Even 97% of respondents had heard about delivery robots. Then again, only 4% of respondents had used them. As outlined before, delivery robots have been in use relatively short time in Finland and only in limited areas, which might effect on this result. Therefore, it can be concluded that it was justified to leave out the constructs of habit and use behavior from this study.

Table 2. Respondents' demographics, familiarity, and earlier use of delivery robots

Variable	Category	Frequency (n=115)	Percentage
Age	15–24 years	7	6 %
	25–34 years	53	46 %
	35–49 years	24	21 %
	50–64 years	23	20 %
	65 + years	8	7 %
Gender	Female	78	68 %
	Male	36	31 %
	Other	1	1 %
Nationality	Finland	114	99 %
	Other	1	1 %
Net income	Less than 1000	9	8 %
	1000-1999	17	15 %
	2000-2999	47	41 %
	3000-3999	29	25 %
	4000-4999	9	8 %
	5000-5999	4	3 %
Education	Primary school	2	2 %
	Second degree (high school, vocational school)	40	35 %
	Undergraduate degree (baccalaureate, university of applied sciences, or comparable)	48	42 %
	Graduate degree (master, doctor, or comparable)	25	22 %
Employment status	Full-time employment	85	74 %
	Part-time employment	5	4 %

	Seeking work	4	3 %
	Retired	9	8 %
	Student	11	10 %
	Unable to work	1	1 %
Have you heard about delivery robots before? (familiarity)	Yes	112	97 %
	No	3	3 %
Have you used delivery robots before? (experience)	Yes	5	4 %
	No	110	96 %

When comparing the above-described demographic characteristics of respondents to Finland's demographics, it can be concluded that the sample does not fully represent Finnish population in its entirety. Meaning, the results can't be directly generalized to all Finnish people. However, the respondents are still from different age groups, genders, and paygrades with different educational level and employment status and thus the sample can be considered to some extend descriptive.

3.3.2 Description of sample data

In addition to respondents' characteristics the empirical research was done based on eight constructs that include three to four questions each. Each question measured to what extent the respondent disagreed or agreed with the statement. The mean and median values of results of each construct and their items are presented in Table 3.

Based on mean and median values the respondents are quite neutral or somewhat agree with delivery robots improving their performance e.g., productivity and flexibility. Nearly same applies to hedonic motivation with mean 4,7 and median 5 implying respondents would find delivery robots somewhat entertaining and enjoyable. On average respondents agree that they would find delivery robots easy to use, and that they have needed resources e.g., smartphone to use delivery robots. Then again, on average respondents somewhat disagree that their close people would have an opinion to their use of delivery robots, or that the use of delivery robots would be risky. Respondents disagreed most with statements related to price. On average respondents disagree on spending a lot of money to use delivery robot as a delivery option.

Table 3. Descriptive data of constructs and their items

Construct	Items/Questions	Mean (n=115)	Median (n=115)
Performance Expectancy (PE)		**4,3**	**5**
	PE1: I find/would find delivery robots useful in my daily life	4,6	5
	PE2: Using delivery robots increases/would increase my flexibility in my daily life	4,6	5
	PE3: Using delivery robots helps/would help me accomplish things more quickly	4,3	5
	PE4: Using delivery robots increases/would increase my productivity	3,8	4
Effort Expectancy (EE)		**5,6**	**6**
	EE1: Learning how to use delivery robots is/would be easy for me	5,9	6
	EE2: It is/would be easy for me to become skillful at using delivery robots	5,8	6
	EE3: My interaction with the delivery robots via the mobile app is/would be clear and understandable	5,3	6
	EE4: I find/would find delivery robots easy to use	5,4	6
Social Influence (SI)		**2,9**	**2**
	SI1: People who influence my behavior think/would think that I should use delivery robots	3	3
	SI2: People who are important to me think/would think that I should use delivery robots	2,8	2
	SI3: People whose opinion I value prefer/would prefer that I use delivery robots	2,9	2
Facilitating Conditions (FC)		**5,8**	**6**
	FC1: I have the resources necessary to use delivery robots (i.e., smartphone)	6,7	7
	FC2: I have the knowledge necessary to use delivery robots	5,3	6
	FC3: Delivery robots are compatible with other technologies I use (e.g., smartphone)	6,1	6
	FC4: I can get help from others when I have difficulties using delivery robots	5,1	6
Hedonic Motivation (HM)		**4,7**	**5**
	HM1: Using delivery robots would be fun	4,9	5
	HM2: Using delivery robots would be enjoyable	4,5	5
	HM3: Using delivery robots would be very entertaining	4,8	5
Perceived Risk (PR)		**3,4**	**3**
	PR1: Overall, using delivery robots is risky	4,1	4
	PR2: Overall, using delivery robots is dangerous	3,2	3
	PR3: Using delivery robots exposes me to an overall risk	2,9	3
Price Sensitivity (PS)		**2,1**	**2**
	PS1: I would not mind spending a lot of money for getting my orders delivered by delivery robots	2	2
	PS2: If I knew that delivery robots as a delivery option were likely to be more expensive than conventional delivery options, that would not matter to me	2,2	2
	PS3: I could pay a lot money for a really great delivery option	2,3	2
Behavioral Intention (BI)		**3,1**	**3**
	BI1: I intend to use delivery robots in the future	4	4
	BI2: I will always try to use delivery robots in my daily life, if possible	2,6	2
	BI3: I intend to use delivery robots frequently, if possible	2,8	2

Note: Mean and median values are based on 7-point Likert scale: 1= "Strongly disagree", 2="Disagree", 3="Somewhat disagree", 4="Neither agree nor disagree", 5="Somewhat agree", 6="Agree", 7="Strongly agree"

On average respondents disagreed or somewhat disagreed that they would use delivery robots frequently if possible. Additionally, respondents had very neutral opinion on whether they would use delivery robots in future or not. As outlined before, Kapser and Abdelrahman (2020) found that German people had neutral acceptance towards the use of delivery robots, which was considered common for emerging technologies as public might need some time to form an opinion of new technology (Liu et al., 2019). Therefore, based on mean and median values of behavioral intention presented in Table 3, the results partly align with Kapser and Abdelrahman's (2020) study but partly differs on what it comes to intention to use delivery robots frequently.

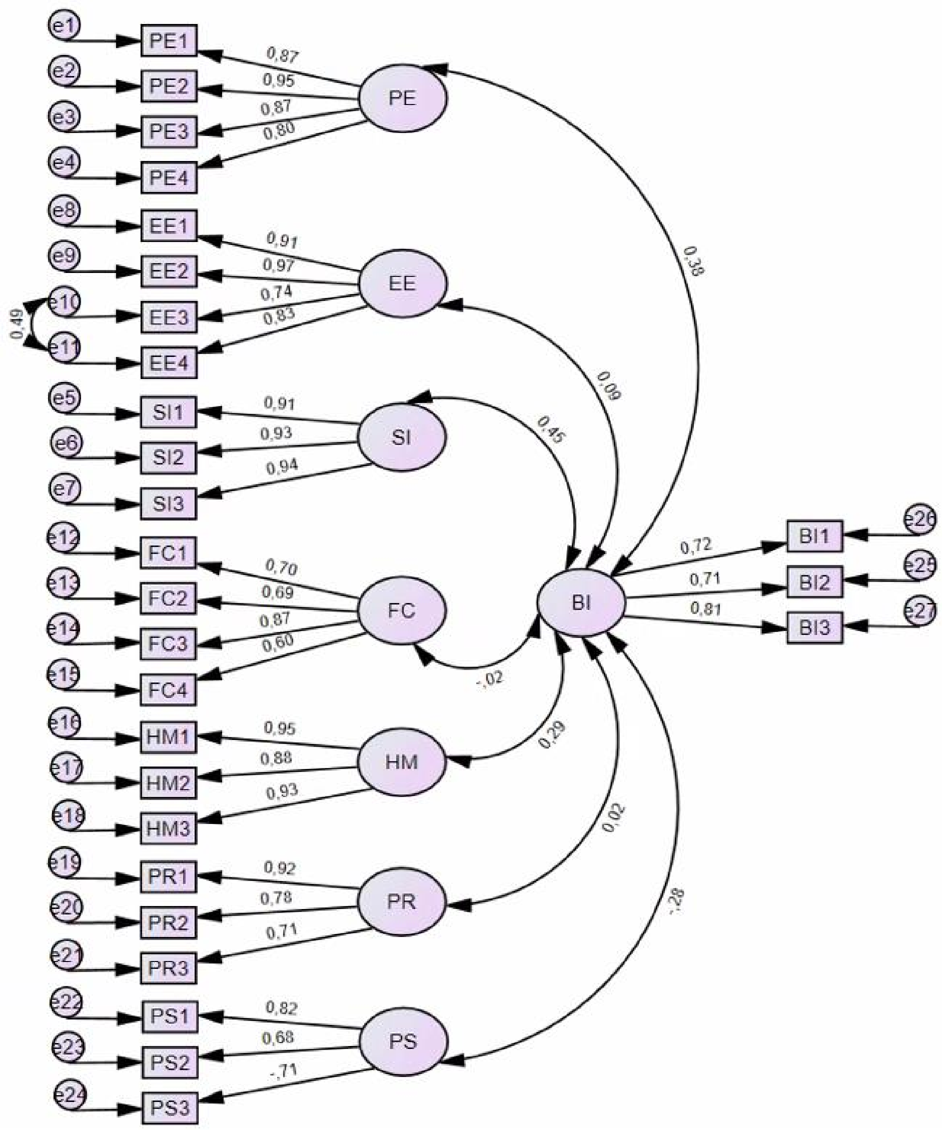
3.3.3 First confirmatory factor analysis

In this subchapter the effect of seven construct; performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price sensitivity, and perceived risk to the construct of behavioral intention to use delivery robots is analyzed. As outlined in previous chapter, CFA was performed in SPSS Amos to test the measurement model of this study. The analysis is presented in Figure 5.

The observed variables are presented with squares and latent variables with ellipses. Two-way arrows indicate the standardized correlations whereas one-way arrows stand for factor loadings. To understand how well an observed item measures the latent variable in question factor loadings were assessed for each item. All factor loadings are between 0.6-0.97 indicating that all the observed items measure well the latent variables (Arifin & Yusoff, 2016). However, the model-fit measures showed that fit indices were not within their common acceptance levels. To assess the model's overall goodness of fit, fit indices of CMIN/df, GFI, CFI, TLI, and RMSEA were examined (Crowson, 2017). As presented in Table 4, only CMIN/df value is within the acceptance level. Therefore, it must be concluded that this factor model yielded a poor fit. Due to the poor model fit the results will not be accurate enough for any decision-making.

Table 4. First output of model-fit indicators

Fit indices	**Recommended value**	**Source**	**Obtained value**
CMIN/df	< 2 good fit, < 5 acceptable fit	Ertas et. al. (2022)	2.183
GFI	>.90	Hair et.al. (2010)	.678
CFI	>.90	Bentler (1990)	.846
TLI	>.90	Bentler (1990)	.829
RMSEA	<.08	Hu & Bentler (1998)	.102



Note: PE=Performance Expectancy EE=Effort Expectancy, SI=Social Influence, FC=Facilitating Conditions, HM=Hedonic Motivation, PR=Perceived Risk, PS=Price Sensitivity, BI=Behavioral Intention

Figure 5. First CFA

It is inevitable that modifications to the factor model need to be done. But regardless of the deficiencies of the model fit, the results of the model are briefly presented in Table 5. The table includes standardized estimates between the latent variable of behavioral intention and other earlier presented variables. Standardized estimates are correlations that partly answer to the research question of which factors influence on behavioral intention to use delivery robots. Possible values of correlation range from -1 to +1, where -1 indicates perfectly negative correlation and where +1 indicates perfectly positive correlation (James, 2023). Additionally, the table includes p-values that report the significance of estimates. All p-values under 0,05 are considered significant. If critical ratio is 1.96 or larger, the estimate is significant at the level of 5%, and standard error is the estimate of standard error. (Shobha, 2020.)

Based on the results presented in Table 5 five out of seven hypotheses are supported. The strongest predictor of behavioral intention is social influence (r=0,446), and the second strongest performance expectancy (r=0,38). Additionally, two hypotheses are rejected as perceived risk and facilitating conditions seem not to have significant effect on behavioral intention (p>0,05), which is contradicting with some other existing studies (Venkatesh et. al.,2012; Kapser & Abdelrahman, 2020). However, due to the deficiencies of the model fit, the more detailed discussion of results will be done after the model-fit modifications are done.

Table 5. First CFA model, hypothesis, and results

	Hypothesis	**Standardized estimate (r)**	**S.E.**	**C.R.**	**p-value**	**Result**
PE → BI	H1	,38	,150	3,562	***	Supported
EE → BI	H2	,092	,100	1,071	,284	Supported
SI → BI	H3	,446	,168	3,959	***	Supported
PS → BI	H6	-,276	,118	-2,641	,008	Supported
PR → BI	H7	,016	,125	,186	,853	Rejected
HM→ BI	H5	,288	,165	2,974	,003	Supported
FC → BI	H4	-,016	,049	-,117	,859	Rejected

Note: S.E.=Standard error, C.R.=Critical ratio, PE=Performance expectancy, EE=Effort expectancy, SI=Social Influence, PS=Price Sensitivity, PR=Perceived risk, HM=Hedonic motivation, FC=Facilitating conditions, BI=Behavioral intention
***p-value <,001

3.3.4 Second confirmatory factor analysis with model-fit modifications

As outlined, to get a good fit for the factor model, some modifications to the original model were required. First, the modifications to the model were done by deleting the lowest factor loadings, in this case PS2, FC4, and FC2. The model did not improve enough, after which the next lowest single factor loadings were removed. This resulted that the model could not be identified anymore. After this it was recognized that some different changes are needed. Next attempt to improve the model fit was to draw covariance between suitable error terms, but this did not improve the model enough. After that the following step was to delete items with high standardized residual covariances. Items deleted with high residual covariances were HM1, HM2, HM3, PE1, PE2, PE3, PE4, FC2, FC4 and EE3. After removing these items, the fit indices started to be within their acceptance levels. However, fit index GFI resulted to be below the good fit but while all other fit indices being good the factor model can be accepted (Juntunen, 2020). New model-fit indicators are presented in Table 6.

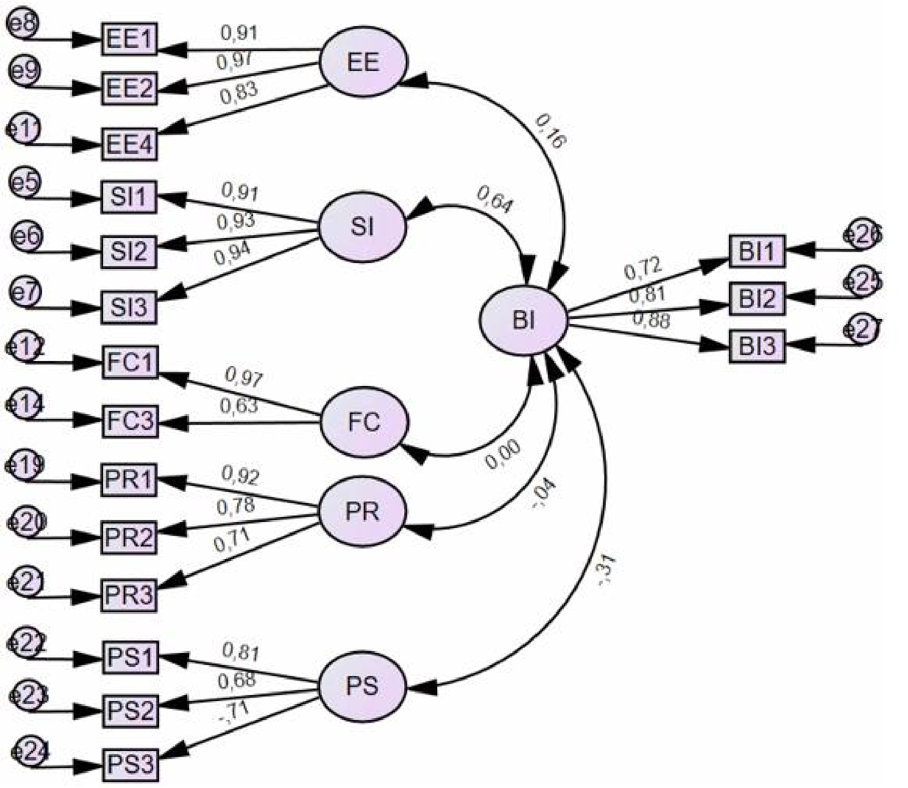
Table 6. Fixed output of model-fit indicators

Fit indices	Recommended value	Source	Obtained value
CMIN/df	< 2 good fit, < 5 acceptable fit	Ertas et. al. (2022)	1.695
GFI	>.90	Hair et.al. (2010)	.831
CFI	>.90	Bentler (1990)	.935
TLI	>.90	Bentler (1990)	.923
RMSEA	<.08	Hu & Bentler (1998)	.078

Note: HM1, HM2, H3, PE1, PE2, PE3, PE4, FC2, FC4, EE3 were removed

As described above, several items needed to be removed to obtain an acceptable factor model. This means the acceptable model of this study leaves out the constructs of *performance expectancy* and *hedonic motivation*. As discussed in previous subchapter, both constructs first seem to influence positively on behavioral intention to use delivery robots, but the results must be disregarded due to the poor model fit. However, among Germans hedonic motivation, e.g., the use of delivery robots is seen enjoyable, was found as an important factor in consumer acceptance of delivery robots (Kapser & Abdelrahman, 2020). Additionally, it has been found to be more critical determinant of behavioral intention in consumer context than the performance expectancy (Venkatesh, et al.,2012). But there are also contradicting results in the field of technology acceptance as of Kwame et al. (2019) found that neither hedonic motivation nor performance expectancy had significant effect on behavioral intention to use mobile banking. But then again Aijaz et al. (2019) found that performance expectancy influences positively on behavioral intention in mobile learning, meaning that the more consumers recognize the use of technology will provide benefits the more intended they are to use them.

In addition to the removal of hedonic motivation and performance expectancy constructs, single items from *facilitating conditions* and *effort expectancy* were removed, but the constructs remained still in the model. The modified model was created based on before-described justifications and is presented in Figure 6. Factor loadings of the model are all still at good level, which indicates that remained items measure well the latent variables. After the good model fit was found and the items have been proven to measure well the latent variables, the next phase was to analyze the influence of other latent variables to the behavioral intention to use delivery robots. Due to the required modifications, six constructs remained in the model instead of the original eight.



Note: EE=Effort Expectancy, SI=Social Influence, FC=Facilitating Conditions, PR=Perceived Risk, PS=Price Sensitivity, BI=Behavioral Intention. Removed items: PE=Performance Expectancy, HM=Hedonic Motivation, FC2, FC4, EE3.

Figure 6. CFA after model-fit modifications

The analysis revealed that two of remaining five hypotheses could be supported (Table 7). Significant positive relationship was found between social influence and behavioral intention (confirming H3), as well as between effort expectancy and behavioral intention (rejecting H2). It was hypothesized that there would be no significant relationship between effort expectancy and behavioral intention. Then again, significant negative relationship was found between price sensitivity and behavioral intention (confirming H6). However, no significant effect was found for the relationship between perceived risk and behavioral intention (rejecting H7), nor between facilitating conditions and behavioral intention (rejecting H4).

Table 7. Improved CFA model, hypotheses, and results

	Hypothesis	Standardized estimate (r)	S.E.	C.R.	p-value	Result
EE → BI	H2	,164	,107	1,985	,047	Rejected
SI → BI	H3	,638	,218	4,832	***	Supported
PS → BI	H6	-,306	,126	-3,029	,002	Supported
PR → BI	H7	-,04	,129	-,487	,626	Rejected
FC → BI	H4	,001	,09	,018	,086	Rejected

Note: S.E.=Standard error, C.R.=Critical ratio, EE=Effort expectancy, SI=Social Influence, PS=Price Sensitivity, PR=Perceived risk, FC=Facilitating conditions, BI=Behavioral intention
***p-value <,001

H2: Effort Expectancy

Effort expectancy revealed to have slightly positive influence on behavioral intention to use delivery robots among respondents which is contradicting with the hypothesized outcome. Even though the hypothesis is rejected, the influence of effort expectancy on behavioral intention is relatively low (r =0,164). The result indicates that when respondents think the use of delivery robots is easy, they also have to some extend intentions to use them. Behind the hypothesis was peoples' increased abilities to adapt new technology faster and faster (MinnaLearn, 2023), but also other existing studies where effort expectancy did not have significant effect on intentions to use technology (Kapser & Abdelrahman, 2020; Madigan et al., 2017). However, some other technology acceptance studies have then again found effort expectancy as a strong predictor of behavioral intention in technology use (Macedo, 2017; Beh et al., 2021; Leicht et al., 2018; Choi & Ji, 2015). For instance, Macedo (2017) found that effort expectancy has an influence on older adults' intentions to use technology such as internet whereas Beh et al. (2021) found that effort expectancy has a positive impact on using smartwatches for health and fitness monitoring.

As described earlier the use of delivery robots require smartphone that is connected to the delivery robot itself which might create a feeling of complexity. However, the use of smartphone and mobile applications seem to be commonplace for people nowadays (Kent, 2022) which might explain why the influence of effort expectancy is relatively weak. In general, the existing studies of the influence of effort expectancy on behavioral intention seem to be contradicting. But in anyhow it is important for industry's professionals to recognize that in case they succeed in making the use of delivery robots seem easy, they might gain more potential customers with intentions to use them.

H3: Social Influence

The construct of social influence has a positive influence on behavioral intention to use delivery robots, which was the hypothesized outcome. Social influence has the strongest correlation of 0,638 with behavioral intention with result being highly significant ($p<0,001$). Meaning, the influence of close people is the strongest predictor of behavioral intention to use delivery robots among respondents. This aligns with other technology acceptance studies (Kapser & Abdelrahman, 2020; Madigan et al., 2017; Rahman et al., 2017; Leicht et al., 2018) where social influence has had a significant role in the acceptance of autonomous delivery vehicles. The result indicates that in regard to delivery robots the respondents of the survey are most likely to depend on their close peoples' opinion.

H4: Facilitating Conditions

The hypothesis regarding the influence of facilitating conditions on behavioral intention to use delivery robots was rejected. There was barely any correlation between facilitating condition and behavioral intention ($r = 0,001$) meaning that resources or support available do not have significant effect on intentions to use delivery robots ($p>0,05$). On average respondents somewhat agreed or agreed that they have needed resources (e.g., smartphone, knowledge) and support (e.g., help from others) to use delivery robots (Table 3). In general smartphones are nowadays widely used and information is easily available due to the megatrends of digitality and technology (Kent, 2022; Project Management Institute, 2022) which support the obtained result. However, the result is contradicting with some other existing studies where consumers with poorer facilitating conditions have had lower intentions to use delivery robots (Kapser & Abdelrahman, 2020; Madigan et al., 2017; Choi & Ji, 2015).

H6: Price Sensitivity

The second strongest predictor of behavioral intention is the construct of price sensitivity. The correlation between these two variables is negative (r =-0,306), which means that when e.g., the price of delivery method increases the intentions to use delivery robots most likely decreases. Meaning, the earlier presented hypothesis is supported. The result is not surprising as in general it is recognized that cheaper prices attract buyers (Fagan, 2023). The result also aligns with Kapser and Abdelrahman's (2020) study where the price sensitivity was the strongest predictor of behavioral intention to use delivery robots. Price being one of the most important factors in marketing (Fagan, 2023) and one of the strongest predictors of behavioral intention to use delivery robots the pricing strategy should be considered carefully.

H7: Perceived Risk

The third rejected hypothesis concerned the relationship between perceived risk and behavioral intention, as perceived risk did not have significant negative effect on behavioral intention to use delivery robots (r=-0,04). The outcome is not too surprising as the existing studies around perceived risk are contradicting. Some of the studies have proven that delivery robots are seen as risky delivery options (Kapser & Abdelrahman, 2020; Marsden et al., 2018; Braun & Buckstegen, 2017) whereas some other studies have not found any significance effect on behavioral intention to use them (Choi & Ji, 2015; Liu et al., 2019). Additionally, the respondents somewhat disagreed with delivery robots being risky delivery options (Table 3). The overall result indicates that respondents' intentions to use delivery robots is not affected by any perceived risk. However, as the existing studies are contradicting it is good to keep in mind the safety matters of delivery robots.

3.3.5 The influence of age, gender, and experience on behavioral intention

As outlined before the effect of age, gender, and earlier use of delivery robots on behavioral intention was examined based on the theoretical framework presented in the second chapter of this study. To test the effect of these characteristics on behavioral intention to use delivery robots, a third CFA was done. It can be seen from the model-fit indicators (Table 8) that the results of this CFA are trustworthy. All indicators are within acceptance levels, except RMSEA that is slightly above the recommended value. However, considering the results as a whole, the model is accepted.

Table 8. Model-fit indicators of respondents' characteristics

Fit indices	Recommended value	Source	Obtained value
CMIN/df	< 2 good fit, < 5 acceptable fit	Ertas et. al. (2022)	1.878
GFI	>.90	Hair et.al. (2010)	.959
CFI	>.90	Bentler (1990)	.960
TLI	>.90	Bentler (1990)	.925
RMSEA	<.08	Hu & Bentler (1998)	.088

Note: Age, gender, and earlier use of delivery robots included

After the model was proven to have a good fit, factor loadings were examined. Factor loadings and the CFA itself are presented in Figure 7. It has been concluded earlier in this study that observed variables are representing well the latent variable of behavioral intention due to their relatively high factor loadings. However, the loadings of age and gender are quite low. Regardless, these demographics were still left in the model based on the theoretical framework utilized in this study. Then again, the correlation between respondents' characteristics and behavioral intention indicates that there is a slight positive correlation between them (r=0,28). However, the p-value is relatively high (>0,05) indicating that the correlation is insignificant (Table 9).

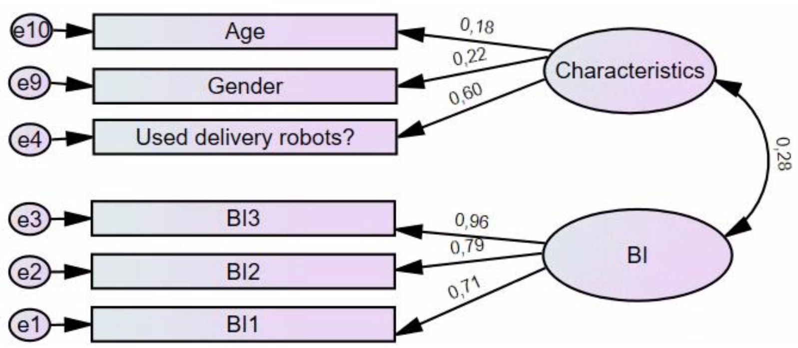


Figure 7. CFA of respondents' characteristics and behavioral intention

It can be concluded that there is no significant effect of age, gender, and earlier use of delivery robots to behavioral intention to use delivery robots. Therefore, the hypothesis regarding the effect of these characteristics on intentions to use delivery robots is supported. The result is contradicting with existing study of Venkatesh et al. (2012) where age and gender were moderating the effect of direct variables on intentions to use technology. Then again, Kapser and Abdelrahman (2020) found that among Germans the demographic characteristics did not have significant effect on the intention to use delivery robots. However, the familiarity of whether the respondent had heard of delivery robots or not, had significant effect on Germans' intentions to use delivery robots.

Table 9. CFA model, hypothesis, and results of respondents' characteristics

	Hypothesis	Standardized estimate (r)	S.E.	C.R.	p-value	Result
Characteristics → BI	H8	,275	,103	,758	,448	Supported

Note: Characteristics include age, gender, and earlier use of delivery robots
S.E.=Standard error, C.R.=Critical ratio, BI=Behavioral intention

It is good to recognize that for instance it is not only certain age group or gender that might have intentions to use delivery robots among respondents. However, it is also important to recognize that there are contradicting studies existing, and that the majority of respondents had not used delivery robots before which might effect on the above presented results.

4 CONCLUSIONS

In this chapter the thesis will be concluded by presenting key results of the study accompanied by the theoretical implications. After that the managerial implications are presented for logistics, retail, and marketing professionals. Following, limitations of the study are discussed and suggestions for future research presented.

4.1 Key results and theoretical implications

In this study the factors influencing behavioral intention to use delivery robots in Finland was examined. Therefore, the main research question of the study was:

Which factors influence on consumers' intentions to use delivery robots in Finland?

To answer to the research question the effect of eight different constructs on behavioral intention to use delivery robots was examined based on the theoretical model presented in Figure 4. The eight hypotheses were formulated based on previous research and literature and analyzed to get final answers to the main research question.

The effect of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price sensitivity, perceived risk and respondents' age, gender, and earlier use of delivery robots to the behavioral intention to use delivery robots was measured and analyzed. The first analysis yielded a poor model-fit resulting that two constructs; *hedonic motivation* and *performance expectancy* needed to be removed from the model. Additionally, three single items measuring facilitating conditions and effort expectancy were removed. After this the second analysis was done and the remained six hypotheses were answered.

The strongest predictor of behavioral intention revealed to be *social influence*, which indicates that the opinions of respondents' close people influence on respondents' intentions towards delivery robots. The result confirmed the hypothesis (H3) and was in alignment with other autonomous delivery vehicle acceptance studies (Kapser & Abdelrahman, 2020; Madigan et al., 2017; Rahman et al., 2017; Leicht et al., 2018). In general, it is also stated that for instance friends and family can influence on consumers in many ways such as how to behave or what to buy (Cavanaugh, 2016). The construct of *price sensitivity* had the second strongest influence on behavioral intention to use delivery robots. The influence was negative as hypothesized (H6) which means that when for instance the use of delivery robots becomes more expensive the intentions to use them decrease. The result aligns with delivery robot acceptance study in Germany (Kapser & Abdelrahman, 2020) and is not a surprising factor as in general it is recognized that lower prices attract consumers (Fagan, 2023).

Effort expectancy had slight positive influence on behavioral intention but was still the third strongest predictor of behavioral intention. Meaning, to the extent that respondents think that using delivery robots is easy, they might have intentions to use them. Due to the peoples' increased abilities to adapt new technology (MinnaLearn, 2023) and existing studies of technology acceptance where effort expectancy did not have significant effect on intentions to use technology (Kapser & Abdelrahman, 2020; Madigan et al., 2017) it was hypothesized that effort expectancy would not have significant effect on behavioral intention and therefore the hypothesis had to be rejected (H2). However, there are other technology acceptance studies where effort expectancy has been found to predict the intentions to use technology such as use of internet or use of smartwatches (Macedo, 2017; Beh et al., 2021).

The hypotheses regarding the influence of *facilitating conditions* and *perceived risk* on behavioral intention were both rejected (H4, H7). Both constructs had negligible effect on behavioral intention with barely any correlation, resulting the influence of these on intentions to use delivery robots was insignificant. The results indicate that resources (e.g., smartphone, knowledge) and support (e.g., help from others) or perceived risk (e.g., possible risks of delivery robots) do not have significant effect on respondents' intentions to use delivery robots. On average respondents agreed that they have needed resources and support to use delivery robots (Table 3) and in general smart devices are nowadays used widely and information is easily available due to the megatrend of technology (Kent, 2022; Project Management Institute, 2022) which support the obtained result. The existing studies around perceived risk are contradicting which is why it is not a surprising result that the hypothesized outcome needed to be rejected. There are studies that have found perceived risk to affect negatively on intentions to use technology (Kapser & Abdelrahman, 2020; Marsden et al., 2018; Braun & Buckstegen, 2017) whereas there are other studies where significance effect was not found (Choi & Ji, 2015; Liu et al., 2019). The last hypothesis regarded the effect of *respondents' age, gender*, and *earlier use of delivery robots* on intentions to use them. There was no significant effect of these characteristics on behavioral intention to use delivery robots, resulting the hypothesis was supported (H8). The result aligns with delivery robot acceptance study in Germany (Kapser & Abdelrahman, 2020) but contradicts with existing study of Venkatesh et al. (2012) where age and gender did have significant effect on intentions to use technology.

These results provide more information and knowledge about the relatively new delivery robots, supplementing the existing knowledge gap of peoples' intentions and acceptance towards delivery robots. Based on the results it is good to recognize that social influence and price sensitivity are the strongest predictors of behavioral intention to use delivery robots, and that ease of use determine to some extend the intentions to use delivery robots. It is also important to identify that availability of smart devices or support from other people, or any possible perceived risk factor do not have significant effect on the consumers' intentions to use delivery robots among respondents.

The theoretical model of this study was based on existing technology acceptance studies (Kapser & Abdelrahman; Venkatesh et al., 2012) that determined the constructs and measured variables in this study. The completed analysis proved that all the observed variables measured well the latent variables. Therefore, it can be concluded that the validity of the study was good. However, the results are not generalizable in their entirety as the demographics of respondents do not fully represent Finland's demographics. However, there were respondents from different age groups, genders and pay grades with different educational degrees and employment statuses which is why the respondent sample can be considered to some extent comprehensive. In the end the reliability of the measurement model was good with all but one fit index being within acceptance levels. However, to get a reliable measurement model some items needed to be removed from the model, meaning, the original theory-based model did not have a good reliability in this study.

4.2 Managerial implications

The purpose of this study was to discover what are the factors influencing on the intentions to use delivery robots among consumers and thus, how retail, logistics and marketing professionals could design, develop, and promote delivery robots properly. Based on the presented results where social influence was the strongest predictor of intentions to use delivery robots, managers should first consider how to utilize the social influence aspect where peoples' intentions to use delivery robots are influenced by their close people. It would be important for marketers to understand which groups influence on their target segments to be able to focus on winning over the opinion of these groups. Within these groups, for instance within families, there might be differences on who is making decisions on what which is why it is important to understand the general tendencies around decision making to succeed in marketing. (Lumenlearning, 2023.)

Price sensitivity being the second strongest predictor of behavioral intention, managers should consider carefully what kind of pricing strategy to build on delivery robots as delivery option. In literature pricing has been claimed to be even the most important element in marketing mix (Hollensen, 2020). Price strategy should take into consideration multiple factors such as prices of competitors, the willingness of people to pay, and the desired positioning in the market (Schryers, 2023). A well-designed pricing strategy might direct people to choose more likely delivery robot as a delivery option instead of traditional delivery options.

The construct of effort expectancy had a slight positive influence on intentions to use delivery robots. Therefore, managers should consider how to make the use of delivery robots seem easy, even for people who have not yet used them. It could be also considered how to provide guidance and support at the time of using delivery robot if problems arise e.g., easy access to support within the application. Additionally, it would be important to ensure that the application that is used for ordering guides the user when browsing the products, choosing the delivery option, and when receiving the goods.

It is also important for managers to recognize that for instance perceived risk did not have significant influence on respondents' intentions to use delivery robots. On average delivery robots were not considered as risky delivery option among respondents, which can be considered as a positive result. Therefore, the focus for managers can rather be on other factors than focusing on emphasizing the safety matters of delivery robots. The same applies to facilitating conditions where availability of smart devices or peer support were not seen to have significant effect on behavioral intention. Additionally, it is good to recognize that there were no differences between age groups or genders on the intentions to use delivery robots which is something to consider in marketing purposes.

4.3 Limitations

The research context of delivery robots poses some limitations for this study. Delivery robots are yet relatively new delivery method not only in Finland but globally as well. Resulting, that there is very limited amount of earlier research regarding delivery robots and their acceptance. Additionally, delivery robots being such a novel delivery method in Finland majority of respondents had not used them before and to some extent they had to imagine delivery robots being part of peoples' everyday lives in future. Because of the lack of experience of delivery robots, some modifications had to be done to the original theoretical model. The constructs of habit and actual use behavior had to be removed, and some modifications had to be done to the price construct. Resulting, the delivery robot specific model ADVAM was used. However, the model yielded to have poor fit following that two other original constructs needed be removed from the model; hedonic motivation and performance expectancy. Therefore, the results gained from the study are not as comprehensive as in the original model.

Another limitation of the study was the respondent sample as the sample did not fully represent Finland's demographics. For instance, females were overrepresented representing 69% of respondents, and age group of 25-34 years was overrepresented covering 46% of respondents whereas age groups of 15-24 and 65+ years were underrepresented. Additionally, unemployed, retired and disabled to work were underrepresented, and the education level within respondents was higher than the education level among Finnish citizens. Therefore, the results of this study are not generalizable in their entirety. To improve generalizability the sample size could be increased, as for now the sample consisted of 115 respondents, and the demographics of respondents could be considered more carefully. The quantitative method used in this study has also its own limitations regarding the lack of more in-depth insight of thoughts, motivations, and emotions of what it comes to delivery robots.

4.4 Suggestions for future research

In this study the factors influencing on intentions to use delivery robots was examined at a time when delivery robots are still not widely used in Finland causing lack of experience among respondents and modifications to the theoretical model used in the study. Therefore, the future research should examine the acceptance of delivery robots in the actual use context after there is continuous use and experience of delivery robots. Additionally, future research could utilize qualitative methods to deepen the understanding of encouraging and discouraging factors affecting the use of delivery robots. For instance, are delivery robots seen problematic in block of flats where robots can only enter the outside door downstairs. More in-depth knowledge with qualitative methods should be considered especially now when delivery robots are still such a novel delivery method worldwide.

As social influence being the strongest determinant of delivery robot acceptance in this study, it could be further examined what are the groups that influence on peoples' intentions to use delivery robots. And what are the actual means used to influence on the use of delivery robots. Price sensitivity being the second strongest predictor of delivery robot acceptance, it could also be further examined what are the precise characteristics or benefits of delivery robots that people are ready to pay for. As for instance, delivery robots are battery-powered providing an energy-efficient solution to last mile delivery, which is why it would be beneficial to understand in more deeply how much value is given in money to the environmentally friendly solution when choosing the delivery option.

REFERENCES

Aijaz, A. A., Zahid, H., Wajid, H. R., & Muhammad S. V. (2019). Extending UTAUT2 toward acceptance of mobile learning in the context of higher education. Universal access in the information society, Vol.18 (3), p.659-673. https://doi.org.10.1007/s10209-019-00685-8

Arifin W. N. & Yusoff, M. S. B. (2016). Confirmatory Factor Analysis of the Universiti Sains Malaysia Emotional Quotient Inventory Among Medical Students in Malaysia. SAGE open, Vol.6 (2), p.215824401665024. https://doi.org.10.1177/2158244016650240

Arntz, E. M., Van Duin, J. H. R., Van Binsbergen, A. J., Tavasszy, L. A., & Klein, T. (2023). In the publication of Frontiers in future transportation, Vol.4. https://doi.org/10.3389/ffutr.2023.1102302

Beh, P. K., Ganesan, Y., Iranmanesh, M., & Foroughi, B. (2021). Using smartwatches for fitness and health monitoring: the UTAUT2 combined with threat appraisal as moderators. Behaviour & information technology, Vol.40 (3), p.282-299. https://doi.org.10.1080/0144929X.2019.1685597

Bentler, P. M. (1990). Comparative Fit Indexes in Structural Models. Psychological Bulletin, 107, 238-246. http://dx.doi.org/10.1037/0033-2909.107.2.238

Bouwman, H., Carlsson, C., Molina-Castillo, F. J. & Walden, P. (2007). Barriers and drivers in the adoption of current and future mobile services in Finland. Telematics and Informatics 24(2), 145-160. https://doi.org/10.1016/j.tele.2006.08.001

Braun, F. and Buckstegen, N. (2017), "Die Zukunft der Logistik [The future of logistics]. Wie die Deutschen über Paketroboter und Lieferdrohnen denken [How Germans think about delivery robots and delivery drones]", Retrieved from: https://d25d2506sfb94s.cloudfront.net/r/52/YouGov_Befragungsergebnisse_Lieferroboter_.pdf

Calfas, J. (2019). Robots Are Coming to Walmart and Making Employees Scared for Their Jobs. Money. Retrieved from: https://money.com/walmart-jobs-robot-union/

Cavanaugh, L. A. (2016). Consumer behavior in close relationships. Current Opinion in Psychology. Volume 10, Pages 101-106. https://doi.org/10.1016/j.copsyc.2015.11.004

Chen, C., Demir, E., Huang, Y., & Qiu, R. (2021). The adoption of self-driving delivery robots in last mile logistics. Transportation research. Part E, Logistics and transportation review, Vol.146, p.102214-102214, https://doi.org/10.1016/J.TRE.2020.102214

Choi J.K. & Ji Y.G. (2015). Investigating the Importance of Trust on Adopting an Autonomous Vehicle. International Journal of Human–Computer Interaction. Volume 31, Issue 10: HCI for Elderly and Smart Vehicle Interaction. https://doi.org/10.1080/10447318.2015.1070549

Cimperman, M., Brenčič, M. M., & Trkman, P. (2016). Analyzing older users' home telehealth services acceptance behavior − applying an Extended UTAUT model. International journal of medical informatics (Shannon, Ireland), Vol.90, p.22-31. https://doi.org/10.1016/j.ijmedinf.2016.03.002

Crowson, M. (2017). Confirmatory factor analysis using AMOS. [Video]. YouTube. Retrieved from: https://www.youtube.com/watch?v=OdBIJrGov_0

Davis, F.D. (1986). A technology acceptance model for empirically testing new end-user information systems: theory and results. Doctoral dissertation. MIT Sloan School of Management, Cambridge. https://dspace.mit.edu/handle/1721.1/15192

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13 13(3), 319–340. https://doi.org/10.2307/249008

Ertas, H. & Filiz E. (2022). Turkish Validity and Reliability Study of Challenge-Hindrance Demands Scale for the Nursing Profession. International Journal of Clinical Practice, Vol.2022, p.1-8. https://doi.org/10.1155/2022/3912003

Fagan, B. (2023). How does price relate to successful marketing?. PandaDoc. Retrieved from: https://www.pandadoc.com/blog/how-does-price-relate-to-successful-marketing/

Featherman, M.S. & Pavlou, P.A. (2003). Predicting e-services adoption: a perceived risk facets perspective. International journal of human-computer studies, Vol.59 (4), p.451-474. https://doi.org//10.1016/S1071-5819(03)00111-3

Gevaers, R., Voorde, E., & Vanelslander, T. (2011). Characteristics and typology of lastmile logistics from an innovation perspective in an urban context. City distribution and urban freight transport: Multiples perspectives (pp. 56–71). Edward Elgar Publishing.

Goldsmith, R.E., Kim, D., Flynn, L.R., & Kim, W.M. (2005). Price Sensitivity and Innovativeness for Fashion Among Korean Consumers. The Journal of social psychology 2005, Vol.145 (5), p.501-508. https://doi.org/10.3200/SOCP.145.5.501-508

Gürbüz, S. (2017). Survey as a Quantitative Research Method. Retrieved from: https://www.researchgate.net/publication/321874371_Survey_as_a_Quantitative_Research_Method

Hair, J. F., Black, W. C., Babin, B. J. et al. (2010). Multivariate Data Analysis (7th ed.). Upper Saddle River, NJ: Pearson Prentice Hall.

Hockstein, N.G., Gourin, C.G., Faust, R.A., & Terris D. J. (2007). A history of robots: from science fiction to surgical robotics. J Robotic Surg 1, 113–118. https://doi.org/10.1007/s11701-007-0021-2

Hollensen, S. (2020). Global Marketing. Pearson Education (eighth edition). Retrieved from: https://bookshelf.vitalsource.com/books/9781292251820

Hu, L. T., & Bentler, P. M. (1999). Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria versus New Alternatives. Structural Equation Modeling, 6, 1-55. http://dx.doi.org/10.1080/10705519909540118.

James, E. (2023). What is Correlation Analysis? A Definition and Explanation. FlexMR. Retrieved from: https://blog.flexmr.net/correlation-analysis-definition-exploration

Joerss, M., Schröder, J., Neuhaus, F., Klink, C., & Mann, F. (2016). Parcel delivery. The future of last mile: McKinsey & Company report. Retrieved from https://www.mckinsey.com/~/media/mckinsey/industries/travel%20transport%20and%20logistics/our%20insights/how%20customer%20demands%20are%20reshaping%20last%20mile%20delivery/parcel_delivery_the_future_of_last_mile.ashx.

Joo, Y. J., Park, S., & Lim, E. (2018). Factors Influencing Preservice Teachers' Intention to Use Technology: TPACK, Teacher Self efficacy, and Technology Acceptance Model. Educational Technology & Society, 21(3), 48–59. https://www.proquest.com/docview/2147866157?parentSessionId=oCRgY3D7F5vzmjRkYJkEc40tK3Kz5rDD31AYbhx0aOY%3D&accountid=13031

Juntunen, J. (2020, May 22). Fit indices and CFA. [Video]. Youtube. Retrieved from: https://www.youtube.com/watch?v=VbxDEMDSkDs&t=5s

Kapser, S. & Abdelrahman. (2020). Acceptance of autonomous delivery vehicles for last-mile delivery in Germany – Extending UTAUT2 with risk perceptions. Transportation Research Part C 111, 210–225. https://doi.org./10.1016/j.trc.2019.12.016

Kent, D. (2022). The Brief History of Mobile Phone: 1973 – 2023. Talkhome. Retrieved from: https://blog.talkhome.co.uk/technology/history-of-mobile-phones/#2019

Kwame, O. K., Atiemo, O., Afo, K. & Charity, A. (2019). Acceptance and use of mobile banking: an application of UTAUT2. Journal of enterprise information management, Vol.32 (1), p.118-151. https://doi.org.10.1108/JEIM-03-2018-0055

Leicht, T., Chtourou A., & Youssef, K.B. (2018). Consumer innovativeness and intentioned autonomous car adoption. The Journal of High Technology Management Research, Volume 29, Issue 1, Pages 1-11. https://doi.org/10.1016/j.hitech.2018.04.001

Li, Y. & Wang, C. (2022). Effect of customer's perception on service robot acceptance. International journal of consumer studies, Vol.46 (4), p.1241-1261. https://doi.org./10.1016/j.trc.2019.12.016

Liu, H., Yang R., Wang, L., & Liu P. (2019). Evaluating Initial Public Acceptance of Highly and Fully Autonomous Vehicles. International journal of human-computer interaction, Vol.35 (11), p.919-931. https://doi.org/10.1080/10447318.2018.1561791

Lumenlearning. (2023). Social Factors. Retrieved from: https://courses.lumenlearning.com/suny-marketing-spring2016/chapter/reading-social-factors/

Macedo, I., M. (2017). Predicting the acceptance and use of information and communication technology by older adults: An empirical examination of the revised UTAUT2. Computers in human behavior, Vol.75, p.935-948. https://10.1016/j.chb.2017.06.013.

Madigan, R., Louw, T., Wilbrink, M., Schieben, A., & Merat, N. (2017). What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of automated road transport systems. Transportation research. Part F, Traffic psychology and behaviour, 50, 55–64. https://doi.org/10.1016/j.trf.2017.07.007

Mander, J. (2022). How to use qualitative and quantitative research to your advantage. GWI. Retrieved from: https://blog.gwi.com/trends/qualitative-vs-quantitative/

Marangunic, N. & Granic A. (2015). Technology acceptance model: a literature review from 1986 to 2013. Universal access in the information society, 14:81–95. https://doi.org.10.1007/s10209-014-0348-1

Marsden, N., Bernecker, T., Zöllner, R., Sußmann, N., Kapser, S. (2018). BUGA: log - A real-world laboratory approach to designing an automated transport system for goods in Urban Areas, IEEE International Conference on Engineering, Technology and Innovation, pp. 72–80. https://doi.org/10.1109/ICE.2018.8436361

Marttila, S. (2023). Verkkokauppa Suomessa 2023 -raportti julkaistu ["E-commerce in Finland 20203 - report published"]. Paytrail by Nets. Retrieved from: https://www.paytrail.com/blog/verkkokauppa-suomessa-2023-raportti-julkaistu

Mathieson, K. (1991). Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior. Information Systems Research 2(3), 173–191. https://doi.org.10.1287/isre.2.3.173.

McCombes, S. (2023). How to Write a Strong Hypothesis | Steps & Examples. Scribbr. Retrieved from: https://www.scribbr.com/methodology/hypothesis/

Michałowska M., Kotylak S., & Danielak W. (2015). Forming relationships on the e-commerce market as a basis to build loyalty and create value for the customer. Empirical findings. Management, 19(1), 57-72. https:doi.org.10.1515/manment-2015-0005

MinnaLearn. (2023). Tulevaisuutta muovaavat globaalit megatrendit ["The future is shaped by global megatrends"]. Retrieved from: https://courses.minnalearn.com/fi/courses/rethinking-health/looking-to-the-future/global-megatrends-shaping-the-future/

Mueller, R. O. & Hancock G. R. (2001). Factor Analysis and Latent Structure, Confirmatory. International Encyclopedia of the Social & Behavioral Sciences. ScienceDirect. Retrieved from: https://www.sciencedirect.com/topics/medicine-and-dentistry/confirmatory-factor-analysis

Muneer M. M. A. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. Education and information technologies, Vol.26 (6), p.7205-7224. https://doi.org/10.1007/s10639-021-10573-5

Opetus- ja kulttuuriministeriö. (2022). OECD-vertailu: suomalaisten nuorten koulutustaso laskenut keskitason alapuolelle. [' OECD comparison: the educational level of Finnish youth has fallen below the average level']. Retrieved from: https://okm.fi/-/oecd-vertailu-suomalaisten-nuorten-koulutustaso-laskenut-keskitason-alapuolelle

Ouyang Z., Leung, E.K.H., & Huang G.Q. (2023). Community logistics and dynamic community partitioning: A new approach for solving e-commerce last mile delivery. European Journal of Operational Research. Volume 307, Issue 1, Pages 140-156. https://doi.org/10.1016/j.ejor.2022.08.029

Project Management Institute. (2022, August 8). Project Management Institute Global Megatrends 2022 Report [Video]. YouTube. Retrieved from: https://www.youtube.com/watch?v=4J6bQr_fPxw.

Rahi S., Othman M., Majeed M., Alghizzawi, M., & Alnaser, F. M. (2019). Integration of UTAUT model in internet banking adoption context: The mediating role of performance expectancy and effort expectancy. Journal of research in interactive marketing, Vol.13 (3), p.411-435. https://doi.org/10.1108/JRIM-02-2018-0032

Rahman, M.M., Lesch, M.F., Horrey, W.J., & Strawderman, L. (2017). Assessing the utility of TAM, TPB, and UTAUT for advanced driver assistance systems. Accident analysis and prevention 2017, Vol.108, p.361-373. https://doi.org/10.1016/j.aap.2017.09.011

Robomart (2023a). About. Robomart. Retrieved from: https://robomart.ai/about

Robomart. (2023b). Robomarts roll out! [Instagram video]. Retrieved from: https://www.instagram.com/robomarts/

Schryers, F. (2023). Pricing Strategy 101: What is Pricing Strategy and why should you look into it?. The house of marketing. Retrieved from: https://www.thom.eu/blog/pricing-strategy-101-what-is-pricing-strategy-and-why-should-you-look-into-it/

Shobha, K. (2020). How to do confirmatory factor analysis SPSS Amos with detailed explanation part II. [Video]. Youtube. Retrieved from: https://www.youtube.com/watch?v=-OVCg-mj2Ls

S-kaupat (2023). Kokeile vikkelää robokuljetusta. S-ryhmä. Retrieved from: https://www.s-kaupat.fi/sivu/robokuljetus

Starship (2023a). The global leader in autonomous delivery. Starship Technologies. Retrieved from: https://www.starship.xyz/company/

Starship. (2023b). Starshiprobots [Instagram]. Starship Technologies. Retrieved from: https://www.instagram.com/starshiprobots/related_profiles/?hl=fi

Statistical database. (2022). Number of pension recipients. Retrieved from: https://tilastot.etk.fi/pxweb/en/ETK/ETK__110kaikki_elakkeensaajat__10elakkeensaajien_lkm/elsa_k01_aikas.px/

Statistics Finland. (2023a). Population and society. Retrieved from: https://www2.stat.fi/tup/suoluk/suoluk_vaesto_en.html

Statistics Finland. (2023b). Palkka- ja palkkiotulojen mediaani 3 028 euroa tammikuussa 2023. [’The median Income 3028 euros in January 2023’]. Retrieved from:https://www2.stat.fi/tup/kokeelliset-tilastot/tulorekisterin_palkat_ja_palkkiot/ 2023-03-08/index.html

Statistics Finland. (2023c). More employed and unemployed in June 2023 than one year earlier. Retrieved from: https://www.stat.fi/en/publication/cl89wrk0dsz7i0bw0isvy1fjo

Swanson R.A. & Holton E.F. (2005). Research in Organizations (1st edition). Berrett-Koehler Publishers. Retrieved from: https://books.google.it/books?hl=fi&lr=&id=AyMZt9AodEEC&oi=fnd&pg=PA29&dq=basics+of+quantitative+study&ots=N6vvFyZI99&sig=ZHt01ByBqEsw1JNpssVcneTToSM#v=onepage&q&f=false

Tarhini, A., Mazen E-M., Maged A., & Alan S. (2016). Extending the UTAUT model to understand the customers' acceptance and use of internet banking in Lebanon: A structural equation modeling approach. Information technology & people (West Linn, Or.), Vol.29 (4), p.830-849. https://doi.org.10.1108/ITP-02-2014-0034

Techblocks. (2022). How Ecommerce Has Changed Over The Last 10 Years. Retrieved from: https://tblocks.com/how-e-commerce-has-changed-over-the-last-10-years/

Tsai, H. S. & LaRose, R. (2015). Broadband Internet adoption and utilization in the inner city: A comparison of competing theories. Computers in human behavior, Vol.51, p.344-355. https://doi.org/10.1016/j.chb.2015.04.022

Tuominen P. & Tommola M. (2022). Robotti tuo ruokaostokset ovelle! Alepa aloitti Suomessa ennennäkemättömän kuljetustavan – katso, miten homma toimii ['The robot brings groceries to the door! Alepa started an unprecedented delivery method in Finland - see how it works']. MTV Uutiset. Retrieved from: https://www.mtvuutiset.fi/makuja/artikkeli/robotti-tuo-ruokaostokset-ovelle-alepa-aloitti-suomessa-ennennakemattoman-kuljetustavan-katso-miten-homma-toimii/8401824#gs.09aw9p

Vakulenko Y., Shamsb P. & Hjorta K. (2019). Service innovation in e-commerce last mile delivery: Mapping the e-customer journey. Journal of Business Research, 101, 461–468. https://doi.org.10.1016/j.jbusres.2019.01.016

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. Decision sciences, Vol.39 (2), p.273-315. https://doi.org.10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A Theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46 (2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B. & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly: Management Information Systems 27(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L. & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly: Management Information Systems 36(1), 157-178. https://doi.org/10.2307/41410412

Väisänen, J. (2015). Consumer acceptance of future My Data based preventive eHealth services [Master's thesis in Marketing]. University of Oulu. Retrieved from: http://jultika.oulu.fi/files/nbnfioulu-201506111860.pdf

Yuen K. F., Cai, L., Lim Y. G., & Wang X. (2022). Consumer acceptance of autonomous delivery robots for last-mile delivery: Technological and health perspectives. Front. Psychol. 13:953370. https://doir.org.10.3389/fpsyg.2022.953370

Zofkie, A. (2023). 9 Last Mile Delivery Trends You Won't Want to Miss. Legacy Supply Chain. Retrieved from: https://legacyscs.com/last-mile-delivery/

APPENDIX

Delivery robots in Finland

The purpose of this survey is to study what are the factors affecting on consumers' intentions to use delivery robots in Finland. This is a master's thesis in the marketing program of Oulu University Business School.

No personal data is asked, and the data will be collected and analyzed anonymously.

The survey consists of three parts:

1. Respondent's profile: basic information of respondent
2. Information of delivery robots: information of the topic to support answering the survey
3. Questions: the actual questions that aim to find answers to the research problem

Answering the survey takes about 5-10 minutes.

Respondent's profile

What is your age?

15–24

25–34

35–49

50–64

65 +

What is your gender?

Female

Male

Other

What is your nationality?

Finland

Other

What is your net income per month?

(Net income = salary and other incomes after taxes)

Less than 1000 €

1000-1999

2000-2999

3000-3999

4000-4999

5000-5999

6000 or more

What is your highest education?

Primary school

Second degree (high school, vocational school)

Undergraduate degree (baccalaureate, university of applied sciences, or comparable)

Graduate degree (master, doctor, or comparable)

What is your current employment status?

Full-time employment

Part-time employment

Seeking work

Retired

Student

Unable to work

Information of delivery robots – read information carefully before answering the survey

In this study, delivery robots are defined as electric, self-driving vehicles that drive on public roads. Delivery robots are equipped with several cameras and sensors, and they can navigate among people and other vehicles. Delivery robots drive on wheels, and they can be smaller on their size (Figure 1) or bigger, car-like vehicles. Delivery robots can delivery, for instance, packages or food.

Figure 1: Starship delivery robot (Starship Technologies, 2023)

For instance, in Espoo, Finland S-group's Starship delivery robots have been used to deliver food for the first time in 2022. Since then, the use of delivery robots has been expanded also to Helsinki, Vantaa, Tampere, Turku, Pori, Rauma, Jyväskylä and Oulu.

To use delivery robots the user needs a mobile device, like smartphone or tablet. A mobile application needs to be downloaded to the device, for instance S-kaupat application in Finland. In the mobile application user can select delivery robot as a delivery method, and for instance browse the wanted products and pick the delivery time. User can track the delivery robot in the application. When the delivery robot arrives to its destination, user will be notified and can open the delivery robot with the help of application.

Questions

Have you heard about delivery robots before?

Yes

No

Have you used delivery robots before?

Yes

No

If you have no previous experience with delivery robots, imagine when answering, that delivery robots will be part of peoples' daily lives in the future.

Based on your own opinion and consideration, tell us to what extend you agree or disagree with the following:

	Strongly disagree	Disagree	Somewhat disagree	Neiter agree nor disagree	Somewhat agree	Agree	Strongly agree
Usefulness							
I find/would find delivery robots useful in my daily life							
Using delivery robots increases/would increase my flexibility in my daily life							
Using delivery robots helps/would help me accomplish things more quickly							
Using delivery robots increases/would increase my productivity							
Accessibility							
Learning how to use delivery robots is/would be easy for me							
It is/would be easy for me to become skillful at using delivery robots							
My interaction with the delivery robots via the mobile app is/would be clear and understandable							
I find/would find delivery robots easy to use							
Social Influence							
People who influence my behavior think/would think that I should use delivery robots							
People who are important to me think/would think that I should use delivery robots							
People whose opinion I value prefer/would prefer that I use delivery robots							
Conditions							

I have the resources necessary to use delivery robots (i.e., smartphone)
I have the knowledge necessary to use delivery robots
Delivery robots are compatible with other technologies I use (e.g., smartphone)
I can get help from others when I have difficulties using delivery robots

Hedonic Motivation

Using delivery robots would be fun
Using delivery robots would be enjoyable
Using delivery robots would be very entertaining

Risks

Overall, using delivery robots is risky
Overall, using delivery robots is dangerous
Using delivery robots exposes me to an overall risk

Price

I would not mind spending a lot of money for getting my orders delivered by delivery robots
If I knew that delivery robots as a delivery option were likely to be more expensive than conventional delivery options, that would not matter to me
I could pay a lot money for a really great delivery option

Intention to use delivery robots

I intend to use delivery robots in the future
I will always try to use delivery robots in my daily life, if possible
I intend to use delivery robots frequently, if possible