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MASTER'S THESIS

FACTORS OF MOBILE SHOPPING IN SLOVENIA

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

TABLE OF APPENDICES

LIST OF ABBREVIATIONS

AI - Artificial Intelligence
B2C - Business to Customer
COD - Cash on Delivery
CVC - Card Verification Code
DIY - Do It Yourself
ECDB – eCommerceDB (https://ecommercedb.com/)
EE - Effort Expectancy
EFA - Exploratory factor analysis
EU - European Union
FC - Facilitating Conditions
GWI - Global Wellness Institute
HM - Hedonic Motivation
KMO - Kaiser-Meier-Olkin Coefficient
OECD - The Organization for Economic Cooperation and Development
PE - Performance Expectancy
PSD2 - European Directive of Payment Services 2
PV - Price Value
PWA - Progressive Web Apps
SMCSS - Social Media Customer Service Software
SURS - Statistical Office of the Republic of Slovenia
TAM - Technology Acceptance Model
TR - Trust
UTAUT2 - Unified Theory of Acceptance and Use of Technology 2
VIF - Variance Inflation Factor

1 INTRODUCTION

M-commerce is a relatively new field where a thorough understanding of customer behavior plays a decisive role in the success or failure of businesses, thereby warranting additional research toward framework development. Researchers are attempting to define the antecedents to the use of m-commerce. Despite this, it is a relatively recent phenomenon; thus, the distinction between the antecedents to use m-commerce versus e-commerce or conventional commerce, often referred to as “brick and mortar commerce,” is unclear now.

The increasing use of mobile devices, particularly shopping apps, has transformed shopping into a continuous activity. As Martin (2013) puts it, “Consumers no longer go shopping; they always are shopping.” This shift challenges the traditional sales funnel model, as the traditional sales funnel no longer fits the shopping process.

In the past, retailers primarily focused on the outcome of the consumer decision process (to purchase or not to purchase). However, with the mobile technologies available today, retailers can actively influence consumers’ decision-making processes at different stages. Retailers are now required to engage with their customers at critical touchpoints of the decision-making process to provide a more personalized or customer-centric experience. The shift in focus from the decision outcome to the decision process signifies an important paradigm shift for the retailing industry (Faulds et al., 2018).

The purpose of this master’s thesis is to expand knowledge in the field of consumer behavior, specifically by investigating the factors influencing the usage of m-shopping in Slovenia. In this study, I aim to apply the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012) to explain variables underlying customer willingness to engage in m-shopping. This work will focus on the frequency of use rather than intention to use and will aim to encompass the entirety of the m-shopping process. Additionally, the study will provide data from users of m-shopping in Slovenia, which, as a minor part of the European market, is relatively underrepresented in academic literature and research.

My thesis aims to examine the antecedents to the use of m-commerce among Slovenian consumers based on the empirical results of my research. In doing so, I intend to improve the understanding of the behavior of customers who use this relatively new shopping channel. Indeed, mastering the m-commerce channel is likely to become one of the core factors for business success in the future retail world.

This research generally answers the following questions: What is the frequency of mobile shopping in Slovenia? How do Slovenian users perceive mobile shopping? What factors impact mobile shopping in Slovenia, and to what extent?

The thesis is divided into four chapters. The first chapter describes mobile commerce and its stages. It continues with an explanation of the importance of receiving information and the accessibility of mobile shopping. Furthermore, it explains the significance of the visual appearance of user interfaces and highlights the problems arising from distribution and return policies. Afterward, the impacts of trust, payment options, customer support, and pricing policies are presented. The same chapter then provides a summary of hedonic and utilitarian shopping motivations that drive shopping in general. The chapter concludes with an overview of the mobile commerce environment globally and in Slovenia.

The second chapter presents consumer behavior in mobile shopping through a literature review, where theoretical models and concepts such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, price value, and trust are examined and discussed.

The third, empirical, chapter of this thesis describes the quantitative research approach. It outlines the operationalization of constructs, variables, research model, and measurement scales. This chapter also explains the questionnaire design process and the data collection procedure. Furthermore, it presents the descriptive statistics of the sample and collected data, followed by the validity and reliability testing of the chosen concepts and the results of the conducted data analysis or hypotheses testing. The chapter then concludes with the presentation of additional tests undertaken to maximize the use of the collected data.

The fourth chapter is dedicated to interpreting key findings and additional findings extracted from our data. These findings are discussed through several managerial implications. The final chapter concludes with an explanation of research limitations and proposes corrections for future research.

2 MOBILE COMMERCE

2.1 Definition of mobile commerce

Mobile commerce, or m-commerce, is defined as the buying and selling of goods and services through mobile devices via wireless networks (Chong, 2013). It is one of the fastest-growing business areas today. Although often considered an extension of e-commerce (Chong et al., 2012), m-commerce has some advantages over its predecessor, as m-commerce users may conduct transactions at any time, from anywhere. Furthermore, m-commerce offers new possibilities, such as location-based services (smart coupons), higher personalization, and precisely targeted advertising.

According to Buchholz (2023), m-commerce is a steadily growing segment of e-commerce solutions. Although noticed by Swilley et al. (2012) over a decade ago, firms continue to face increasing pressure to deploy m-commerce strategies to sustain competitive advantage for attracting new and preserving existing customers. In this regard, business models intertwined with technological advancements are pivotal to success. Consequently, to develop more efficient and effective technology interfaces and formulate their marketing strategies, firms must understand how consumers perceive and utilize m-commerce.

E-commerce is driving significant changes and experiencing rapid growth compared to other sales channels. With the advantages offered by online shopping, m-commerce is becoming increasingly popular among both customers and sellers. The simplicity, constant accessibility, and quicker comparison of prices and product characteristics, coupled with a broader product range, lower prices, and the convenience of delivery, are some of the key reasons why shoppers are opting for online shopping. Moreover, m-shopping provides even greater accessibility (regardless of location and time), as smartphones are always within reach. While customers benefit from these advantages, sellers also experience lower operational costs and have access to a theoretically unlimited product range compared to the traditional sales channels (Lieber & Syverson, 2012; Armstrong et al., 2009).

Smartphones and new mobile gadgets with robust Internet technologies have transformed the old-fashioned market into an innovative marketplace known as mobile commerce services. Mobile commerce services vary from fundamental features to indefinite cutting-edge features such as mobile socializing, mobile wallet, mobile retailing, mobile purchasing, mobile ticketing, food ordering, car sharing, healthcare, voice assistant, and many others. The mobile application sector is expanding rapidly, with thousands of retailers creating their apps to engage with customers in a more personalized manner. These apps offer highly personalized experiences to every user, thus demanding (and receiving) a far wider range of personal data than the average online shopping experience. Most mobile phone users spend a significant amount of their time on the phone by using apps (Data.ai, 2017), irrespective of their country or age. However, convincing users to download an app is a challenging task. One could say in-app customers and website customers represent two different populations. App users are already aware of the app's benefits; they recognize and utilize its added value. On the other hand, website customers may shop less frequently, or maybe they only compare prices. Therefore, these customer segments require different approaches.

Many successful online companies like Amazon, AliBaba, JD.com, and eBay have developed mobile apps or voice assistant gadgets like Alexa. Mobile-compatible websites are essential for businesses to cater to this expanding market. According to Marroitt et al. (2017), the integration of m-shopping into business strategies provides customers with an additional shopping platform and increases the likelihood of initial interest and subsequent revenue. Practitioners emphasize the importance of understanding consumer behavior in marketing, as it is critical for the successful management and development of m-shopping in the retail industry (Hung et al., 2012). However, companies like Shein and Temu enter and retain markets primarily through mobile apps. For instance, Shein.com received 31% of visits from desktops, while 68% of visitors came from mobile devices in 2023 (DataReportal, 2023).

Hillman et al. (2012) described m-shopping as “the shopping for and purchasing of items online using mobile devices.” According to Chen (2013), m-shopping is “a process that involves the browsing, purchasing, and payment of goods or services using mobile phones, smartphones, or other mobile devices.” In the following year, Groß (2014) considered m-shopping as: “An alternative approach for searching, browsing, comparing and purchasing products and services online at any time and place while using a mobile device,” and in 2015 further expanded the definition to “M-shopping entails the gathering of product information from multiple sources, checking product availability and offers, and alter product selection throughout the purchasing process; m-shopping is a critical part of m-marketing” Groß (2015).

For this research, the definition “An alternative approach for searching, browsing, comparing and purchasing products and services online at any time and place while using a mobile device” (Groß, 2014) has been adopted.

2.1.1 Stages of m-shopping

The smartphone has revolutionized the path to purchase, rendering the traditional sales funnels inadequate for the shopping process. Instead, they are being replaced by a shopping life cycle. Consumers use complementary channels as an integral part of their shopping experience, aiming to optimize the benefits and costs associated with different channels (Lemon & Verhoef, 2016). The original shopping process framework, which has long been used by marketers (attention to a product, interest in the product, desire, and action), might still be valid. However, it cannot be considered anymore as a single-way linear process; it is more of a two-way circular process where the consumer must be influenced throughout the process, and the seller must be within reach at each stage. This change induced pressure on retailers to redesign their channels in accordance with the new shopping processes. Hure et al. (2017) argue that the integration of digital technologies into the consumer shopping experience enables new means of value creation and value capture. Retailers today must utilize omnichannel strategies to accompany consumers on their circular shopping journey. Verhoef et al. (2015, p. 176) describe omnichannel retailing as “the synergetic management of the numerous available channels and customer touchpoints, in such a way that the customer experience across channels and the performance over channels are optimized.” Since mobile shopping developed from online shopping, we consider it to include the same stages of the process. However, the technology, such as mobile devices, and their availability differentiate it from online shopping.

Kuo et al. (2004) described online shopping behavior and process by following stages: motivation, search for websites or apps, browsing the web stores, search for products, examination of products, evaluation and comparison, temporary purchase, payment, invoicing, and product acceptance or return. However, the research has disregarded a phase that has a significant impact on business growth: a consumer's feedback or a review of a product or service based on their overall experience. According to Bizrate Insights (2021), it has become increasingly important for online shoppers to check product reviews and read up on a business or service before spending money. In 2021, more than 70% of online shoppers typically read one to 10 customer reviews before making a purchasing decision. Less than 10% did not have a habit of reading customer reviews before buying. Based on Global Wellness Institute (GWI) statistics from 2022, as reported by DataReportal (2023), the main factors that encourage buyers to complete an online purchase are free delivery (49%), coupons and discounts (38%), reviews from other users (32%), easy return policies (30%), and a quick and easy online checkout process (28%). In contrast, the number of likes on social media encouraged 20% of buyers, and the "buy button" on social networks worked only for 12%.

In their study, Luceri et al. (2022) have chosen to divide the shopping process into five consecutive steps: attitude toward m-shopping, intention to purchase, actual purchase, satisfaction, and intention to continue purchasing through mobile channels. As customers progress through these stages, they develop different evaluations of the purchasing process and the product, akin to traditional shopping, where factors such as distance to stores, available time, past experiences, and deals are considered. This information is acquired consciously or subconsciously through media exposure and customer reviews. The simplicity of online payments (in-app payments) can also substantially increase impulsive purchases, which were not given much attention in the past research on online shopping.

Mobile shopping enables consumers to create their shopping lists or baskets, serving as a reminder. Users can access a virtual shopping assistant or maybe even engage in live chat assistance. They have the ability to search, query, compare, and purchase products and services and exhibit post-purchase behaviors, such as sharing information about their recent purchase experiences through social networks. Throughout this process, their data is collected and processed for further assistance or to assist similar users (autosuggestion or targeting development through machine learning and data science).

2.1.2 Information asymmetry and information quality

When one party involved in a transaction possesses more information than the other party, an information asymmetry occurs. This may result in adverse selection or moral hazard. According to Akerlof (1970), an adverse selection occurs when the party with less information makes decisions based on incomplete or less accurate information, leading to unfavorable outcomes.

The information asymmetry in the online shopping context might be more acute than in the context of conventional shopping. Online vendors often possess more information about a product's quality, including its actual size, color, and texture, compared to what online purchasers may have access to. When consumers are not entirely sure about product qualities or the trustworthiness of a retailer, they are faced with decisions regarding whether to trust the retailer. Trust is intertwined with risks in online transactions. Adverse selection occurs when online buyers trust an unreliable seller and end up purchasing a low-quality product due to insufficient information about the product quality and the seller (Mavlanova et al., 2012). A moral hazard arises when an online seller behaves inappropriately, such as selling a defective product, resulting in losses for the buyers (Pavlou et al., 2007).

Product reviews and information technology help reduce the information asymmetry between consumers and sellers by providing consumers with access to additional information about products and insights into other consumers' usage experiences. Unlike offline shopping, online buyers can access more information through search engines or word-of-mouth, such as product reviews, thereby reducing transaction risks and fostering trust in online retailers (Poturak & Turkyilmaz, 2018). Information quality affects trust in online retailers (Lee et al., 2019). Insufficient information or misinformation may result in distrust or mistrust in online retailers. Information quality also plays a crucial role in shaping a positive attitude towards the benefits of using a particular information technology, and it is considered to be a key antecedent of users' satisfaction (Tam & Oliveira, 2016).

Research conducted by Google (2016) revealed that 76% of people took a relevant action on their phone prior to making a purchase, such as looking up additional information on a product or a business via their mobile device. While consumers can easily access product attributes for search products like electronics through product descriptions, it is more challenging to access information for experience products such as wine, food, music, or the comfort of a sofa prior to purchasing. Product reviews help minimize information asymmetry by providing more information about a product and user experiences for customers. These reviews can influence our decision-making process by establishing trust and shifting our focus away from the characteristics of a product. In such cases, we may decide to end our search for additional information, reasoning that if others liked the product, we would likely enjoy it too. In such moments, information asymmetry is no longer an important factor as we lean on the experiences of those whom we trust. According to Bizrate Insights (2021), when customers were given a choice between a coupon or discount, loyalty program, free shipping, or a high review/rating, the top response from online shoppers was that a high rating is the most important factor when deciding on a purchase.

2.1.3 Accessibility of m-shopping

Online stores offer the advantage of being accessible at all times, unlike most traditional stores, and theoretically, they can offer an unlimited selection of products. This eliminates the need to visit multiple locations or competitors, thereby reducing the time and effort required for a purchase. Moreover, m-shopping offers even greater accessibility (independent of location and time), as smartphones are always within our reach. Research by Dynamic Yield (2020) revealed that 43% of consumers have shopped on their smartphones while at work in the past month. This confirms that we do personal shopping anywhere at any time, even when individuals should be focusing on other tasks. The study conducted by the OECD (2019) on online credit card transactions in Spain found that the likelihood of purchasing fashion items via e-commerce increases when the product is not readily available nearby, and this likelihood varies significantly across different product categories.

Indeed, by eliminating time and location constraints, customers can engage in shopping more conveniently, more easily, and faster (Soopramanien & Robertson, 2007). This, in turn, makes customers more motivated to adopt online shopping, as stated by Kim et al. (2010). Users who frequently use phones are more inclined to engage in m-shopping, highlighting the significance of businesses' presence on social networks. Social media platforms are used to generate prosperous and swift modes of communication between customers and businesses through visual content (Pelet & Papadopoulou, 2015). Additionally, livestream shopping, which is gaining popularity in the Chinese market, represents a modernized version of traditional TV sales channels, which have experienced a decline in recent years. Phones offer features like SMS messages, quick response (QR) codes, and location-based services, enhancing the overall mobile shopping experience (Okazaki et al., 2018).

It has been found in the literature that while social media platforms like Facebook contribute to enhancing privacy and trust among consumers (Ayaburi & Treku, 2020), they also indirectly influence customers purchasing intentions through their engagement on social networks with mobile phone payment systems (Kim et al., 2010). However, many consumers base their buying decisions more on observations influenced by social media rather than their perceptions of products and services. Furthermore, the adoption of digital payment methods and the preference for social media use are influenced by the education level of the consumers, as those who are more internet-savvy are more likely to use digital payment modes due to a higher level of trust (Gibson & Trnka, 2020; Kim & Park, 2013). Another study indicates that one-third of consumers reported purchasing products online through smartphone advertisements, which enhanced their purchase intentions (Martins et al., 2019).

2.1.4 Visual appearance and personalization

According to Kim et al. (2017), mobile users intermittently read content because mobile content is shown on smaller screens. Ghose et al. (2013) found that the smaller screens of mobile devices increase search costs (time-consuming and frustrating). This means that the first search result is relatively more attractive than each subsequent result when we are bound to small screens. The Google search engine well utilizes this fact by positioning sponsored search results higher than the rest of the results. Mobile and online shoppers often encounter substandard web design, with poorly placed navigation links and fonts that are difficult to read or of poor visibility due to the low contrast. The main frustration with the mobile shopping experience in the research done by Dynamic Yield (2020) was the “fat fingers” problem. Bang et al. (2013) noticed that mobile interfaces were inferior to interfaces on computer screens, and consumers browsing multiple categories were less likely to adopt shopping apps. However, the trend is changing. What used to be the case in the past, when users shopped on their phones primarily to save time but rarely considered the mobile to be the most convenient shopping medium, has changed in recent years with the adoption of mobile-friendly web design and availability of mobile apps, along with the accessibility of online payments. According to research conducted by Lee et al. (2022), the visual appeal of e-wallets positively influenced perceived enjoyment, and the perceived enjoyment of using an e-wallet positively affected impulse buying.

Another advantage of an app over the website is that users do not need to log in with each access. Repeatedly entering the same information on each purchase may lead to frustration and impact purchase decisions. According to Baymard Institute (2022), 17% of shopping cart abandonments are due to the inconvenience of entering their vital data over a small screen. To avoid this barrier, some websites have started to offer unregistered “guest” purchases, but that infringes on the idea of personalization. To overcome the disadvantages of apps and those of websites, companies started to use progressive web apps (PWA), which to some extent combine the benefits of both (user does not need to download, content is highly personalized, shopping path is tracked, forms are auto-filled, push notifications).

According to Saker & Evans (2016), m-commerce is also powered by consumer data such as location and user identity. The system adapts its functions to individual usage by learning or recognizing some information about the user. This data is collected from our mobile phones once we allow access to the installed application of social media or the seller’s app. Social networking (chats, interactions, connections) is well used for the promotion of m-commerce by identifying the topics we are interested in and creating personalized offers. Research conducted by Epsilon (2018) indicates that 80% of customers prefer buying from a brand providing customized experiences. Carefully planned personalization strategies with due permission of data usage can drive customer satisfaction to higher levels. Personalized communication based on user data enhances sales conversions as it allows brands to provide each customer with relevant information at the optimal moment.

2.1.5 Delivery and return policies

The traditional point of sale is constrained by the store location, spatial dimensions, and opening hours, whereas online stores are not bound to a specific location or time. However, the new shopping process is constrained by the possibility and speed of delivery. Distribution can often be problematic due to the cost of the service. Small-value purchases sometimes need to be bundled together, which makes the purchase cost inefficient (delivery is too expensive, or the item is needed sooner than delivery is possible). Additionally, delivery may not be available in certain regions or locations available.

Free shipping used to amaze people, making it a competitive advantage. However, today, it is something that consumers in developed markets expect by default when shopping online. Businesses are shifting their focus to shipping speed, which began with options like "next-day delivery" (such as Amazon Prime). However, as people become accustomed to fast and free shipping, businesses need to offer even same-day deliveries to retain their competitive advantage. The same-day delivery option is prevalent among online grocery shopping, which experienced rapid growth during lockdown periods in 2020 and 2021.

Research conducted by Coşar et al. (2017) showed that the delivery process in online purchases plays a significant role in customer satisfaction and in the decision-making process regarding whether one should purchase goods from a webshop. According to a FedEx (2023) report that cites various sources, 56% of abandoned carts are attributed to concerns related to delivery, and 75% of users have already paid for faster shipping.

2.1.6 Types of trust in online shopping

Practically all business encounters require some level of trust, especially when they occur under ambiguous circumstances. Risks associated with internet use, such as online fraud and data privacy concerns, become significant since online purchases often involve transactions with third parties, sometimes even through intermediaries. One of the primary reasons people avoid online shopping is a lack of trust. According to Marriott et al. (2017), the literature often highlights four elements of overall trust: a disposition to trust, trust in the m-vendor, trust in m-service, and trust in the m-device.

Disposition to trust refers to a person's tendency to trust others. It is defined as the general tendency to have faith or belief in humanity and to adopt a trusting stance toward others (McKnight et al., 2002). Trust in a mobile vendor is essential for consumers to feel comfortable engaging in m-shopping activities. According to Zeithaml et al. (1996), trust in service relates to the favorable attitudes toward websites or applications that facilitate efficient and effective shopping, purchasing, and delivery. Trust in m-device is technically trust in technology or technological process, where consumers are concerned about the security aspects of their provided personal data. Businesses often use social networking applications to increase customers' trust in online payments by building trust among existing and potential customers (Yang et al., 2015).

According to Koyuncu & Bhattacharya (2004), customers cannot be sure about the results of using online shopping and whether products purchased online match the quality standards identified on the website. However, compared to offline shopping, online buyers can access more information through search engines (for price comparison) or word-of-mouth (product reviews), aiming to reduce transaction risks and build trust in online retailers (Poturak & Turkyilmaz, 2018). When shoppers receive recommendations from their close friends or colleagues on social media, they can promptly visit the websites offering the desired product or service. Social media effectively combines accessibility with trust, a strategy efficiently utilized by marketers. It is important to emphasize that individuals' perception of data sources influences their process of acknowledging the provided information (Hu, 2015).

Research by Poturak & Turkyilmaz (2018) highlights that comments from close friends and family significantly influence the decision-making process of readers on social media. A study conducted by Hajli (2014) found that social media directly contributes to increased trust among consumers. Drakopoulou (2017) suggests that it indirectly encourages buying intentions through consumer involvement and commodification on social networking sites. According to Accenture (2017), 40% of Gen Z shoppers provide feedback often or very often, compared to about 35% of Millennials. The most popular method they use is writing reviews on retailer websites. They are also more likely to offer feedback via Tweets or posts on Facebook and Snapchat. Consumers who read product reviews and those who post reviews share similar interests in a product and intentions to purchase products, thus facilitating the exchange of product information to help each other.

The research conducted by Dynamic Yield (2020) surveyed 500 active mobile shopping users in 2020 about how retailers can enhance their mobile shopping experience. 57% indicated that providing more information and reviews of products would make the experience more enjoyable. Lee et al. (2019) also argue that information quality impacts trust in online retailers. This suggests that users base their shopping decisions on the information available. Additionally, 42% of respondents identified security concerns as a major issue preventing them from completing their shopping process. A study by Song et al. (2017) confirms that internet-savvy individuals are more likely to use digital payment methods if the vendor can ensure secure payment authentication. The relationship between trust in online retailers and consumers' actual online purchases varies across countries. For instance, when surveyed about their willingness to buy things via social media, shoppers in Sweden are almost twice as willing compared to the global average, whereas in Germany, less than half are willing (Accenture, 2017). Research conducted by Marriott et al. (2017) indicates that overall trust plays an equally important role in both genders' intention to shop via mobile devices. However, concerning age, younger consumers exhibit greater concern regarding trust perceptions in mobile shopping compared to older consumers.

2.1.7 Payment possibilities

Innovative mobile technologies provide new tools (apps) that separate the moment of purchase from the moment of consumption. They allow consumers to make purchases via mobile phones and collect them at home or at a designated pick-up location, compared to the traditional in-store service, where purchases are made and collected/consumed in-store. Customers now expect a seamless, nearly instantaneous mobile shopping experience, influencing their shopping habits. When it comes to payment options, customers prioritize secure, trustworthy, and easy-to-use methods. According to the Baymard Institute (2022), a complicated checkout process accounts for 17% of all shopping cart abandonments, 9% are due to the lack of suitable payment methods, and 4% encounter problems with their cards. Simplifying this process could lead to higher customer conversion rates. Preregistered credit cards offer the simplest and quickest way of online payment. However, many users hesitate to trust websites or apps with their data, fearing unknown charges or that sellers would lose data to hacking.

From the trust perspective, Cash on Delivery (COD) is the safest option for customers. A customer who chooses this option pays a delivery service provider with cash or a card at the time of delivery. The service provider then transfers the payment to the seller. This type of payment increases the interaction between customers and the delivery staff, as physical presence is necessary for payment, possibly increasing inconvenience. While COD addresses some concerns of customers, such as trust issues and unfamiliarity with online payments, it is a relatively costly payment method for sellers to process. Additionally, such purchases are associated with higher returns, as buyers may be less committed to the purchase than if they had paid in advance. Since the purchase is not paid upfront, it often leads to multiple delivery attempts (inconvenience of timing) for a single order. Even if the delivery is successful on the first attempt, the time taken to process the transfer of funds is usually 3 - 5 days, increasing the seller's working capital costs and becoming costlier to maintain with the bigger business scale.

Using an intermediary for online payments, such as PayPal, AliPay, or WePay, can help alleviate some of the concerns associated with direct card payments. These intermediaries securely store our credit card or debit card data, providing an added layer of protection. However, the process may require multiple confirmations and can be more complex to set up, potentially discouraging some users from adopting this method unless they plan to use it frequently.

A system of similar security and complexity to an intermediary payment system is a virtual card system, where mobile banks issue virtual cards that are eliminated after each purchase. The disadvantage of this system is that it cannot be used when the seller pre-authorizes the card or when the card is used to freeze funds until the service is utilized (booking.com and similar platforms). It is also a very inconvenient system when making repetitive small purchases (such as public transport), as the card number, CVC code, and expiration date change with each use.

A direct bank transfer is the least convenient, most time-consuming method during both the payment and ordering process, and usually most costly due to a fixed charge. In this system, the seller must issue a proforma invoice, upon which the buyer either scans the QR code or manually inputs the data into the payment order. The transfer of funds is usually executed within a day or more if payment is sent abroad. Non-working days and holidays can delay the transaction. Only after the seller receives the payment will the ordered goods be shipped.

The concept of payment with cryptocurrencies was initially promising; however, it has not yet been firmly integrated into everyday shopping processes. Cryptocurrencies have proven to be highly volatile in value, undermining their sense of security as a reliable form of payment. Additionally, they do not expedite the payment process compared to credit cards. Furthermore, a relatively high familiarity with the technology is necessary to adopt and utilize the crypto-system. Therefore, cryptocurrencies are seldom a payment option and are seldom chosen by customers. Significant barriers must be addressed to ensure cryptocurrency's widespread acceptance and usage.

2.1.8 Customer support

The online market knows no boundaries, and customers are often from various time zones. Regarding customer support, m-commerce retailers are often more responsive than those from physical or online stores. The mobile phone is a convenient medium for such a process, as it facilitates communication between the seller and the buyer. Mobile shopping may be gaining popularity due to its ability to offer live or real-time chatting with customer support without making a phone call. A prime example is AliBaba or AliExpress, where either the seller or the customer support team replies within a few minutes, eliminating communication barriers such as language or accent differences that may arise during phone calls. Chatting is also faster and more informal than sending an email, saving time for both parties involved. Vonage (2023) states that social platforms are a two-way communication channel between customers and sellers. Many m-commerce retailers utilize social apps like Instagram, TikTok, etc., as their sales channel, through which they provide an "instant response" by a natural person or an AI bot.

Companies today also incorporate Social Media Customer Service Software (SMCSS), a sophisticated, AI-driven tool that assists support teams by identifying public tweets, posts, or comments. With such rapid assistance, support teams can detect issues before customers contact customer support, helping the company retain its brand image before negative issues spread on social media. SMCSS typically covers three areas:

- Analytics: The software taps into online data, providing insights about customers. It tracks what customers say on social media and the data they provide online.
- Chatbot: Chatbots can significantly impact mobile shopping by enhancing customer service (offering 24/7 support), providing personalization based on previous interactions, reducing response times, and sometimes even boosting sales through product recommendations and personalized promotions.
- Social scheduling: Social scheduling affects mobile shopping by increasing visibility (ensuring consistent posting), targeting specific audiences, and improving engagement (posting at optimal times).

2.1.9 Pricing Policies

Fueled by sufficient user data and real-time information, the online commerce model theoretically enables perfect price discrimination. By leveraging various dynamic pricing strategies, retailers can maximize their profits. No commerce model known to date offers the option of such precise price adaptation in each millisecond based on supply and demand, apart from the stock exchange (e.g., real-time bargaining). However, inappropriate dynamic pricing strategies can have adverse effects. Cases like Ryanair demonstrate that businesses with highly variable pricing policies negatively impact consumers' trust and satisfaction. Additionally, a negative correlation between the frequency of price changes and the perception of price fairness was established in a study by Xu (2021).

E-commerce giants like Amazon, Alibaba, Otto, and JD possess a wealth of financial and informational resources that they utilize to fuel price competition. Nowadays, consumers can conduct a comprehensive price comparison for every product they seek or its equivalents with just a few clicks. Consumers search through results from nearby stores to those from online giants. Small local retailers can barely compete in online commerce since deliveries from online giants are being expedited.

As quoted by Xu (2021), the most common dynamic pricing strategies used by online vendors include: Segmented Pricing - offering different prices to different consumer segments (high-value customers charged higher prices); Time-based Pricing – charging more for providing faster services (same-day delivery), charge more for priority (new releases in fashion), offering discounts for early-birds; Peaking Pricing - charge more during high-demand periods or peak hours; Penetration Pricing – introducing new products to the market with lower prices compared to the market price, to reach a significant market share; Random Market Fluctuations - adjusting prices based on various random factors; Competition Driven Pricing - actively adjusting prices on competitor pricing strategies. To determine which dynamic pricing strategy a business should employ, factors such as time scale, weather conditions, customer relationships, elasticity of demand, and others (Victor et al., 2018) should be considered.

2.2 Hedonic and utilitarian shopping motivations

Buyers engage in online shopping for various reasons, encompassing hedonistic and utilitarian motivations. Hedonistic reasons include seeking convenience and enjoyment during and after the shopping process. However, it can be challenging to classify certain aspects, such as perceived quality derived from product reviews (based on recommendations or social influence) or personalization quality. Only recently, researchers have started to focus on hedonistic reasons and the role of emotions (Verkijika, 2019; Marriott et al., 2017), while utilitarian reasons are pretty well researched, as simplicity of use and usefulness were always considered among the main reasons why buyers decide to shop online (Perea Y Monsuwé et al., 2004).

Hedonistic shopping involves experiential values such as fantasy, arousal, sensory stimulation, enjoyment, pleasure, curiosity, and escapism (Scarpi, 2006; Hirschman & Holbrook, 1982). These aspects contribute to the sense of pleasure and fun that consumers derive from their purchasing experiences. However, the challenge arises in integrating these hedonistic features into the m-commerce experience, particularly considering the absence of physical contact between the product, seller, and buyer.

According to Arnold & Reynolds (2003), hedonic shopping motivation comprises five primary dimensions:

- Adventure Shopping: This dimension views shopping as an adventurous activity, where engaging in shopping can elevate motivation and allow consumers to immerse themselves in their world.
- Gratification/relaxation shopping: Shopping is an alternative to alleviating stress, improving mood, and addressing problems and fatigue.
- Value Shopping: Consumers engage in shopping when seeking discounts and deals offered by shopping destinations.
- Social Shopping: Shopping is perceived as a pleasurable activity when done in the company of family or friends, facilitating social interaction and information exchange about potential purchases.
- Idea Shopping: Consumers shop to stay updated on the latest fashion trends and innovations and explore new products and designs.

The utilitarian shopping value of goods or services originates from their basic properties. Scholars began studying utilitarian shopping values as early as the 19th century. While the topic has been extensively researched for traditional shopping, it has regained popularity as a research topic due to the changes brought by e-commerce and m-commerce. Babin et al. (1994) argued that utilitarian shopping value arises from a conscious pursuit of an intended consequence. Bridges & Florsheim (2008) suggested that online shoppers derive utilitarian value when they are goal-oriented and seek purchase convenience, information accessibility, ease of use, selection, and other factors. Kesari & Atulkar (2016) conducted a study on the satisfaction of mall shoppers, categorizing utilitarian shopping values as monetary saving, selection, convenience, and customized products. Moon et al. (2017) indicated that in addition to convenience, the online shopping environment offers a richness of product information and ease of use.

Generally, the utilitarian aspects of users' behavior toward shopping pertain to the usefulness, value, and perceived efficiency of the behavior or process. This stage of the shopping decision-making process involves rational and practical considerations. Utilitarian motivations in the shopping process primarily reflect the task-related benefits of a shopping experience or expectations, such as perceived usefulness, performance expectancy, and effort expectancy. For instance, when examining cart abandonment rates by interface type, sites accessed via mobile phones show a significant increase, with 97% of all check-out abandonment, compared to only 20% on mobile apps (Baymard Institute, 2022). Interestingly, these users are utilizing the same technology (smartphone), yet traditional websites prove to be considerably more inconvenient due to factors such as lack of autofill, difficulties in logging in, payment process issues (such as not saving cards), and non-personalized experiences (resulting in longer searches for desired products), among others.

This indicates that ease of use (effort expectancy) is essential for a satisfactory customer experience. Moreover, the findings of a study conducted by Shen et al. (2016) should also be considered, indicating that consumers prefer utilitarian products from offline stores and hedonic products from online stores. It is worth noting that distinct hedonic and utilitarian shopping motivations can vary based on the product category, distinguishing between utilitarian and hedonic products.

2.3 Global m-commerce environment and the situation in Slovenia

2.3.1 Global and EU situation of m-commerce

The world is becoming increasingly shoppable as retailers introduce various retailing channels with easy access to their offers. QR codes are being added to streaming videos, and social media platforms such as TikTok, Instagram, and YouTube are introducing their shopping tools, making it easier for brands to drive higher conversions and users to gain easier access to special personalized offers.

According to Buchholz (2023), m-commerce was valued at 2.169 trillion USD in 2023, with expected growth to 3.436 trillion USD by 2027. Despite doubling of e-commerce from 2018 to 2023, the m-commerce segment is experiencing even faster growth. In 2023, m-commerce accounted for 60% of all e-commerce sales, compared to 56% in 2018.

Among an estimated 8.0 billion people, there were 4.248 billion smartphone users (53%), a number projected to reach 6.4 billion by 2029 (Degenhard, 2024). According to DataReportal (2023) and GWI (2023), the median age in 2023 is 30.4 years old. On average, people spent 6 hours and 37 minutes daily on the internet in 2022, with developing countries seeing higher usage rates than developed countries. Similarly, the percentage of users accessing the internet through smartphones is higher among developing countries than in developed ones. On average, people spend 2 hours and 31 minutes using social media (GWI, 2023). The same report states that 43.4% of respondents use the internet to research products and brands, among other things, and 36.4% use it for researching places for vacation and traveling, while 76% reported using the internet for shopping in the past month.

According to GWI (2023), from 2018 to 2022, there was an 11% decrease in reasons of primary motivations for using the internet, contrary to the general expectation that the internet reaching more areas and more users should lead to increased diversity. The DataReportal (2023) report based on Statcounter data notes that in November 2022, there was a 9.3% year-on-year increase in webpage access through mobile phones and a 10.4% drop for laptops and desktops. The age of tablet use seems to be ending, as there was a 19.8% drop in webpage access through tablets. This trend can be attributed to more user-friendly webpages and apps, rendering tablets with large screens, akin to desktops, no longer necessary.

Statista's data (Gelder, 2023) reveals that when it comes to deciding what product or service to buy online versus in-store, the most popular category in 2023 was "Holidays and entertainment." Providers like Booking.com, Airbnb, Ryanair, etc., significantly impact this industry, and they no longer have physical offices. Tech followed this category with 54%, possibly due to the easier product comparison and price competitiveness. Likewise goes for the clothing category with 46%. Grocery accounted for only 22%. The most popular product categories were Electronics, Fashion, Food, and Furniture, but the percentages of these categories vary drastically depending on the statistics provider (Statista, Data.ai, GWI). According to DataReportal (2023), based on Data.ai statistics (excluding China), the most used shopping apps in 2022 were Amazon, Shopee, Flipkart, AliExpress, and Lazada. The same report states that 45% of B2C commerce in 2022 was conducted with Digital and mobile wallets, 32% with debit or credit cards, 11% with bank transfers, and only 4% with cash on delivery, as this option is often not even available anymore.

According to a study by GWI (2023), social commerce penetration is advancing globally, but the growth varies between regions. Latin America leads with 42% of platform users having used Facebook Marketplace or Instagram Shopping Bag in the past month of the research (Q1 2023) but with a 4% drop from year 2021. North America follows with 39% of users and a 16% growth. Europe lags behind the Middle East and Asia-Pacific with only 26% of users engaging in social commerce but with an 11% growth rate. As ECDB (2024) suggests in their article on this phenomenon, the initially slower acceptance by European users might be due to the presence of legacy retail systems, stringent data protection laws, and stricter competition infringement detection practices (such as those seen in the EU Commission vs. Meta case about unfair trading conditions on competitors).

The fact that Europeans favor social media for chatting over shopping might also be a reason. However, these statistics could change in the future once Europeans discover the simplicity of this retail channel. The cause-result relationship is complicated to prove in this case. There are also significant differences among countries in Europe. For example, when asking shoppers whether they are willing to buy things via social media, compared to the global average, shoppers in Sweden are almost twice as willing to buy, yet in Germany, less than half are willing (Accenture, 2017). According to an E-commerce report (Lone &

Weltevreden, 2023), in 2022, Western Europe's e-commerce turnover amounted to 67%, more than the rest of the EU combined (33%). The lowest usage rate of e-commerce was noted in Eastern Europe, with only 46% of individuals engaging in e-commerce. Among individuals who purchased online in the last three months, the most popular product category was clothes (fashion) with 68%, followed by 34% physical multimedia, food through food deliveries was 30%, and groceries at 17%.

Regarding services in the last three months, 31% bought or used streaming services, 29% purchased event tickets, 25% bought music or streaming, and 15% spent on games. Individuals who purchased online in the last three months bought from national sellers (81%) and EU sellers (31%), with non-EU sellers amounting to 19%.

Many users are reluctant to use mobile shopping due to data sensitivity and trust issues, especially when purchasing higher-value items. The European Union is trying to solve this by regulating a general return policy (14 days, with no explanation needed) and the new European directive of Payment Services (PSD2) introduced in 2021, which targets the security of online payments. The directive demands a Strong Authentication, achieved by the combination of at least two out of three independent security elements. These elements prove that the payer is also the owner of the cards. Such security regulations will further popularize the usage of mobile phones for financial services and online shopping, as they offer simple technological solutions such as fingerprint or face recognition, SMS authentication, and PIN insertion. Once a mobile phone is used in a process, why not use it for the process itself?

2.3.2 Situation of m-commerce in Slovenia

According to ECDB (2021), Slovenia ranked as the 77th largest market for e-commerce (B2C) in 2021, with a revenue of 641 million USD, placing it ahead of Uzbekistan and behind Ghana, the two of which are by population approximately 15 times bigger than Slovenia, but somewhat 100 places lower or Human Development Index in 2019. However, by 2023, Slovenia dropped to the 81st position among the most prominent e-commerce markets, with a predicted revenue of 663.4 million USD and an expected growth of 5.6% in the following year (Uzungolu, 2024). This drop in ranking can be attributed to the gradual ascent of other developing markets surpassing Slovenia's position due to its small population size.

In 2023, the internet was utilized by 90% of the population aged between 16-74 (SURS, 2023), indicating a high level of digital connectivity within the country. According to Uzunoglu (2024), the leading player in the Slovenian e-commerce Market is mimovrste.com, which generated a revenue of 115 million USD in 2022. This is significantly ahead of its competitors, with Merkur generating 33 million USD in revenue and BigBang 27 million

USD. Together, these top three stores accounted for 27% of online revenue in Slovenia in 2022 (Uzunoglu, 2024).

In Slovenia, 66% of residents made at least one online purchase (bought or ordered a product or a service) in the 12 months from April 2022 to March 2023. This percentage represents a steady growth from 56% in 2019, indicating a continuous increase in online shopping activity. However, Slovenia still lags behind Western Europe, where the percentage is 84%. The highest shares of e-buyers were found in the Obalno-kraška (73%) and Gorenjska (72%) statistical regions, while the lowest shares were observed in the Savinjska and Zasavska regions (59% each). The share of e-buyers was highest among 16–24-year-olds (84% compared to 82% in 2022) and the lowest among 65–74-year-olds (30% compared to 25% in 2022). Notably, the share among 55–64-year-olds experienced the most significant increase, rising by ten percentage points to 52% (compared to 35% in 2019), according to SURS (2021, 2023). According to Mastercard (2023), 60% of respondents made a payment using a smartphone or another smart device in 2023, a sharp increase from 40% in 2020. However, despite this growth in online payment methods, Slovenia remains in the lower third of e-commerce users compared to the EU average, as reported in the E-commerce report (Lone & Weltevreden, 2023).

According to SURS (2023a), in three months before the interview, approximately 833.135 residents, or 53% of the population, made at least one online purchase (bought or ordered a product or service), while in 2019, this percentage was 45%. We can notice that online shopping frequency is increasing in Slovenia, with most e-buyers (41%) in 2023 making 1–2 online purchases, compared to 51% in 2020. Additionally, 37% made 3–5 online purchases, up from 31% in 2020. Furthermore, 13% made 6–10 purchases (compared to 10% in 2020), and 9% made more than ten online purchases (compared to 8% in 2020). According to the Statistical Office of the Republic of Slovenia (SURS, 2021), in 2020, 54% of respondents spent up to 299 EUR in the last three months on online purchases, while 13% spent more than 500 EUR. Only 2% of e-shoppers could not estimate the value of their online purchases during the same period. Unfortunately, SURS has not updated information on online shopping expenditures to date.

In 2023, the most popular product category among physical products was clothes, including sports clothing, shoes, or accessories, with 66% of respondents purchasing these items. This was followed by 25% of respondents buying sports goods (excluding sports clothing), while 24% purchased cosmetics, beauty, or wellness products. Additionally, 24% of respondents bought furniture, home accessories (e.g., carpets or curtains), or gardening products (e.g., tools, plants), and the same percentage bought medicine or dietary supplements (e.g., vitamins). It is important to note that these percentages do not sum to 100 as it was a multiple-choice question. Regarding services, 41% of e-buyers ordered or purchased at least one service online. The most popular service was accommodation in a hotel, hostel, etc., via a web portal or website or through a travel agency, with 31% of respondents choosing this option. Following this, 18% of respondents purchased plane tickets, tickets for bus or train, hired a ride (e.g., via GoOpti), taxi, or car (SURS, 2023a). According to Uzunoglu (2024), in 2023, Hobby & Leisure was the largest market segment, accounting for 26.2% of Slovenian e-commerce revenue. This was followed by electronics at 20.9%, fashion at 17.4%, furniture and homeware at 11.6%, care products at 9.3%, DIY at 8.9%, and grocery at 5.7%.

In 2020, only 20% of 16–74-year-olds purchased digital products or services, while in 2023, this percentage increased to 37%, indicating a substantial rise in the popularity of streaming services. Streaming services nearly tripled in usage, climbing from 8% in 2020 to 22% in 2023. Additionally, there was considerable growth in music downloads or streaming services (such as iTunes, Google Play, Amazon Music, Deezer, and Spotify), rising from 4% in 2020 to 14% in 2023. However, gaming (from 6% to 9%) and e-magazine purchases (from 4% to 6%) remained relatively stable during this period (SURS, 2021; SURS, 2023a).

A negative trend in cash payments upon delivery was observed in 2020, with rates decreasing from 44% in 2019 to 39% in 2020. Credit cards emerged as the most common payment method, constituting 60% of all payments (Mastercard, 2021). This trend continued, according to SURS (2023a), with 43% of the population in 2023 making online purchases using cash on delivery or bank transfers (non-digital), while 66% opted for debit or credit cards. This represents a significant difference from global statistics, where only 4% of buyers paid cash on delivery (DataReportal, 2023). According to the E-commerce report (Lone & Weltevreden, 2023), buyers in Slovenia are among those who purchase the least from sellers in unknown countries, with less than 3% engaging in such transactions. Such behavior is also observed in buyers from Serbia, Romania, Portugal, North Macedonia, Latvia, Lithuania, and Bulgaria. This could indicate a level of suspicion among the population towards foreign sellers. Alternatively, it might be attributed to the limited presence of foreign sellers in these markets, given their comparably smaller size or lower purchasing power.

Pošta Slovenije is the most frequently offered delivery service provider among online stores in Slovenia. Among those stores that indicate which service they use to transport their goods, 52% cited Pošta Slovenije as one of their providers. Moreover, GLS and DPD are among the top three shipping service companies offered by online retailers in Slovenia at rates of 30% and 19%, respectively (Uzunoglu, 2024).

It is worth mentioning that the percentage of users considering mobile devices as their favorite means of payment in the following five years rose from 10 % in 2015 to 36% in 2020. In 2023, 60% of users made a payment via smartphones or devices. A similar trend was observed among users considering payment cards as their preferred method, rising from 59 % in 2015 to 72 % in 2020 (Mastercard, 2021; Mastercard, 2023).

2.3.3 Overview of the future trends

Although e-commerce is expanding rapidly, in-store purchasing will continue to exist, likely evolving into a hybrid online/offline buying experience. Today's hybrid solutions include curbside pickup, click and collect, augmented reality, and AI assistants. Virtual reality enhances the online shopping experience by integrating physical retail items with the virtual world, creating a seamless online/offline shopping experience. Augmented reality has emerged as an ideal way to use technology to help online shoppers virtually "try" or experience the products they wish to purchase. Brands like IKEA are leveraging augmented reality to enable shoppers to use their smartphones to superimpose images of its furniture catalog within their living rooms, making shopping more innovative and personal.

Another important change is occurring in pricing, where trends point towards machine learning-based pricing through extensive data analysis. This implies that prices will be highly competitive and volatile, and the intelligence will forecast pricing trends and adapt current pricing accordingly. It could be said that online markets would reach the phase of perfect competition. However, this has been the development of the past few years, while the new player, AI, is on the horizon to accelerate things even further.

Another trend is voice search, which is extensively used for researching products, placing orders, tracking delivery, contacting customer support, reviewing, and reordering items. The convenience of voice shopping and its quick accessibility will likely make it a preferred feature for mobile shopping in the future. This technology also enables mobile phone users to ask hyperlocal questions like "find the closest grocery" or "library near me." Although the estimation in 2018 was that voice commerce would grow from 2 billion USD in 2018 to 40 billion USD in 2020, it reached only around 4.6 billion USD in 2021. Today's estimation is that voice shopping will reach 19.4 billion USD in worldwide traffic by 2023 (Chevalier, 2023). The missed forecast might be because the population is unfamiliar with this option or because businesses are still testing this channel.

Cryptocurrencies promise faster transactions, lower transaction fees, anonymity, and enhanced security. Businesses are increasingly considering including this feature in their applications or websites to future-proof their selection as more customers show interest in crypto payments and the possibility of making frequent purchases using virtual currency. In addition to its apparent mobility, cryptocurrency also offers support for QR codes, simplifying immediate digital payments. However, the major disadvantage of these currencies is their volatility and the general need for technical knowledge to deal with cryptosystems. According to GWI (2023), by the end of 2022, only 11.9% of internet users owned cryptocurrency, with a slight declining trend noticeable from the 1st quarter of 2022.

It appears that companies such as Shein and Temu are leveraging the social media era better than anyone before. Their extreme growth speed can be attributed to the successful recognition of online trends and in reality. Previously, brands have used social media primarily to increase brand awareness, but in the future, the focus is shifting towards sales and customer conversion. The rise of social commerce can be attributed to the normalization of firms using social media for marketing and direct sales.

Social media platforms such as Facebook, Instagram, TikTok, YouTube, and others have created a direct bridge for customers to purchase products they encounter. Users even have a button to interact with the products. They can be redirected to the product page without opening a browser or another app (in-app browsing). Companies such as Shein are even employing AI to identify trends and create products to match these trends on a weekly basis, thus transforming the concept of fast fashion into real-time fashion. However, one might question how ecology and sustainability align with these statistics and trends. According to GWI (2023), there was a 13% drop (since Q3 2019) in global consumers who expect brands to be eco-friendly. This is worrisome news regarding future trends.

3 MODEL SELECTION AND FRAMEWORK DEVELOPMENT

In this chapter, a process of model selection through a systematic literature review is described. As mobile commerce is a steadily growing segment of e-commerce, understanding consumer behavior plays a decisive role in the success or failure of ventures. Additional research on framework development is suggested in the literature. Researchers are still striving to define the antecedents to the use of m-commerce, even though mobile commerce has been present for approximately ten years now.

3.1 Selection of the UTAUT2 model through the literature review

In 2017, Marriott et al. conducted a literature review on m-commerce, analyzing 138 journal articles. They concluded that current studies highlighted several problems: a) limitations in data collection methods in m-shopping literature, b) the size of study samples, c) sample characteristics, and d) the geographical origins of the collected data, thereby limiting the applicability of findings to other countries. It is important to note that recent studies show the global unification of shopping culture (Luceri et al., 2022; data.ai, 2017), driven by technology and media exposure. Comparing recent research findings to those from the early 2010s is challenging due to significant technological advancements in this field.

In 1989, Davis developed a Technology Acceptance Model (TAM), which identified two key variables influencing consumer behavioral intention to use new technologies: perceived usefulness and perceived ease of use. Subsequently, many studies in the fields of e-commerce and m-commerce focused on the antecedents of the use of technology as a sales channel by adapting Davis's TAM model. Researchers alternated determinants, incorporating variables such as risk, trust, and social influence, leading to various outcomes.

These outcomes depended on the cultural background of the sample population (Chong, 2013; Wu & Wang, 2005; and others).

In 2007, Bagozzi criticized several shortcomings of the TAM model, suggesting that it is no longer suitable for investigating and explaining usage behavior. This is because perceived usefulness and perceived ease of use may not adequately examine usage behavior, especially with different types of technologies. Ingham et al. (2015) argue that TAM, including attitude as a mediator, provides a better explanatory model than TAM without attitude. In 2003, Venkatesh et al. incorporated the TAM into the Unified Theory of Acceptance and Use of Technology (UTAUT) by merging perceived usefulness and perceived ease of use into their factors “performance expectancy” and “effort expectancy,” alongside “social influence,” and “facilitating conditions,” all moderated by age, gender, experience, and voluntariness of use, that have a significant effect on behavioral intention.

In 2012, Venkatesh et al. developed the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), which includes additional factors such as “hedonic motivation,” “price value,” and “habit.” Marriot et al. (2017) recommended UTAUT2 for future m-shopping research as an appropriate theoretical basis due to its contemporary and comprehensive nature. UTAUT2 contains 36 questions merged under nine constructs: performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation, price value, habit behavior, behavioral intention, and use behavior. However, a review conducted by Verkijika (2019) on 23 previous studies based on TAM, UTAUT, and UTAUT2 showed that emotion-related factors were highly underrepresented in those studies.

Analyzing some of the research surveys that have been used (Liébana-Cabanillas et al., 2017; Chong et al., 2012; Wu & Wang, 2005), it is noticeable that older research focused more on the industrial or functional point of view of the technology (TAM), but ignored the hedonic or attitude views towards technology. Furthermore, researches were focused exclusively on feelings towards the given website or application, thus disregarding the broader shopping process. As m-shopping is essentially shopping, it inherently involves hedonic reasons, particularly in industries like fashion apparel and services. Hubert et al. (2017) argue that existing studies display inconsistent results regarding the drivers of m-shopping. This inconsistency could be attributed to the testing of only a few drivers without considering the direct or indirect effects of other determinants and potential mediators.

In summary, previous studies have focused on distinguishing mobile shopping usage from other phases, such as mobile payment, delivery service, and user interface appearance. Some studies have concentrated solely on users' technical knowledge while overlooking their satisfaction with the m-shopping process. Luceri et al. (2022) found that the variables of the triad satisfaction–trust–continuance are highly interrelated. Satisfaction is determined as the most important predictor of repurchase intention by Limayem et al. (2007).

Luceri et al. (2022) established a framework for their research, dividing the m-shopping journey into five steps: attitude, intention, purchase behavior, satisfaction, and continued usage intention, all based on the general customer journey concept by Lemon & Verhoef (2016). In m-shopping, often the entire process is managed through a single mobile application. Luceri et al. (2022) also concluded their meta-analytical research with a suggestion to further research the impact of new technologies (i.e., artificial intelligence, augmented reality, internet of things) on different phases of the m-shopping journey.

This research will use the UTAUT2 model, with a primary focus on the emotional factors of m-shopping, and include constructs that best align with the entirety of the m-shopping process. Service in m-shopping is an integral part of the shopping journey, just like in traditional shopping. Thus, a survey will maximally include questions that represent services that may affect the frequency of use of m-shopping.

3.2 Selection of factors through the literature review

In the following eight sections, we aim to analyze the relevance of key UTAUT2 constructs, specifically within the context of mobile shopping. By exploring these factors, this study seeks to illuminate their significance and interconnections, providing valuable insights for enhancing user engagement and adoption in the mobile commerce landscape. For further research, the constructs of Performance Expectancy, Effort Expectancy, Facilitating Conditions, Hedonic Motivation, Price Value, Trust, and Frequency of use were chosen.

3.2.1 Performance Expectancy

According to Venkatesh et al. (2003), performance expectancy (PE) pertains to the extent how much people perceive a new technology as useful in their daily lives in terms of enhancing productivity and saving time and effort. Many other authors have used the construct of perceived usefulness, which has been confirmed as a factor that affects consumers' intention to continuously use mobile commerce (Hung et al., 2012; Groß, 2014; Sohn, 2017). Pascual-Miguel et al. (2015) proved that PE has a significantly positive impact on the behavioral intention to adopt online shopping by both genders. Lee et al. (2019) found that after Habit, PE was the strongest factor impacting the continuous use intention of food delivery apps in Korea. Information Quality strongly influenced both factors. It is essential to add that Sohn (2017) identified that consumers form their usefulness evaluations depending on the respective shopping tasks and that usefulness predictors differ in relevance across product categories and shopping touchpoints.

According to Accenture (2017), Gen Z craves speedy delivery much more than Millennials. Many more Gen Z will cancel an online order if delivery timing is ambiguous, and fewer are willing to wait for free deliveries. They desire to schedule their deliveries and preferably receive them on the same day. Additionally, they are more willing to pay extra for these conveniences. Research by Dynamic Yield (2020) revealed that 76% of respondents shop on mobile devices because "it saves time"; however, 88% of shoppers still believe other mediums provide more convenient shopping experiences. Speedy delivery, quick payment processing, and overall convenience are among the factors that should be grouped under the construct of performance expectancy (PE). Therefore, PE will be included in our model.

3.2.2 Effort Expectancy

The research done by Dynamic Yield in 2020 (Dynamic Yield, 2020) surveyed 500 active mobile shopping users, asking them how retailers can make their mobile shopping experience more enjoyable. Among the respondents, 53% indicated, "By helping me find what I am looking for faster," 57% responded, "By making it easier for me to check out," and 57%, "By providing more information and reviews of products." These responses suggest that users prioritize ease of use, including speed and smooth process when it comes to their shopping experience.

In the UTAUT, Venkatesh et al. (2003) integrated three constructs, perceived ease of use by Davis from 1989, complexity by Rogers from 2003, and ease of use by Moore & Benbasat from 1991, into the construct of Effort expectancy (EE), which was defined as the "degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450). UTUAT2 adopted the exact formulation of Effort expectancy from the UTAUT. Smartphone shoppers must complete the purchase independently, without direct help from store employees. While smartphones provide ubiquitous shopping opportunities, the inconvenient interfaces increase search costs and inhibit mobile purchasing (Bang et al., 2013; Chong, 2013; Ghose et al., 2013).

According to Luceri et al. (2022), the usage of mobile applications improves convenience by enabling easy shopping and reducing consumers' cognitive, physical, and psychological efforts. Kim et al. (2017) argue that mobile purchases are determined solely by digital experience (i.e., online experience and mobile experience). Consumers who browse and buy through mobile apps expect a higher quality of the shopping process, as they are convinced to make an effort to download an app and register. However, users may delete the app to free up screen and memory space if it is not used frequently. The necessity to download an app presents a barrier for the retailer. Retailers overcome this by providing easier access to the download option through social media or offering special deals on apps. Social media allows brands to create posts where products can be tagged in images and generate clickable and shopping-friendly links. Bekmagambetov et al. (2018) suggest that social media serves as a rapid assessment method for m-commerce websites, enabling users to access specific pages without getting lost on the website, thereby reducing user effort.

Ingham et al. (2015) empirically observed a significant association between perceived ease of use (a similar construct as effort expectancy) and customers' attitudes toward online shopping. Yang (2017) further demonstrated that consumers are more likely to purchase a broader scope of products if they are already familiar with the technology. Wang et al. (2015) demonstrated that low-spending customers increase their order rate and order size as they start to use m-shopping, indicating that the barrier to using technology lowers with the frequency of usage. Pascual-Miguel et al. (2015) confirmed that the role of effort expectancy essentially predicts the intention to use online shopping among the female population, while for male groups, this correlation is likely to vanish. Based on the importance the construct of EE, it will be included in our model.

3.2.3 Social Influence

In the UTAUT, Venkatesh et al. (2003) proposed that social influence captures the role of subjective norms, social factors, and image. According to Venkatesh et al. (2003), social influence is "the extent to which an individual perceives that important others believe he or she should apply the new system." We could also understand social influence as an impact of people such as relatives, colleagues, or friends, whom a customer could ask for either information or receive social approval by using online shopping (Chong et al., 2012; Clemes et al., 2014; Pascual-Miguel et al., 2015; Ingham et al., 2015).

One could also consider the effect of social network influencers since by following their posts a few times per day, people might feel closer to them rather than to their relatives or friends. Several online shopping studies have proved the impact of social influence on the customer's intention to use online shopping and mobile shopping. Ingham et al. (2015), in their review, supported that social influence has been able to maintain its significant influence on customers' intentions over most studies that have examined the customers' adoption of online shopping. Chong et al. (2012) demonstrated that the role of social influence statistically predicted Malaysian consumers' decisions. Clemes et al. (2014) stated that subjective norms, as a similar factor to social influence, have also been confirmed to have a significant impact on the customers' adoption of online shopping.

According to Accenture (2017), social media plays a central role in the lives of Generation Z individuals. Similar to Millennials, Gen Z shoppers mostly base their purchasing decisions on three factors: receiving the lowest price, seeing products in stores, and reading reviews. However, Gen Z consumers place a greater emphasis than Millennials on listening to friends and family and turning to social media for inspiration before deciding what to buy (Accenture, 2017).

Research by Dynamic Yield (2020) found that 22% of users shop on smartphones because they arrive at the page after checking social media or an email. Accenture's research from 2017 showed that social media has a significantly greater impact on Gen Z shoppers' purchasing behaviors than it does on Millennials, and this younger generation is expressing a greater willingness to buy products and services via this channel.

Even marketers define their social media platforms as an essential means to reach their consumers. Using electronic word-of-mouth in social media allows for constant connection to a vast audience. The findings in the study of Hossain et al. (2020) show that social media has an impact on the usage of m-commerce applications, advertising on social media websites, and the development of trust among consumers in making online payments via mobile phones. Similar findings are reported by Saprikis et al. (2021), where social influence has a positive effect on trust toward the use of technology. As the research scope is limited, the construct of Social influence will be omitted, but the impact of online reviews will be tested under the concept of trust.

3.2.4 Facilitating Conditions

"Facilitating conditions are defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003, p. 453). In reality, facilitating conditions refer to the external factors that may influence the use of technology, such as the availability of necessary resources and support. In the context of mobile shopping, facilitating conditions can include factors such as access to reliable internet connectivity, access to mobile devices and device features, and access to technical support. Mobile shopping is a process in which technology needs to be used, for example, mobile phones, smartwatches, and house assistants, to reach the desired sales channel.

Consumers must have the necessary technology to engage in online shopping through mobile devices. While such an argument is intuitive, it might not be so simple when we look deeper into the technological process of mobile shopping itself. To do m-shopping, the user does not need just a smartphone and internet connectivity, but it also depends on the quality and size of the user's interface (phone) (Baymard Institute, 2022), quality of the system (payment options, safety of payments connected with trust issues), information quality (Mavlanova et al., 2012), availability of delivery options (Koyuncu & Bhattacharya, 2004) and many others. According to Statista (2022), in 2020, 53% of consumers said that free delivery would increase the likelihood of purchasing products online. A notable 35% also cited reviews from other customers and 33% mentioned easy returns policies.

Coşar et al. (2017) argued that any difficulties with the delivery process can have a negative effect on the purchase. All of these and more have to be up to the consumer's satisfaction level for the process of mobile shopping to be done. These factors also change with the accessibility of technology. Luceri et al. (2022) found out in their study that mobile shopping is influenced by variables that reflect the evolution of technological innovations and the consequent improvement of the functionality and convenience of mobile devices (previous digital experience and ubiquity). They also suggested that further research about the impact of new technologies (i.e., artificial intelligence, augmented reality, internet of things) on different phases of the m-shopping journey should be conducted. The construct of facilitating conditions will be included in the model.

3.2.5 Hedonic Motivation

Hedonic shopping motivation (HM) is a behavior related to fun, amusement, fantasy, and the sensorial stimuli aspects of consumption (Babin et al., 1994). In the technology context, HM is defined as fun or pleasure that results from technology use (Venkatesh et al., 2012). While it is present in all shopping channels, Arnold & Reynolds (2003) argue that hedonic motivation varies across different retail formats.

Scarpi (2006) found that hedonic shopping motivation has a more important role in online shopping than traditional shopping. A study conducted by Luceri et al. (2022) points out that hedonic factors: innovativeness, hedonic value, and enjoyment, are the key drivers of m-shopping. The same study concluded that whether or not an app is used affects the role of hedonic aspects, quality, and satisfaction. The exact impact of innovativeness is confirmed by Accenture (2017), which found that Gen Z shoppers are far more likely to experiment with new services provided by retailers.

Research by Dynamic Yield (2020) found that 27% of users shop with a smartphone because they find it enjoyable and 29% because it "gives them something to do." The same research (Dynamic Yield, 2020) found that 43% of consumers shopped on their smartphones even at work, which might be the result of our need for amusement during mundane tasks. The results of the research by Činjarević et al. (2011) indicated that impulse buying behavior was significantly related to adventure, gratification, value, and idea shopping motivations, which are factors of hedonic shopping. Testing the factors of social influence on impulse buying through social networks, Sri (2018) found out that Adventure Shopping, Relaxation Shopping, Value Shopping, Social Shopping, and Idea Shopping have positive and significant influences on Impulse Buying of online consumers on Instagram. Unplanned spending and impulse purchases were also identified by Tyrväinen et al. (2020) as high hedonic motivation factors in all shopping channels (omnichannel approach). Therefore, HM will be included in our model.

3.2.6 Habit

Habit is an important factor in the continuous usage of information systems (Limayem et al., 2007). Venkatesh et al. (2012) described Habit as an individual's degree of inclination to execute behaviors automatically in the learning process. Likewise, Liao et al. (2006) state that habit requires learning and will adopt an automatic response within a limited range towards specific situations or stimuli.

Cheung & Limayem (2007) state that past online behaviors significantly affect continued usage, and initial use can significantly impact future repeated use. Past online behaviors connect to acquaintance with technology and, therefore, can be seen as an antecedent of a habit. Liao et al. (2006) found that habit strongly determines online purchase behavior and has shown that habit has a positive impact on perceived usefulness, continuance intention, and trust.

Kim & Park (2013) found strong relationships between habit, perceived switching costs, and continuance intention. Per the results of Kim & Park (2013), we can also interpret the finding of a study by Wang et al. (2015), where m-shoppers started to use mobile devices to shop for habitual products that they already had a history of purchasing in the traditional way. After adoption, they increased their frequency and quantity. Lee et al. (2019), in their study of underlying factors of continuous use of mobile applications for food delivery, tested Habit as the factor with the strongest positive impact. Although it's importance, this factor will not be included in the model, as we are looking for the reasons why m-shopping is used, and the concept of habit does not answer the research question.

3.2.7 Price Value

Price value is described by Dodds et al. (1991) as consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost of using them. Venkatesh et al. (2012) argue that there is an important difference between a consumer use setting and an organizational use setting because consumers usually bear the monetary cost of such use, whereas employees do not. They assume the cost and pricing structure may have a significant impact on consumers' technology use. With mobile devices, customers can easily compare prices and product information across different retailers and products, making it easier for them to make informed decisions about their purchases.

According to Accenture (2017), Gen Z, as well as Millennial shoppers, mostly buy items based on three factors: receiving the lowest price, seeing products in stores, and reading reviews. Getting a good deal can create a positive perception of value for the customer (Koyuncu & Bhattacharya, 2004), which can lead to increased satisfaction and loyalty towards the retailer (Limayem et al., 2007; Luceri et al., 2022). Providing good deals and value to customers can be an effective strategy for enhancing customer satisfaction and loyalty and increasing the likelihood of repeat business.

However, we must also take into account the findings of Xu (2021), which state that consumer trust and loyalty are negatively affected if price fairness is perceived as unfair and caused by frequent price changes. Online, we tend to notice such deals more often (Hure et al., 2017) as the algorithm might still show the same product we were interested in. The construct of PV consistently emerged as important throughout the literature. Thus, it will be included in the model.

3.2.8 Trust

According to Luceri et al. (2022), trust is one of the variables influencing consumer repurchase intentions and is positively associated with m-shopping continuance intention. Moreover, customers seem to be more careful and concerned if the targeted products are highly expensive and comprise a high degree of risk (Koyuncu & Bhattacharya, 2004). Customers are also more likely to refuse to purchase these products from online stores if the firm does not assure them that these products are reliable and trustworthy (Koyuncu & Bhattacharya, 2004).

Hossain et al. (2020) found that social media is involved in raising trust among consumers and also indirectly encourages the buying intentions of customers through their involvement in social networks. The same study found that even personalization and interface design affect the consumers' trust. The study by Natarajan et al. (2017) reveals that personal innovativeness and perceived risk play a major role in deciding the intention to use mobile shopping applications. Wang et al. (2015), in their study of consumer habits before and after the adoption of mobile shopping, found an interesting pattern that m-shoppers start to use mobile devices to shop for habitual products that they already have a history of purchasing in a traditional way.

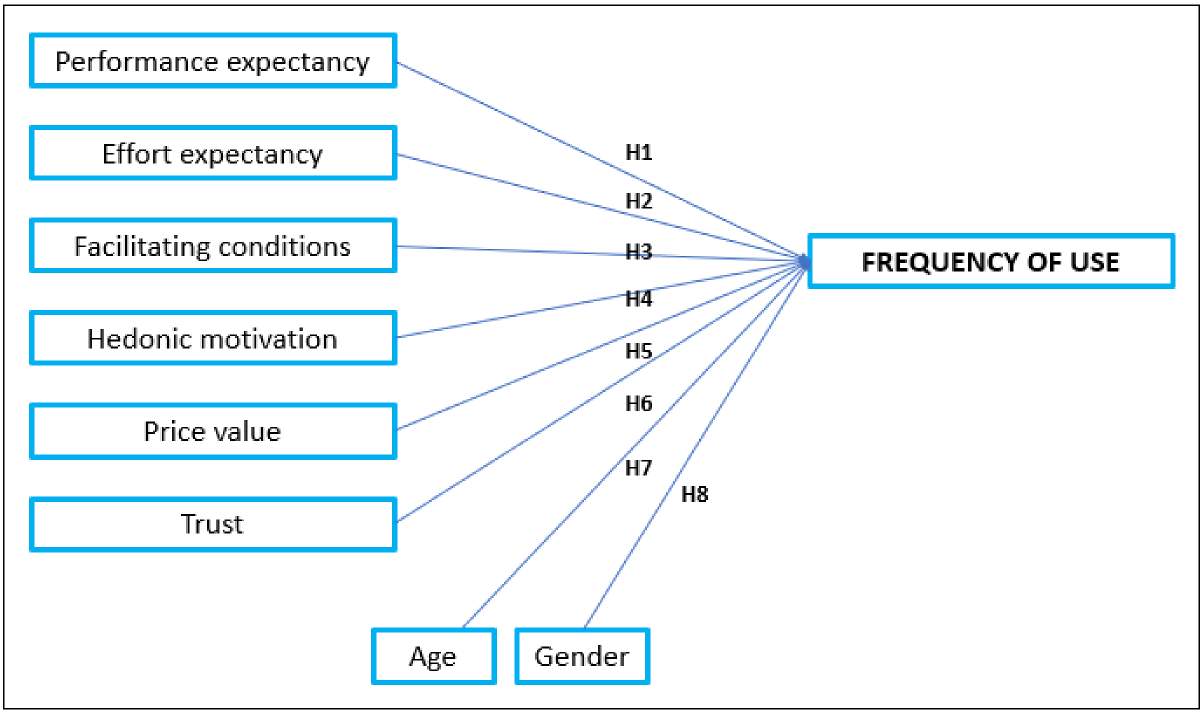
This might happen because the buyer is already familiar with the product. Therefore, they trust the specifications and the quality (reduced risk), and buyers might find that ordering online is more utilitarian (less effort than going to the physical store). Based on the importance of the construct of trust, it will be included in our model.

4 EMPIRICAL RESEARCH – FACTORS OF M-SHOPPING IN SLOVENIA

This section of the thesis discusses the study methods, the constructs in the conceptual model, the questionnaire design, the data collecting process, and data analysis. To achieve the study's goals, a survey was chosen as the research approach.

Based on the literature background provided, the conceptual model of the study and the hypotheses were developed. The proposed model is based on the conceptual model of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) developed by Venkatesh et al. (2012), outlined in Appendix A. The proposed model was adapted to the research setting of services that use mobile technology (mobile shopping) in Slovenia, excluding the variables that were deemed irrelevant to this study. The research model for this study focuses on the relationship between six factors, the frequency of use of mobile shopping, and an added factor of Trust. The conceptual model for this study is presented in Figure 1, providing a graphical summary overview of all hypotheses tested in this research.

Figure 1: Research model and hypotheses



Source: Own work.

4.1 Hypotheses development through UTAUT2 model of m-commerce usage

In both mobile shopping and traditional shopping, emotions and feelings heavily influence our decisions. Therefore, an extension of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012), which includes additional factors such as "hedonic motivation," "price value," and "habit," serves as a suitable theoretical framework for further research in mobile commerce, as recommended by Marriot et al. (2017). UTAUT2 comprises 36 questions grouped into nine constructs, namely Performance expectancy, Effort expectancy, Social influence, Facilitating conditions, Hedonic motivation, Price value, Habit behavior, Behavioral intention, and Use behavior. However, due to questionnaire length limitations and certain variables not precisely corresponding to mobile shopping, factors such as Habit and Social influence were omitted. Additionally, Social influence was partially incorporated into the trust factor. Factors Behavioral intention and Use behavior were substituted with Frequency of use, as the focus of the research is on users who already have experience with mobile shopping, rendering it unnecessary to test their Behavioral intention.

Following the literature overview and the conceptual model presented, the following hypotheses were developed and tested in this empirical study:

- H1: Performance expectancy will positively correlate with the frequency of mobile shopping.
- H2: Effort expectancy will positively correlate with the frequency of mobile shopping.

- H3: Facilitating conditions will positively correlate with the frequency of mobile shopping.
- H4: Hedonic motivation will positively correlate with the frequency of mobile shopping.
- H5: Price value will positively correlate with the frequency of mobile shopping.
- H6: Trust will positively correlate with the frequency of mobile shopping.
- H7: A higher age will negatively correlate with the frequency of mobile shopping.
- H8: Gender influences the frequency of mobile shopping; female users will have a higher frequency of use than male users.

4.1.1 Hypotheses with the six identified factors

Performance expectancy

In the context of mobile shopping, performance expectancy can impact user behavior. It shapes users' perceptions of the platform's efficiency, speed, and convenience. If users perceive that using a mobile shopping app or website will streamline the shopping process compared to other methods, they are more likely to engage in mobile shopping (Dynamic Yield, 2020). Overall, performance expectancy is a crucial factor in determining whether users will engage in mobile shopping (Sohn, 2017) and their overall satisfaction with the experience (Pascual-Miguel et al., 2015). It follows that customers are more inclined to utilize mobile shopping if they perceive it to be useful in their daily lives. Consequently, the following hypothesis is put forth:

H1: Performance expectancy will positively correlate with the frequency of mobile shopping.

Effort expectancy

Effort expectancy significantly influences user satisfaction with mobile shopping (Luceri et al., 2022). Users who perceive mobile shopping apps or websites as easy to use, easy to navigate, and requiring a minimal effort to complete transactions are more inclined to engage in mobile shopping frequently (Wang et al., 2015; Baymard Institute, 2022). Conversely, if users perceive the mobile shopping process as complicated, time-consuming, or confusing, they may be less likely to use the platform regularly (Ingham et al., 2015). Satisfied users are more likely to return to the platform for future purchases. Considering all, this study proposes the following hypothesis:

H2: Effort expectancy will positively correlate with the frequency of mobile shopping.

Facilitating conditions

In the context of mobile shopping, facilitating conditions encompass essential factors such as access to reliable internet connectivity, availability of mobile devices and their features, technical support, and process-specific factors like System Quality (Chen, 2013), including payment options and information quality (Lee et al., 2019), as well as the availability of delivery services (Coşar et al., 2017; FedEx, 2023), among others. Users who have access to these facilitating conditions are more inclined to engage in mobile shopping and utilize the platform more frequently (Venkatesh et al., 2003). As mobile shopping becomes

increasingly accessible, and barriers such as easier payments, quicker deliveries, improved phones and apps, and higher information quality are lowered (Luceri et al., 2022), this study proposes the following hypothesis:
H3: Facilitating conditions will positively correlate with the frequency of mobile shopping.

Hedonic motivation
Mobile shopping offers users the flexibility to shop anytime and anywhere (Dynamic Yield, 2020), coupled with the convenience of doorstep delivery (FedEx, 2023). This satisfies hedonic motivations for instant gratification and convenience. Additionally, personalized recommendations and tailored product offerings enhance the shopping experience, fulfilling hedonic motivations for novelty and excitement (Accenture, 2017). Hedonic motivation can impact the frequency and duration of shopping sessions (Luceri et al., 2022), as individuals may engage in shopping more frequently and for longer durations if they find the experience enjoyable. Thus, the following hypothesis is proposed:
H4: Hedonic motivation will positively correlate with the frequency of mobile shopping.

Price value
Getting a good deal can foster a positive perception of value for the customer (Natarajan et al., 2017), potentially resulting in increased satisfaction and loyalty towards the retailer (Mariott, 2017). According to Accenture (2017), receiving the lowest price was one of the three main reasons why Gen Z and Millennial shoppers buy items online. By offering customers a broad selection of products at competitive prices, mobile shopping platforms can enhance customer engagement and encourage repeat purchases, thereby increasing shopping frequency. Consequently, the following hypothesis is put forth:
H5: Price value will positively correlate with the frequency of mobile shopping.

Trust – extension factor
According to Luceri et al. (2022), trust is one of the factors that play a crucial role in mobile shopping. When a consumer chooses to shop using a mobile device, they entrust their personal and financial information to the mobile shopping platform. Mobile shopping platforms that prioritize security, reputation, transparency, and user experience can better build trust with consumers and increase the likelihood of completing transactions (Liébana-Cabanillas et al., 2017; Song et al., 2017). Additionally, positive reviews and recommendations from friends or influencers (Kim & Park, 2013; Hossain et al., 2020) can further enhance trust with new customers. This study proposes the following hypothesis:
H6: Trust will positively correlate with the frequency of mobile shopping.

4.1.2 Demography influences on the m-shopping frequency and its factors

Age can play a significant role in technology acceptance among consumers (Jain & Kulhar, 2019), particularly due to technological anxiety. Younger individuals also have a faster learning curve, making them more open to testing new digital services (Accenture, 2017).

Technological anxiety is also connected with the fact that newer generations are considered digital natives versus older generations, characterized as digital immigrants; thus, the following hypothesis is proposed:
H7: A higher age will negatively correlate with the frequency of mobile shopping.

According to Venkatesh et al. (2012), gender can play a significant role in technology acceptance, namely influencing different factors differently. As the mobile shopping process differs from traditional (in-store) shopping, behaviors observed in traditional shopping cannot be directly applied to online or mobile shopping (Shen et al., 2016; Sri, 2018). Likewise, technology is pushing shopping culture into global unification (Luceri et al., 2022; data.ai, 2017), and traditional gender roles have shifted. Therefore, generalizations based on gender can be challenging. The convenience of mobile shopping, including features such as discounts and limited-time offers, can be appealing to individuals regardless of their gender. In order to ascertain if there is a significant difference in shopping frequency between genders, the following hypothesis is proposed:
H8: Gender influences the frequency of mobile shopping; female users will have a higher frequency of use than male users.

4.2 Constructs, Variables, Research Model, and Measurement Scales

The empirical segment of the research was conducted using quantitative research methods to collect primary data. Surveys allow the collection of a large amount of data from a sizeable population in a highly economical way (Saunders et al., 2003). The questionnaire was designed based on previous studies related to m-shopping and online shopping. Questions pertaining to the constructs of performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, and price value were adapted from the UTAUT2 study by Venkatesh et al. (2012). Some of the questions were either substituted or added to encompass the entirety of the m-shopping process better. Questions regarding the construct of Trust required significant modification to better align with the research objectives. The construct of Behavioral intention was replaced with the dependent variable Frequency of use, as online shopping frequency is a leading factor in determining purchase intentions (Pavlou, 2003). All variables, except frequency of use, were measured on a 5-point Likert scale, and each variable was subjected to exploratory factor analysis to confirm its fit within the construct. Once all variables were tested fit, their average was calculated within each of the constructs. Subsequently, the constructs were subjected to statistical testing.

Frequency of use (FQ), adapted from Pavlou (2003), is a scale for measuring habits or behavior related to the usage of technology or service. It assesses how often individuals engage in the activity, which is measured over a specific period. In the context of m-shopping, this scale evaluates how frequently consumers use smart devices to make their online purchases. The scale has been shortened by discarding the yearly time frame and substituting it with a monthly timeframe while retaining the seven levels (see Table 1).

Table 1: Operationalization of the construct Frequency of use

Frequency of use	
ORIGINAL	ADAPTED
I use the Internet for product purchases: (Never/Once a year/Few times a year/Once a month/Once a week/Few times a week/Daily)	FQ: frequency of use of mobile shopping in the last month (never, once a month, few times a month, every week, several times a week, every day, few times a day)

Source: adapted by Pavlou (2003).

Performance Expectancy (PE), adapted from Venkatesh et al. (2012), measures the extent to which people perceive a new technology as useful in their daily lives, particularly in terms of increasing and saving time and effort. The original scale consisted of three items, which required adaptation to fit the context of mobile shopping while considering the limitations of questionnaire length. PE2 has been modified to address the finding of Dynamic Yield (2020) better: "43% of consumers shop on their smartphones even while at work". This modification (see Table 2) ensures that the scale captures the specific context of mobile shopping and its impact on users' productivity and time management.

Table 2: Operationalization of the construct Performance expectancy

Performance expectancy	
ORIGINAL	ADAPTED
PE1. I find mobile Internet useful in my daily life.	PE1: I find m-shopping useful in my daily life.
PE3. Using mobile Internet helps me accomplish things more quickly.	PE2: Using m-shopping gives me more flexibility (anywhere & anytime).
PE4. Using mobile Internet increases my productivity.	

Source: adapted by Venkatesh et al. (2012).

Effort Expectancy (EE), adapted from Venkatesh et al. (2012), measures the ease associated with using a system. The original questions were partially adapted and modified to better align with the entire online shopping process and address concerns beyond just technological aspects. The original EE1 question was dropped, as there is not much learning required specifically for mobile shopping once users are already familiar with using their phones, online payments, and managing deliveries in everyday life. The original EE2 was adapted to focus on the usage of mobile shopping channels, such as apps and websites. The original EE3 was divided into two statements: "I find online payments simple" and "I find mobile shopping easy to use" to better address the specificity of the mobile shopping process, as each phase demands a different level of effort from the user. EE4 was adapted to represent the user's effort to keep up with acquiring new technologies, as mobile apps constantly change and evolve (see Table 3).

Table 3: Operationalization of the construct Effort expectancy

Effort expectancy	
ORIGINAL	ADAPTED
EE1. Learning how to use mobile Internet is easy for me.	EE1: My interaction with m-shopping apps or websites is clear and understandable.
EE2. My interaction with mobile Internet is clear and understandable.	EE2: I find online payments simple.
EE3. I find mobile Internet easy to use.	EE3: I find m-shopping easy to use.
EE4. It is easy for me to become skillful at using mobile Internet.	EE4: It is easy for me to become skillful in using new apps.

Source: adapted by Venkatesh et al. (2012).

The construct Facilitating Conditions (FC), adapted from Venkatesh et al. (2012), pertains to the degree to which an individual believes that organizational and technical infrastructure exists to support the use of a system, in this case, the resources required for the mobile shopping process. The original questions were modified to better align with the entire online shopping process while also considering the limitations of the questionnaire's length (see Table 4).

Table 4: Operationalization of the construct Facilitating conditions

Facilitating conditions	
ORIGINAL	ADAPTED
FC1. I have the resources necessary to use mobile Internet.	FC1: My phone features fully support the m-shopping process (apps, payments, comfortable screen size, etc.).
FC2. I have the knowledge necessary to use mobile Internet.	FC2: I have the appropriate means of payment for m-shopping (credit cards, Apple Pay, Google Pay, Revolut, etc).
FC3. Mobile Internet is compatible with other technologies I use.	
FC4. I can get help from others when I have difficulties using mobile Internet.	FC4: I can get help from customer support when I have difficulties using mobile shopping.

Source: adapted by Venkatesh et al. (2012).

The original FC1 statement, "I have resources necessary to use mobile Internet," was deemed too broad for mobile shopping and was therefore separated into two statements: "FC1: My phone features fully support the m-shopping process (apps, payments, comfortable screen size, etc.)," focusing on the limitations posed by the technical capabilities of the device (Ghose et al., 2013; Dynamic Yield, 2020). The second statement originating from FC1 is "FC2: I have the appropriate means of payment for m-shopping (credit cards, Apple Pay, Google Pay, Revolut, etc.)," emphasizing the necessity for suitable payment options accepted by sellers and addressing complications related to payment options as part of the organizational and technical infrastructure of mobile shopping. The question of compatibility (original FC3) was not applicable as it primarily concerns the compatibility of technological systems, which is not the focus of this study. FC4 was adapted to place greater emphasis on customer support within the mobile shopping process.

Hedonic motivation (HM) was adapted from Venkatesh et al. (2012) and refers to the enjoyment or pleasure derived from using technology. Given that mobile shopping involves a lengthy process and is used in various contexts, the original variables were refined to suit the specificities of mobile shopping better (see Table 5). HM2 was adapted into HM3, while original HM1 and HM3 were dropped and changed with the variable HM1 to better align with the findings from Dynamic Yield (2020). This research indicated that 29% of shoppers use m-shopping because it “gives them something to do,” and 43% of consumers shop on their smartphones even at work to evade “mundane tasks.” Additionally, variable HM2 was introduced to better represent the findings of Tyrväinen et al. (2020), where impulse purchases were identified as a high hedonic motivation factor in the omnichannel shopping approach and according to the Idea shopping motivation concept developed by Arnold & Reynolds (2003).

Table 5: Operationalization of the construct Hedonic motivation

Hedonic motivation	
ORIGINAL	ADAPTED
HM1. Using mobile Internet is fun.	HM1: Sometimes I do m-shopping when I have nothing better to do. (Dynamic Yield, 2020)
HM2. Using mobile Internet is enjoyable.	HM2: I use m-shopping to see what new products are available. (Arnold & Reynolds, 2003).
HM3. Using mobile Internet is very entertaining.	HM3: Using m-shopping is enjoyable.

Source: adapted by Venkatesh et al. (2012); Dynamic Yield (2020); Arnold & Reynolds (2003).

The Price value (PV) scale was adapted from Venkatesh et al. (2012). PV, as described by Dodds et al. (1991), reflects consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost associated with their use, specifically addressing the cost-efficiency of using mobile shopping applications. Since m-shopping is typically free if users already possess the necessary equipment, the original PV1 item, “Mobile Internet is reasonably priced,” was modified to emphasize the additional benefits that mobile shopping offers consumers; thus, PV1: "M-shopping allows me to find better deals" was used. Given that mobile shopping is not a product or technology for which consumers pay directly, items PV2 and PV3 from the original scale were excluded. Instead, the focus is on the perceived added value or lack thereof in the mobile shopping service or process (see Table 6).

Table 6: Operationalization of the construct Price value

Price value	
ORIGINAL	ADAPTED
PV1. Mobile Internet is reasonably priced.	PV1: M-shopping allows me to find better deals.
PV2. Mobile Internet is a good value for the money.	
PV3. At the current price, mobile Internet provides a good value.	

Source: adapted by Venkatesh et al. (2012).

Trust (TR) encompasses a broad concept, and various studies have expanded the UTAUT2 model by incorporating trust with different approaches and scales. Similarly, this research employs its scale, derived from multiple sources. TR1 draws from variables identified in studies by Liébana-Cabanillas (2017) and Chong et al. (2012), with a specific emphasis on the safety of payments, aligning with findings from Song et al. (2017). This adaptation recognizes that internet-savvy individuals are more likely to utilize digital payment methods if vendors can ensure secure payment authentication. On the other hand, TR2 synthesizes two variables from the research of Pavlou (2003) and Liébana-Cabanillas et al. (2017), and Chong et al. (2012), modified to place greater emphasis on information quality, as highlighted by Lee et al. (2019). This adaptation acknowledges the significant impact of information quality on trust perceptions following the findings of Dynamic Yield (2020), where 57% of respondents answered that providing more information and reviews of products would make their purchase more enjoyable. TR3 is an adaptation of the TM2 variable from Marriott et al.’s (2017) research, expanded to align more closely with the findings of Coşar et al. (2017), which suggests that difficulties with the delivery process can negatively impact purchases, particularly in the context of mobile shopping. This adaptation aims to address the specific challenges associated with mobile shopping. As for TR4, there is a lack of direct research on how online reviews from other users influence consumer trust in a product or retailer. The closest related research is that of Cenfetelli & Schwarz (2011), where the construct “Deceptiveness of online reviews towards Decision making quality” was examined. While indices such as those from Dynamic Yield (2020) provide insights, there is a gap in directly connecting these findings with social influence. Therefore, this research will incorporate the TR4 variable to assess its relevance and suitability in the context of the study (see Table 7).

Table 7: Operationalization of the construct Trust

Trust	
ORIGINAL	ADAPTED
"Transactions via m-commerce are safe." (Liébana-Cabanillas et al., 2017; Chong et al., 2012);	TR1: I feel monetary transactions in m-shopping are safe.
"This Web retailer is trustworthy" (Pavlou, 2003); "This Web retailer is one that keeps promises and commitments" (Pavlou, 2003); "M-commerce transactions are reliable." (Liébana-Cabanillas et al., 2017; Chong et al., 2012);	TR2: I trust the retailer that items I buy via m-shopping will be the same as presented (picture, size, quality, etc.).
TM2: Purchasing on my mobile device involves a time-consuming payment procedure (Marriott et al., 2017)	TR3: I believe that the delivery will be done on time.
DEC2. The recommendations information was truthful (Cenfetelli & Schwarz, 2011)	TR4: I trust online reviews of other users (either rating, product photo, or video).

Source: adapted by Liébana-Cabanillas et al. (2017); Chong et al. (2012); Pavlou (2003); Marriott et al. (2017); Cenfetelli & Schwarz (2011).

All statements under the concepts of PE, EE, FC, HM, PV, and TR were measured on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

4.3 Research Methods

4.3.1 Questionnaire Design, Data Collection and Sampling

In order to test the research model and hypotheses, a questionnaire containing all the necessary constructs was developed. The questionnaire was initially created in English and later translated into Slovene, as the majority of the sample population speaks Slovene. A back translation from Slovene to English was conducted to ensure an accurate translation and comprehension of the constructs. To assess the understandability and interpretability of the questions, a pilot study involving ten users of mobile shopping was conducted. The pilot survey revealed that some questions had unclear meanings when translated into Slovene, necessitating minor adjustments to clarify the translated statements. The final versions of the questionnaire used in the research can be found in Appendix C (English version) and Appendix D (Slovene version).

Closed-ended questions were utilized in the questionnaire, with responses marked on Likert scales ranging from 1, “strongly disagree,” to 5, “strongly agree.” Due to the sensitivity of the scale, a 7-level scale was employed for assessing the frequency of mobile shopping, ranging from 1 “never” to 7 “few times a day.” In the final section of the questionnaire, participants were asked to provide biodata, including their age and gender. Age groups were predefined, with six options available: 16-24, 25-34, 35-44, 45-55, and over 56. Additionally, participants were asked to estimate their average monthly expenditure on mobile shopping, with seven available options: 0€, 0-50€, 51-100€, 101-300€, 301-500€, 501-1000€, unknown/I do not track. This information was collected to provide deeper insights into the population's descriptive statistics.

The questionnaire was accessible online for 30 days, spanning from January 15th, 2023, to February 15th, 2023. A primarily non-probability sampling was employed, selecting cases that were the most readily accessible (Saunders et al., 2003). The questionnaire access was initially sent to friends and colleagues, who were then encouraged to share it with others in their network. Respondents were required to have engaged in either browsing for a product or making a purchase using their smartphone within the previous month. Actual purchases were not a prerequisite for participation, as the focus was on gathering feedback from individuals familiar with mobile shopping. This approach allowed for insights into the factors influencing purchase decisions, including those who had only browsed but not yet made a purchase. The sample consisted of 154 consumers in Slovenia who had used mobile phones or tablets for mobile shopping at least once in the last month. Data collection continued until the minimum required sample size of 100 respondents was achieved (Saunders et al., 2003).

The gathered data from 154 respondents was initially screened for inconsistencies. Five respondents did not complete the questionnaire, resulting in their responses being excluded from further analysis. Nineteen respondents indicated they do not use m-shopping, but they also provided information on their expenditure either as zero or unknown, which is considered acceptable for further analysis. The responses of these 19 respondents had significantly different values compared to users of mobile shopping, and including them generated results with higher statistical significance. Therefore, they were kept in the sample, and the analysis was carried out using the responses from 149 questionnaires that were collected.

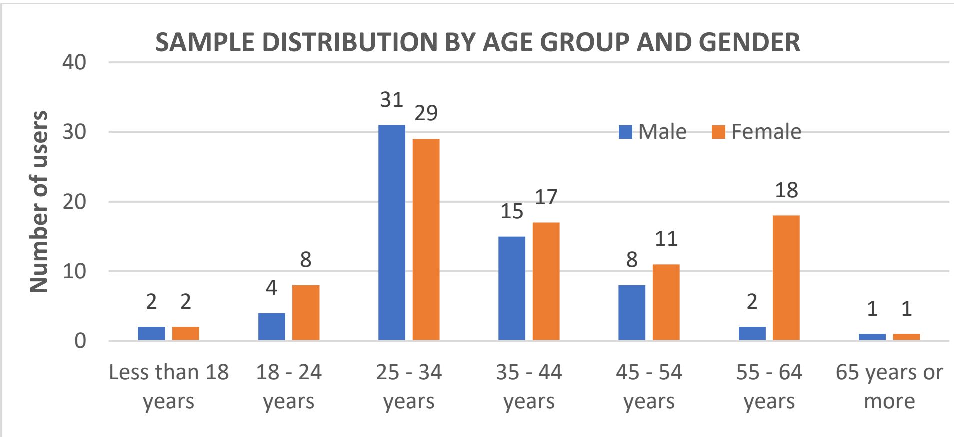
4.3.2 Descriptive statistics

The primary objective of descriptive statistics is to provide a concise summary of a large dataset by extracting useful information. Descriptive statistics aim to offer insights into the data's central tendency, variability, and distribution, enabling researchers to understand key characteristics and patterns without delving into the entirety of the dataset.

Figure 2 and Figure 3 depict the distribution of mobile shopping users in Slovenia according to age, gender, and frequency of use based on sample data. Figure 4 represents the frequency of mobile shopping by age group and gender, while Figure 5 represents the distribution of average estimated monthly expenditure by age and gender within our sample.

In terms of gender, the sample was comprised of 63 males (42,3%) and 86 females (57,7%). The next characteristic, age, was determined based on respondents' selection of an age group (15–24, 25–34, 35–44, 45–54, 55–64, and above 65 years). The distribution of respondents across age groups was uneven (refer to Figure 2), with the majority (60) falling into the 3rd group (25-34 years old).

Figure 2: Sample distribution by Age Group and Gender

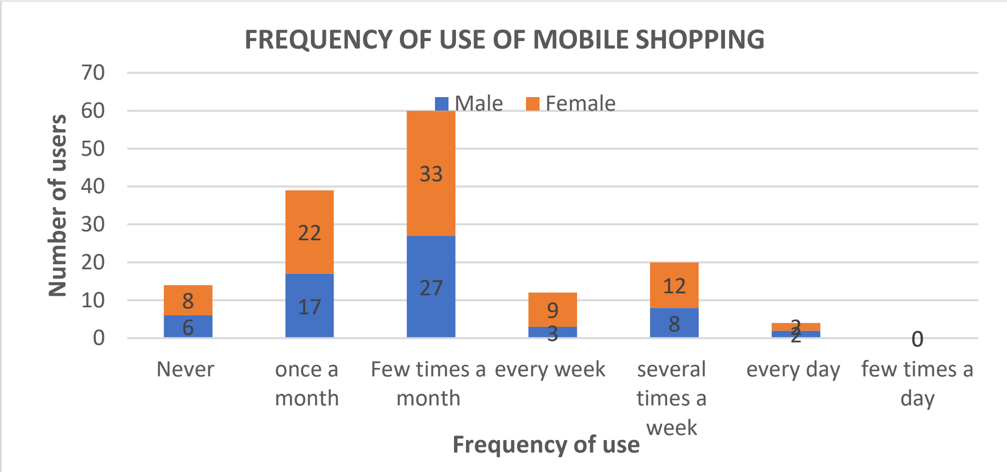


Source: own work.

The second-largest group consisted of individuals aged 35-44, with 32 respondents. The average age (weighted average of the groups, considering a minimum age of 10 and a maximum age of 74) of the respondents was 37,6 years, with a standard deviation of 12,7 years. The average age of the male population was 35 years, and for the female population, it was 39,6 years. Gender-wise, all age groups were approximately equally represented, except for the age group 55-64, where the male-female ratio was 1:9.

Mobile shopping is utilized by 90,6% of respondents. Among them, 64,5% reported using it at least a few times a month, with 13,4% indicating they use it several times a week, and only 2,7% as everyday users of mobile shopping. The largest frequency group was "few times a month" for both genders. On average, the frequency of use was slightly higher among the female population, scoring at 3,01 with a standard deviation of 1,232, while the male population's average frequency was 2,94 with a standard deviation of 1,230. This suggests that, on average, there is no significant difference between genders in their usage rate of mobile shopping, which was later also tested with Hypothesis 8 (see Table 15).

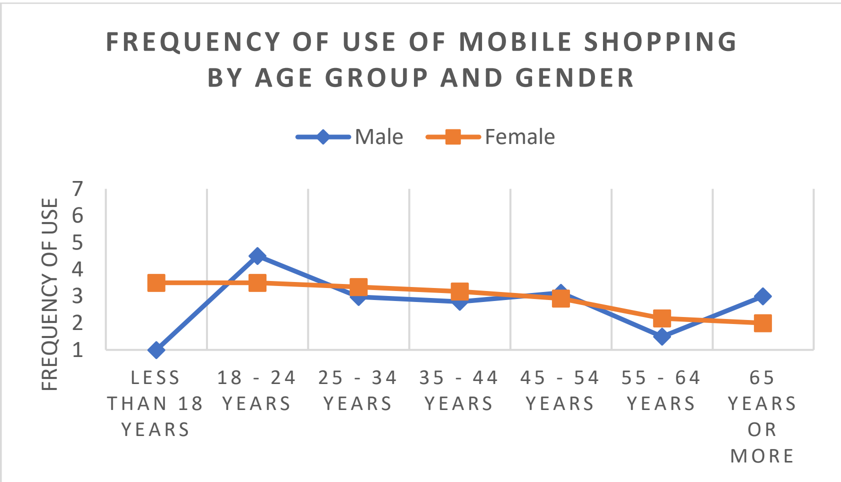
Figure 3: Frequency of use of mobile shopping



Source: own work.

Age is one of the important moderating factors in UTAUT2. Figure 4 represents the frequency of use of mobile shopping among the surveyed users grouped by age. On the vertical axis, frequency is measured with a scale of 1 - never, 2 - once a month, 3 - a few times a month, 4 - every week, 5 - several times a week, 6 - every day, 7 - a few times a day.

Figure 4: Frequency of use by age group and gender

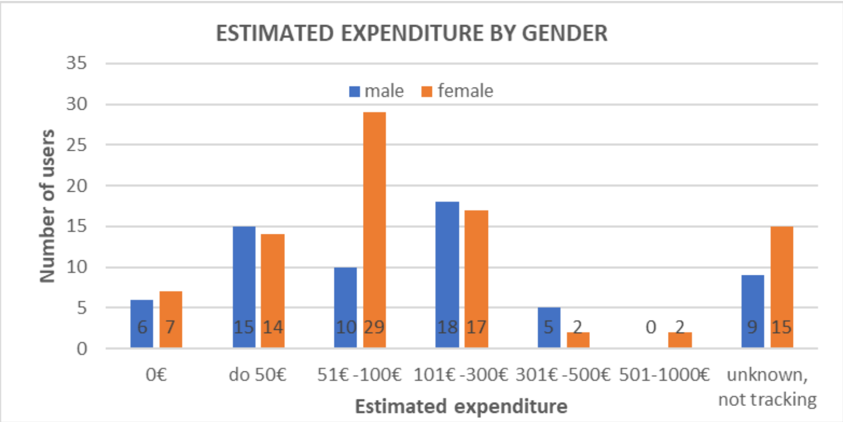


Source: own work.

The highest frequency of use score (4,5) was observed among the male population in the age group 18-24 years, indicating that they use m-shopping somewhere between every week and several times a week. The lowest score was among the male population in the age group less than 18, with an average score of 1.0 (once a month). However, it is important to note that only two responses were collected in this age group, so caution should be exercised in interpreting this result. Groups with a higher number of samples seem to exhibit more consistent patterns.

Respondents were also asked to estimate their average monthly mobile shopping expenditure. Out of those who tracked their expenditure and provided their spending data (112), the average estimated expenditure for mobile shopping was 133.85 €, with a high standard deviation of 129.91 €. Approximately 50% of respondents reported spending between 51€ and 300€ per month, with the largest group spending between 51€ and 100€, representing 26.2% of respondents or 31.2% of those who actually track their mobile expenditures (see Figure 5). Interestingly, 16.1% of respondents stated that their expenditure is unknown or that they do not track it; however, 37.5% of these individuals who do not know their expenditure use mobile shopping at least once per week. Furthermore, 62.5% of those who did not track their online expenditure were female.

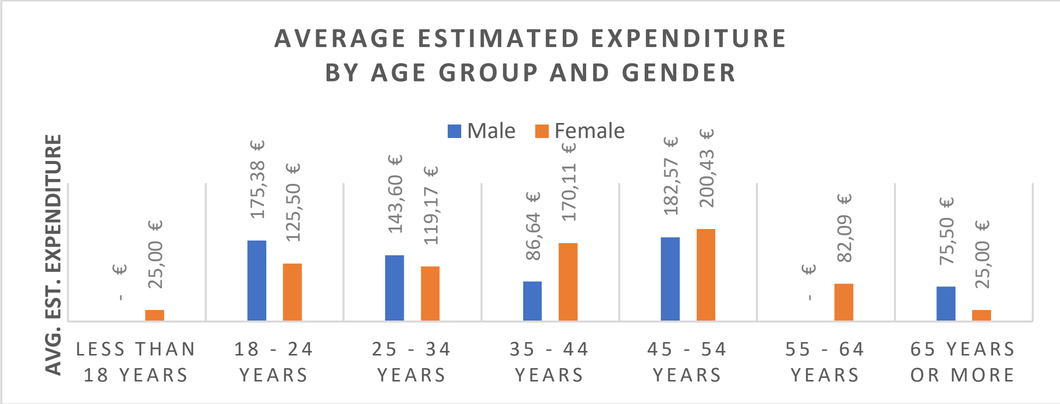
Figure 5: Estimated monthly m-shopping expenditure by gender



Source: own work.

When comparing the male and female populations, the male population exhibits an average expenditure of 140.45€ with a standard deviation of 115.93€. In contrast, the female population shows a lower expenditure of 128.91€ with a higher standard deviation of 139.27€. This discrepancy may be attributed to the fact that the median expenditure group for the female population was 51€-100€, whereas for the male population, it was 101€-300€ (18). Additionally, it is noteworthy that the median age group for the male population was 25-34 years, which is one age group younger than that of the female population (35-44 years). The second largest age group for the female population was 55-64 years. However, considering the sample distribution (see Figure 6), we should discard the age groups with an uneven number of responses (age 55-64) or groups where we have three or fewer responses per gender (e.g., under 18 years and 65 years or older).

Figure 6: Average estimated monthly expenditure by Age Group and Gender

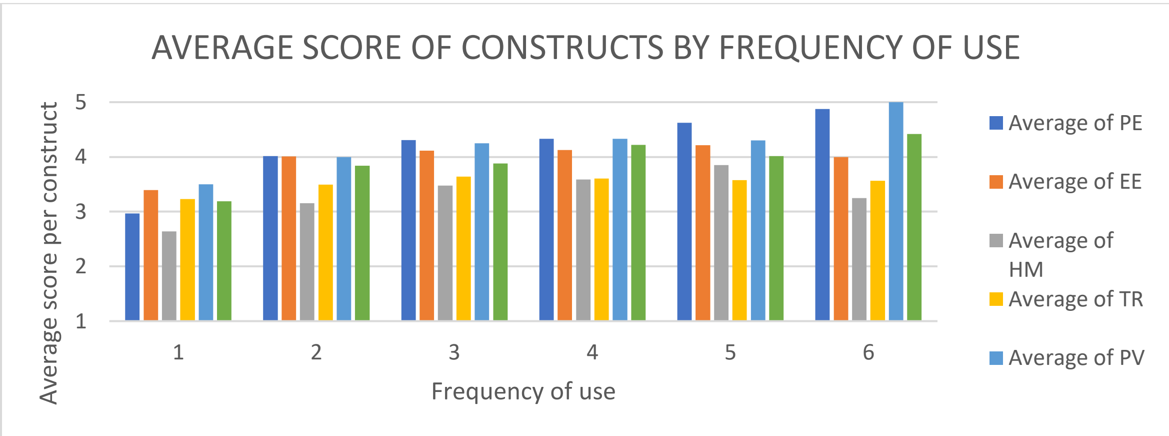


Source: own work.

Calculating the average expenditure by age group and gender and considering the sample distribution, we discarded the age groups with an uneven number of responses and groups with three or fewer responses per gender. By doing so, we observed a slightly higher average estimated expenditure for the female group, 153.80 €, compared to 147.04 € for the male group.

Figure 7 displays the average scores of measured constructs grouped by the frequency of use. Although measured on a scale from 1 to 7, the frequency in the figure is depicted only on a scale from 1 to 6 (X-axis), as there were no responders who chose the 7th group. We can observe a visual correlation between Performance Expectancy, Facilitating Conditions, Price value, and Frequency of Use. Trust does not appear to be correlated anymore after the 3rd group of frequency of use. Interestingly, Hedonic Motivation drops in the 6th group (frequency: every day). Effort expectancy does not seem to correlate with frequency of use after the 3rd group.

Figure 7: An average score of constructs grouped by the frequency of use



Source: own work.

Additionally, we asked respondents to rate their frequency of use of social apps, and 76.5% answered that they use social networks every day (at least one application), of which 53.7% use multiple social network applications daily. These percentages are similar to the findings of SURS (2023[b]), where 86% of respondents used the internet every day, and 64% exchanged messages via chatting apps such as Viber, WhatsApp, Messenger, and Snapchat (86% among young residents), while 63% participated in social networks (90% among young residents).

4.4 Data Analysis

4.4.1 Validity and Reliability of the Constructs

The study constructs were first tested with exploratory factor analysis to extract the strength of the effect that measured variables (observed variables) have on our constructs (latent variables or factors). The association between latent and observed variable is called factor loading, which confirms the statistical importance of the variable in the construct if its magnitude exceeds 0.3, but preferably 0.5. Loadings closer to 1 indicate a very strong relationship between the variable and the factor. Exploratory factor analysis (EFA) is a technique within factor analysis developed by Spearman in 1904. The main goal of EFA is to identify the underlying relationships between measured variables. According to Fabrigar et al. (1999), researchers should examine the factor pattern to see which items load highly on which factors and then determine what those items have in common. Field (2012) suggests that data reduction in exploratory factor analysis is achieved by looking for variables that correlate highly with a group of other variables but do not correlate with variables outside of that group. The EFA was conducted on 13 variables, which were merged into four constructs in the questionnaire (see Table 8).

Whether the factor analysis is the appropriate method for the collected data can be assessed using the Kaiser-Meier-Olkin (KMO) coefficient. It can be calculated for individual and multiple variables and indicates diffusion in the pattern of correlations between all variables in the model. The value of the KMO coefficient ranges between 0 and 1. When the coefficient's value is close to 0.00, the correlation between variables is very diffused, and the factor analysis is inappropriate. A value close to 1.00 would indicate a relatively compact pattern of correlations; thus, factor analysis should yield distinct and reliable factors. According to Field (2012), a value greater than 0.50 is barely acceptable for conducting factor analysis; values between 0.50 and 0.70 are moderate, values between 0.70 and 0.80 are good, and values above 0.90 are superb. In our data analysis, the KMO coefficient was 0.785, indicating that factor analysis is a useful method for determining the underlying structure of the questionnaire used. To determine whether the data set of correlations is appropriate for conducting the factor analysis, Bartlett's Test of Sphericity was used. When Bartlett's test is significant, it indicates that the correlations between variables are significantly different from zero (Field, 2012), thus confirming that the data set of correlations is suitable for conducting factor analysis. The approximate value of the chi-square was 717.58, with a significance level of 0.000.

As Table 8 shows, the factor analysis revealed tree components with eigenvalues greater than 1, with another component being very close at 0.997. However, Performance expectancy (the 4th component) is one of the core factors in UTAUT2; therefore, it was included in the further analysis. The factor Facilitating conditions (FC) was dropped from further analysis as it consistently loaded together with Effort Expectancy but had a low Cronbach's alpha (0.597). The four extracted components explained 66.01% of the total variance. In hierarchical order, the first component (EE) explained the majority (36.20%), the second (TR) explained 11.48%, the third (HM) explained 10.65%, and the fourth (PE) explained 7.67% of the variance. The correlation matrix of components is presented in Table 8.

Table 8: Exploratory factor analysis

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings^a
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	4,707	36,205	36,205	4,707	36,205	36,205	3,704
2	1,493	11,484	47,689	1,493	11,484	47,689	2,304
3	1,385	10,650	58,340	1,385	10,650	58,340	2,658
4	,997	7,672	66,012	,997	7,672	66,012	2,629
5	,828	6,371	72,383				
6	,690	5,306	77,689				
7	,650	5,002	82,691				
8	,559	4,300	86,991				
9	,489	3,761	90,751				
10	,406	3,125	93,876				
11	,341	2,625	96,502				
12	,287	2,207	98,708				
13	,168	1,292	100,000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Source: own work.

Sociological constructs often exhibit significant correlations; therefore, rotation was used to clarify the pattern of loadings. Two different methods of rotation can be employed. Oblique rotation is used when components are dependent or correlated, whereas components must be completely independent for orthogonal rotation (Field, 2012). The component correlation matrix serves as a useful indicator when determining the appropriate rotation method. Oblique rotation should be used when components are interdependent (correlations between components exceed 0.30). The correlations of our four components are presented in Table 9.

The next step in our data analysis is to examine the reliability and validity of each measured construct. According to Field (2012), an instrument must first be reliable in order to be valid. Reliability is one of the most important characteristics of a questionnaire, alongside its objectivity and validity. It implies that a questionnaire consistently reflects the construct that it is measuring. One form of reliability is internal consistency, which applies to the consistency among the variables in a summated scale. According to Field (2012), statistical methods like test-retest, split-half reliability, or Cronbach's alpha coefficient assess the internal reliability of the questionnaire and determine whether it is internally reliable enough to provide a good measurement of research constructs.

Table 9: Component correlation matrix

Component Correlation Matrix

Component	1	2	3	4
1	1,000	,300	,326	,379
2	,300	1,000	,176	,142
3	,326	,176	1,000	,221
4	,379	,142	,221	1,000

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

Source: own work.

Validity means that an instrument actually measures what it sets out to measure. Validity is a necessary but not sufficient condition for a measurement. The concepts measured in our study were mainly drawn from international literature but were adjusted in some parts to fit the m-shopping field better. The reliability and validity have been confirmed by several studies (Venkatesh et al., 2012; Arnold & Reynolds, 2003; Liébana-Cabanillas et al. (2017), Chong et al. (2012), Marriott et al. (2017), Cenfetelli & Schwarz (2011)).

Internal consistency or reliability of the construct was tested using Cronbach's alpha, which measures the consistency of a set of variables or how closely connected they are to one another and is the most common measure of scale reliability. In general, if Cronbach's alpha is 0.70 or above, the consistency is acceptable, particularly with socio-psychological constructs. If it is 0.90 or above, it indicates the best consistency, thus a very reliable construct. Cronbach's alpha is a measure of a construct's unidimensionality; thus, it was calculated for each construct (PE, EE, FC, HM, TR) separately to determine the internal consistency and reliability of the scales. The verification of scale reliability and their Cronbach's alpha coefficients are presented in Table 10.

According to Table 10, the results of the reliability analysis show that alpha coefficients for concepts Performance expectancy (PE) and Effort expectancy (EE) were around or above 0.8, indicating exemplary results. The coefficient for the concept of hedonic motivation (HM) was 0.759, which still indicates exemplary results, taking into account that it is a socio-psychological construct. Meanwhile, the concept Trust (TR) reached 0.639, which is lower than generally expected yet acceptable considering the size of the sample. The concept of facilitating conditions (FC) was removed from further analysis since the alpha coefficient was too low, and its factors would often load under different concepts, particularly likely under the concept of effort expectancy. Overall, factor loadings in each concept were quite strong, with few exceptions, such as TR1, TR4, and HM3. However, they were all retained in concepts since removing them would reduce the concept's Cronbach's alpha.

Table 10: Cronbach's Alpha and Factor Loadings

N149	**KMO= 0,785**		
Construct	Scale item	Cronbach's Alpha	Factor Loading
PE	PE1	0,862	0,872
	PE2		0,808
EE	EE1	0,794	0,728
	EE2		0,732
	EE3		0,831
	EE4		0,74
FC	FC1	0,574	x
	FC2		x
	FC3		x
HM	HM1	0,759	0,858
	HM2		0,865
	HM3		0,652
PV	PV1	1,0	x
TR	TR1	0,639	0,578
	TR2		0,748
	TR3		0,777
	TR4		0,417

Source: own work.

Thus, three scales proved to be valid and reliable, and an additional one with limited reliability. The next step was to conduct descriptive statistics parameter calculation. For each construct, we have to compute the composite scale, mean, and standard deviation. Furthermore, we conducted the Kolmogorov-Smirnov test, a non-parametric test used to determine whether a sample comes from a specific probability distribution (normal, uniform, Poisson, exponential). It is often used to test the hypothesis of normal data distribution (Gaussian distribution) for each variable. The conducted K-S test showed Z-values lower than 1 with highly significant p-values for all tested variables, suggesting a departure from normality for all variables. Thus, non-parametric analyses should be used for hypothesis testing.

Table 11 provides descriptive statistics of four constructs and two variables (Fq, PV). Average scores were calculated to determine the levels of Performance Expectancy, Effort Expectancy, Hedonic Motivation, and Trust. Additionally, the two variables, Price Value and Frequency of Use, were processed.

The average composite scale score of Frequency of Use was 2.98 out of 7.0, with a moderate standard deviation of 1.23, which corresponds on our scale to answers 2 (once a month), 3 (a few times a month), and 4 (every week). The majority of our respondents use mobile shopping a few times a month.

Table 11: Means and standard deviations of variables and concepts

CONSTRUCT	Scale item	Mean	Standard Deviation (SD)	K-S test Z	K-S test P
Fq of use		**2,98**	**1,23**	0,252	0,000
PE	PE1. I find m-shopping useful in my daily life.	4,09	0,80	0,302	0,000
	PE2. Using m-shopping gives me more flexibility (anywhere & anytime).	4,24	0,76	0,261	0,000
	AVG	**4,16**	**0,73**		
EE	EE1. My interaction with m-shopping apps or websites is clear and understandable.	3,93	0,78	0,340	0,000
	EE2. I find mobile payments easy.	4,03	0,79	0,322	0,000
	EE3. I find m-shopping easy to use.	4,09	0,65	0,312	0,000
	EE4. It is easy for me to become skillful at using new apps.	4,06	0,82	0,296	0,000
	AVG	**4,03**	**0,60**		
HM	HM1. Sometimes I do m-shopping when I have nothing better to do.	2,74	1,20	0,194	0,000
	HM2. I use m-shopping to see what new products are available.	3,58	1,09	0,286	0,000
	HM3. Using m-shopping is enjoyable.	3,78	0,85	0,314	0,000
	AVG	**3,37**	**0,87**		
PV	PV1. M-shopping allows me to find better deals.	**4,15**	**0,69**	0,276	0,000
TR	TR1. I feel monetary transactions in m-shopping are safe.	3,62	0,68	0,316	0,000
	TR2. I trust the seller that the items I buy via m-shopping will be the same as presented	3,42	0,80	0,265	0,000
	TR3. I believe that the delivery will be done on time.	3,56	0,74	0,330	0,000
	TR4. I trust online reviews of other users (either rating, product photo, video).	3,61	0,82	0,287	0,000
	AVG	**3,55**	**0,53**		

Source: own work.

Respondents were found to have a high level of Performance Expectancy (PE) for mobile shopping, as the average composite scale score was 4.16 out of 5.0, with a low standard deviation of 0.73. This score surpasses the neutral point of 3.0 (“neither agree nor disagree”). Most respondents strongly agreed with the usefulness of m-shopping in their daily lives, and even higher was their perception of additional flexibility with the usage of m-shopping.

When measuring the Effort Expectancy (EE), the composite mean of four items was 4.03 out of 5.0, with a low standard deviation of 0.60, which is above the neutral point of 3.0 (“neither agree nor disagree”). The high average score of effort expectancy means that respondents find using mobile shopping easy. The majority of Slovenians still find m-shopping apps easy to use, and websites are clear and understandable to them. However, the variable measuring this statement is slightly lower than the composite average for this construct, suggesting that user interface experiences could be improved in general. Most Slovenians agree that mobile payments are easy, m-shopping is easy to use, and they feel it is easy for them to become skillful in using new apps. However, the last statement had a slightly higher standard deviation than other statements under this construct, which we might explain better with a more detailed analysis of the age categories of the respondents.

Respondents were recognized as having medium Hedonic Motivation (HM) (3.37 out of 5.0) for mobile shopping, with a standard deviation of 0.87. The statement with the highest disagreement among all was regarding conducting m-shopping when they have nothing better to do, with a score of 2.74 out of 5.0 and the highest standard deviation of 1.20. The interpretation of this question could pose challenges, as it may prompt individuals to engage in critical self-reflection. Results also showed that not many Slovenians use m-shopping to discover new products, but they do perceive it as slightly enjoyable.

The eclectic concept of Trust (TR) reached slightly lower reliability according to Cronbach’s alfa coefficient; thus, we should be cautious with interpreting the results. Respondents evaluated the statements on a Likert scale from 1 (strongly disagree) to 5 (strongly agree). An average score was calculated to determine the level of trust of Slovenian users for mobile shopping. Respondents were recognized as having somewhat positive trust (3.55 out of 5.0) towards mobile shopping, with a low standard deviation of 0.53. They feel that monetary transactions are safe, are slightly trustworthy towards online reviews, and marginally believe in on-time delivery. However, they show a lower level of trust (score 3.42) towards the quality of received products compared to how they were presented online during the purchase process.

Regarding the Price Value (PV), Slovenians feel they find better deals with mobile shopping, with an average score of 4.15 out of 5.0 and a standard deviation of 0.69. This suggests that the online market in Slovenia is lively and competitive, and Slovenian users are inclined to search for the best deals.

4.4.2 Hypotheses testing

Since the dependent variable (Frequency of Use) is not normally distributed, and we aim to examine the relationships between the dependent variable and the factors (multiple independent variables), we must consider the use of non-parametric correlation or regression methods. When dependent variables are ordinal and not normally distributed, Spearman's rank-order correlation coefficient should be used to assess the relationship between the dependent variable and each of the independent variables. Non-parametric correlation methods focus on the ordinal relationship between variables and are less sensitive to the distributional assumptions compared to parametric correlation methods.

Correlation denotes dependency or a relationship between two variables. The strength of a correlation is typically assessed using the absolute value of the correlation coefficient. The correlation coefficient ranges from -1 to 1, where 1 indicates perfect positive correlation, 0 indicates no correlation, and -1 indicates perfect negative correlation. The closer the absolute value of the correlation coefficient is to 1, the stronger the correlation. According to Field (2012), a commonly used guideline for interpreting the strength of correlations is as follows: 0.00 – 0.19 a weak relationship; 0.20 – 0.39 a medium relationship; 0.40 – 0.59 a moderate relationship; 0.60 – 0.79 a strong relationship; and 0.80 – 1.00 a very strong relationship.

Table 12 provides the results of Spearman's rho correlation test with the statistical significance for tested hypotheses H1 to H6. Hypothesis 3 was not tested due to the low reliability of the Facilitating conditions construct. All following analyses were conducted using the Statistical Package for the Social Sciences (SPSS) program.

Table 12: Correlation coefficients and significance by Hypotheses

Hypothesis number	Dependent variable	Independent variable	Correlation coefficient	Sig. (1-tailed)
H1	Frequency of use	Performance expectancy	0,537	0,000
H2	Frequency of use	Effort expectancy	0,250	0,001
H3	Frequency of use	Facilitating conditons	x	x
H4	Frequency of use	Hedonic motivation	0,345	0,000
H5	Frequency of use	Price value	0,347	0,000
H6	Frequency of use	Trust	0,166	0,022

Source: own work.

H1: Performance expectancy will positively correlate with the frequency of mobile shopping.

According to the correlation analysis, the correlation between frequency of use and performance expectancy was r = 0.537, indicating a moderately strong positive relationship with a very high statistical significance level (p = 0.000). Therefore, it can be concluded that surveyed Slovenians highly value performance expectancy in mobile shopping, particularly the perception of additional flexibility with the usage of m-shopping. The alternative hypothesis can be accepted based on correlation analysis; thus, **we accept Hypothesis 1** and conclude that a moderate positive relationship exists between frequency of use and performance expectancy.

H2: Effort expectancy will positively correlate with the frequency of mobile shopping.
As the correlation analysis showed, the correlation between frequency of use and effort expectancy was positive with medium strength (r = 0.25) and high statistical significance (p = 0.001). This indicates that a higher level of frequency of use is connected with a higher degree of effort expectancy, where a high degree of effort expectancy means that respondents find using mobile shopping easy or understandable, thus requiring low effort. Based on the correlation analysis, we can accept the alternative hypothesis. M-shopping users in Slovenia value low effort for accessing and using mobile shopping; hence, **Hypothesis 2 was accepted**.

H3: Facilitating conditions will positively correlate with the frequency of mobile shopping.
Hypothesis 3 was not tested, as the construct of facilitating conditions did not meet the reliability requirements (low Cronbach's alpha coefficient). Nonetheless, in Appendix F: Appendix Tables 17 and 18, results of additional tests are presented, where FC was included. It suggests FC could potentially impact the Frequency of use. Further research should be conducted to solidify the concept of facilitating conditions in mobile shopping.

H4: Hedonic motivation will positively correlate with the frequency of mobile shopping.
The correlation between mobile shopping frequency and hedonic motivation was moderate, with a positive tendency (r = 0.345) and a very high statistical significance (p = 0.000). Thus, it can be concluded that the frequency of mobile shopping among consumers in Slovenia is moderately influenced by their hedonic motivation. Based on the correlation analysis, the alternative hypothesis can be accepted; thus, **we accept Hypothesis 4**.

H5: Price value will positively correlate with the frequency of mobile shopping.
As the correlation analysis showed, the correlation between frequency of use and price value was positive with medium strength (r = 0.347) with very high statistical significance (p = 0.000). This indicates that a higher level of frequency of use is connected with a higher degree of price value. Based on the correlation analysis, we can accept the alternative hypothesis. M-shopping users in Slovenia value good deals found by mobile shopping which is one of the reasons why they increasingly use m-shopping. Hence, Hypothesis 5 was accepted.

H6: Trust will positively correlate with the frequency of mobile shopping.
According to the correlation analysis, the correlation between frequency of use and trust was $r = 0.166$, indicating a weak positive relationship with a medium statistical significance level ($p = 0.022$). Therefore, it can be concluded that surveyed Slovenians' trust towards monetary transactions, online reviews, quality of products, and on-time delivery does influence their frequency of mobile shopping. The alternative hypothesis can be accepted based on correlation analysis; thus, we accept Hypothesis 6 and conclude that a weak positive relationship exists between frequency of use and trust.

H7: A higher age will negatively correlate with the frequency of mobile shopping.
To test this hypothesis a linear regression analysis was used. The results show that the frequency of use of mobile shopping drops -0.234 points for each increase in unit of age (see Table 14), keeping in mind that age was measured by age groups and not years per se. Results were generated with a high statistical significance ($p = 0.002$, see Table 13). Therefore, results suggest a weak negative relationship exists between age and the frequency of use of mobile shopping. This suggests that age negatively affects the frequency of mobile shopping among Slovenians. The alternative hypothesis can be accepted based on linear regression analysis; thus, **we accept Hypothesis 7.**

Table 13: Linear regression analysis: The effects of Age on Frequency of use; model significance

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,966	1	13,966	9,824	,002[b]
	Residual	208,974	147	1,422		
	Total	222,940	148			

a. Dependent Variable: Fq m-nakupovanje uporabljam

b. Predictors: (Constant), Age

Source: own work.

Table 14: Linear regression analysis: The effects of Age on Frequency of use; factor significance

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3,868	,300		12,905	,000		
	Age	-,234	,075	-,250	-3,134	,002	1,000	1,000

a. Dependent Variable: Fq m-nakupovanje uporabljam

Source: own work.

H8: Gender influences the frequency of mobile shopping; female users will have a higher frequency of use than male users.

To test this hypothesis, the non-parametric Mann-Whitney test was used. If the p-value is below a predetermined significance level (commonly 0.05), we may conclude that there is a significant difference in the frequency of use between male and female users. However, according to the test, the one-tailed p-value was 0.329 (as seen in Table 15). The result is much higher than the predetermined level of 0.05, indicating a low statistical significance. Therefore, we **cannot accept Hypothesis 8,** which means that the frequency of use of mobile shopping among the female population in Slovenia was not significantly different from the frequency of use of the male population. Among Slovene mobile shopping users, gender does not affect the frequency of use.

Table 15: Mann-Whitney test of Gender on Frequency of use

	Frequency
Mann-Whitney U	2599,000
Wilcoxon W	4615,000
Z	-0,442
Asymp. Sig. (1-tailed)	0,329

a. Grouping Variable: gender

Source: own work.

5 DISCUSSION OF FINDINGS

5.1 Key findings and Interpretation of results

The majority of our respondents use mobile shopping a few times a month. They strongly perceive m-shopping as useful in their daily lives, and there is even better perception of the additional flexibility that m-shopping offers. Most Slovenians in the sample find m-shopping apps easy to use and websites clear and understandable to them. However, there is still some room for improvement in user interface experiences. Consumers in our sample agree that mobile payments are easy to use, m-shopping, in general, is also easy to use, and they feel it is easy for them to become skillful in using new apps. Results align with the findings of DataReportal (2023) in a study of global m-commerce users and with theoretical propositions from several studies (Bridges & Florsheim (2008); Kesari & Atulkar (2016); Moon et al. (2017)).

M-shopping users in Slovenia were found to highly value the low effort required to access and use mobile shopping. Interestingly, the statement with the highest disagreement was, “I use m-shopping when I have nothing better to do.” This could imply that users view m-shopping as practical and efficient, driven by genuine interest rather than as an unplanned activity conducted out of boredom. This finding contrasts somewhat with the conclusions of

Dynamic Yield (2020). Additionally, users perceive mobile shopping as a slightly enjoyable task.

Results also indicate that few Slovenians use m-shopping to discover new products, meaning that users engage in mobile shopping with a plan or a goal in mind. Respondents feel that monetary transactions are safe and are also slightly trustworthy regarding online reviews. According to the national statistics (SURS, 2023a), the choice for cash upon collection payment system (43%) remains high above the global average of 4% reported by DataReportal (2023). Slovenians do marginally believe that on-time delivery is not an issue.

Users showed a lower level of trust towards the quality of received products versus how these products were presented online during the purchase process, indicating there is still informational asymmetry between the seller and the user. Slovenians feel they do find better deals with online shopping, which means that the online market in Slovenia is lively and competitive. Slovenian users are prone to searching for the best prices. Thus, users do appreciate the added value that mobile shopping brings in terms of better online offers, a wider scope of products, and the ability to also discover new products with an immediate ability to compare prices, which corroborates with the findings of Kesari & Atulkar (2016).

This research has found that among Slovene mobile shopping users, on average, gender does not affect the frequency of use of mobile shopping. Instead, it is age that affects the frequency of use. This finding can additionally support the general observation of other researchers (Luceri et al., 2022; data.ai, 2017) regarding the overall shopping habits becoming globally unified as gender, origin, and religion start to hold only marginal importance. Furthermore, the research discovered that the frequency of social media app usage was nearly identical among both genders. Moreover, the use of social media apps positively correlates with the frequency of mobile shopping usage, as well as with the estimated expenditure of users.

The research shows that age does affect shopping habits. It was found to have a direct negative effect on the frequency of use as well as the effort expectancy (see chapter Additional findings). Later is a fairly intuitive result as Technology aversion or technophobia plays an important role with age, as suggested by Lee et al. (2019), among others.

This study also found out that the male population had, on average, a higher average estimated monthly expenditure than the female population. However, this is a dubious result as the gap between genders narrows once we exclude the outliers in both groups. A more uniform sample across age groups should be acquired.

Additionally, the research shows that the frequency of mobile shopping strongly correlates with the estimated monthly expenditure. This is corroborated by the result mentioned above that only a few users use m-shopping for product discovery rather than for planned purchases. It can also suggest that the shoppers in the sample were sufficiently tech-savvy as purchases were completed (incurring expenditure). Unfortunately, we did not gather information about the users' incomes and education. This could have provided a better understanding of whether users utilize m-shopping due to busier lifestyles and less time for traditional shopping. Another reason behind the correlation between frequency of use and expenditure could be the personalized recommendations, as those who frequently use m-shopping better train the algorithms that generate personalized results for them, simplifying a multistep process into one easy search (Walmart, 2024).

Figure 7 shows an interesting characteristic, where a significant gap in average scores of factors between non-users and users of mobile shopping can be noticed. However, among the users, the trend in the first three frequency groups is almost flat and gets steeper for the last two groups (users with the highest frequency of use). The lower average values of factors could be somewhat explained by the technology aversion of the non-users or possibly their past bad experiences. Additional findings describe this subject in a bit more detail (see page 56).

Technophobia among users can also hinder their use of technology, according to Lee et al. (2019). It is important to conduct research that distinguishes between the factors affecting technology use and those influencing technology adoption. If this research acquired a bigger sample of users of mobile shopping who only search for products online but do not finalize their purchases or those who do not use online shopping at all, we could obtain interesting statistics that would likely provide insights into the differences among the underlying factors.

In this research, we attempted to examine the effects of facilitating conditions, which initially showed correlations (as seen in Figure 7) with the frequency of use. However, the concept was later omitted from further analysis due to its high internal inconsistency, and its variables would often load on another concept of Effort expectancy. This is somewhat understandable, as a low level of facilitating conditions should affect the amount of effort necessary to use a service or a product.

Additional findings

In order to utilize the collected data more effectively, we conducted additional tests to examine the relationship between factors and frequency of use, as well as estimated expenditure. Due to the high correlation based on VIF values, the analysis of factors' effects on the frequency of use was conducted for each factor separately. The findings are as follows:

Performance expectancy was found to explain the most variation in our dependent variable (Fq) with 26.7% (R^2=0.267, p= 0.000). The second strongest predictor was Price Value, explaining 11.4% (R^2=0.114, p= 0.000), followed by Hedonic Motivation with 9.7% (R^2=0.097, p= 0.000). Facilitating conditions would have ranked 4th with 8.4%, but corrections are needed for this factor due to problems with internal inconsistency. Effort expectancy did explain 6.1% of the variation, while Trust explained only 1.8% (p=0.102), according to the regression analysis conducted separately for each factor. All results can be found in Appendix F (see Appendix Tables 5-14 and 17-18). We also tested the relationship between the Frequency of use of social media apps (FqS), the frequency of use of mobile shopping (FQ), and the estimated monthly expenditure (EXP). Results show that FqS and FQ have a medium-strong positive correlation (rho= 0.259, p=0.002; see Table 16). Linear regression showed that the variation of FqS explains 3.9% (R^2=0.039) of variation in the frequency of use, with a beta coefficient of 0.234 (see Appendix Tables 15 and 16).

Table 16: Correlation between variables (FqS, EXP, FQ)

Correlations[b]

			FqS (social apps)	EXP (expenditure)	FQ (mobile shopping)
Spearman's rho	**FqS (social apps)**	Correlation Coefficient		0,221**	0,259**
		Sig. (1-tailed)		0,007	0,002
	EXP (expenditure)	Correlation Coefficient	0,221**		0,584**
		Sig. (1-tailed)	0,007		0,000
	FQ (mobile shopping)	Correlation Coefficient	0,259**	0,584**	
		Sig. (1-tailed)	0,002	0,000	

**. Correlation is significant at the 0.01 level (1-tailed).

b. Listwise N = 125

Source: own work.

Additionally, FqS positively correlates with EXP with moderate strength (rho= 0.221, p=0.007), and the variation of FqS explains 5.9% of the variation in estimated expenditure (see Appendix Table 16). This suggests that our initial decision to drop social influence as a factor might be premature, as this concept might hold significance for deeper analysis, and it should be refined to include contemporary notions of social influence.

To determine the relationship between age and estimated expenditure, we used a Spearman's rank-order correlation coefficient test (see Table 17). This test resulted in a weak negative correlation (rho = -0.146), but the value fell just outside the conventional limit for significance (p= 0.052).

Table 17: Correlation between Estimated expenditure and Age

			EXP (expenditure)
Spearman's rho	**EXP (expenditure)**	Correlation Coefficient	
		Sig. (1-tailed)	
	Age	Correlation Coefficient	-0,146
		Sig. (1-tailed)	**0,052**

Listwise N = 125

Source: own work.

Additionally, to test the effect of age on estimated expenditure, we employed linear regression analysis, excluding cases where the response was “unknown/not tracking” (listwise exclusion). The linear regression test yielded a p-value higher than the acceptable threshold ($p= 0.152$, B-coefficient= -0.112). Therefore, we may conclude that in our analysis, no statistically significant relationship between the age of users and their estimated monthly expenditure was found (see Appendix Tables 20 and 21).

To determine differences between genders across different factors, we conducted an independent sample t-test. Among the factors tested (PE, EE, FC, TR, HM, PV), only Hedonic Motivation showed statistical significance $p=0.004$ (see Appendix Table 24), indicating that this factor is influenced by gender. The mean for the female population was 3.54 compared to 3.13 for the male population. Interestingly, when we repeated the test with the grouping variable as users versus non-users of mobile shopping, all variables except Age showed a statistically significant difference between the means of their groups (see Appendix F: Appendix Table 25). This suggests that non-users of mobile shopping have a different perception of mobile shopping systems in contrast to those who use them.

The non-significant difference in age between users and non-users is also intriguing, as it would be expected that generations at the extremes of the age distribution would likely be non-users of mobile shopping. The reason for such a result might be the sample size in these age groups. This finding also reinforces the notion that the theory of Tech-aversity influences mobile shopping (Lee et al., 2019), and this differentiation should be considered in further research as well as managerial implications. Users of mobile shopping demonstrate a different perception towards it, suggesting that once users overcome the entry barriers (such as technological skills, security concerns, trust, shipping cost considerations, lack of information, etc.) and start to use it, they realize the true value that mobile shopping offers, leading to a change in their initial perception.

To test whether factors PE, EE, HM, TR, and PV are affected by age, Spearman's rank-order correlation coefficient test was used. If the significance level is below a predetermined value (commonly 0.05), it may be concluded that there is a significant correlation between age and factors. According to the results shown in Appendix Table 19, age has a significant correlation (p-value = 0.001) only with the factor Effort Expectancy, where the correlation is negative and of medium strength (ρ coefficient = -0.263). This implies that older users have a lower level of Effort expectancy, thus they find the use of mobile shopping harder. Other factors do not show a statistically significant correlation with age.

Further, the relationship between the effect of age and the factor EE and their combined effect on the dependent variable Frequency of use was analyzed. Moderated regression analysis was used for the examination. As EE was the only factor that significantly correlated with age, the analytical process and results are described only for this factor.

After centering and standardizing our data, we tested the relationships between the factor EE, the moderator (age), and the dependent variable (Frequency of use). The results show that Age had a beta coefficient of -0.191 (p-value = 0.013), which means if the independent variable Age increases by 1 point (keeping in mind these are age group points, not years per se) and the EE is neutral, the frequency of use of m-shopping drops by 0.191 points; thus, age directly negatively affects the Frequency of use. EE in this setting had a beta coefficient of 0.245 (p-value = 0.014), meaning if EE increased by 1 point and the Age is neutral, the Frequency of use increased by 0.245; thus, EE directly positively affects the frequency of use.

After introducing interaction terms between age and factors in moderated regression analysis, regardless of the acceptable level of statistical significance, the overall results were **not valid** as VIF (Variance Inflation Factor) was high above the recommended value of 1,0 and even above the maximum acceptable value of 10, even though the standardization of variables was conducted to reduce the multicollinearity. The presence of multicollinearity casts doubts on the validity of generated results and even the overall reliability of the model (Field, 2012). For details, see Appendix Tables 22 and 23, where the outcomes of the tests are presented.

Based on the moderated regression analysis and Spearman's rank-order correlation coefficient test, we conclude that there is a significant correlation between age and Effort Expectancy. Additionally, there is a statistically significant negative direct effect of age on frequency of use. However, this study was unable to find valid evidence of age acting as a moderating factor.

5.2 Managerial Implications

The findings of this research hold significant implications for businesses and organizations engaged in online retail or m-commerce. Below are some potential applications of these findings.

As age and effort expectancy have been identified as significant factors affecting the frequency of online shopping, not only should marketing strategies be tailored according to age groups, but also user interfaces of shopping channels that are generally all designed from the point of view of UI designers and app programmers. Mobile shopping should be made easier throughout the shopping process to attract older generations who are slowly but steadily discovering and adopting the possibilities offered by mobile apps and simplified website shopping interfaces. According to SURS (2023b), in 2022, only 12% of the residents used so-called basic mobile phones, i.e., phones that allow only basic functions. Such mobile phones were most frequently used by 65–74-year-olds (37%).

The most frequent non-users of the internet are in the age group 65–74 (33%). 42% of non-users stated they lack the skills to use the Internet or computer SURS (2023b). This means there is still a huge untapped pool of potential customers if businesses manage to approach older users. Since many older people have already learned to use chatting apps, it is also possible to encourage them to engage in mobile shopping if the apps are designed to be simple and intuitive. The age group from 55 to 64 years old had the highest increase in the share of users, e.g., by ten percentage points to 52% in 2023 from only 35% in 2019, according to SURS (SURS 2021; SURS 2023b). Particularly, food retailers in Slovenia should give more emphasis to this problem as they operate daily with these customers. However, their apps are so vast and ambiguous that they can bring frustration even to younger, tech-savvy users.

Understanding that performance expectancy and hedonic motivation are strong predictors of mobile shopping frequency should guide businesses in designing their services and interfaces to access their services or products. Businesses should strive to increase users' perception of m-shopping usefulness by providing better user interfaces and personalized services and primarily increase users' everyday flexibility. Users appreciate the added value of mobile shopping, including better online offers, a wider range of products, and the ability to discover new items while instantly comparing prices. Sometimes, we might feel pushed to use new applications and systems, which can be displeasing. However, once we embrace the new system and become comfortable with it, we begin to see its full potential. As a result, we start to utilize all the features it offers and use it more frequently (Wang et al., 2015) if it meets our expectations and demands.

From this perspective, online shopping companies should invest more in overall tech education for the population, particularly older generations and younger individuals who are just starting to use smartphones. The goal is to make these shopping channels closer and more accessible to those who currently do not use them, as users recognize that mobile shopping saves time, allows for finding better prices, and offers greater everyday flexibility. The same approach should apply to governments, as increased digitalization of public administrative systems through the utilization of mobile apps could alleviate the physical burden on administration units, automate processes, and result in overall time savings and cost savings for both parties (population and government). Governmental app user interfaces should mirror the characteristics of successful mobile shopping apps, ensuring reliability, intuitiveness, clarity, speed, and safety.

In summary, these managerial implications underscore the importance of understanding consumer demographics, motivations, and preferences when designing effective marketing and business strategies, optimizing the shopping experience, and growing businesses within the mobile commerce industry.

5.3 Research Contribution, Limitations, and Future Research Suggestions

This master's thesis has made both theoretical and practical contributions to the rapidly evolving field of mobile shopping. The influence of socio-psychological factors such as Performance Expectancy, Effort Expectancy, Facilitating Conditions, Hedonic Motivation, Price Value, and Trust has not been previously investigated among mobile shopping users in Slovenia, partly due to the small market size. This study also contributes significantly to the literature on underlying factors of online shopping, focusing specifically on the use of mobile technology. The research took a comprehensive approach to address mobile shopping as a holistic process, covering aspects from product search to payment capabilities and other variables involved in the process.

This research empirically confirmed that mobile shopping in Slovenia is indeed influenced by factors such as Performance Expectancy, Effort Expectancy, Hedonic Motivation, Price Value, and Trust, with some of these factors being partially moderated by the age of the users.

Despite providing valuable insights and enhancing understanding of mobile shopping in Slovenia, the study is not without limitations. Due to the scale and complexity of the study, a decision had to be made regarding the reduction of the number of factors or the precision of each factor (by reducing the number of variables grouped within a factor). To encompass the length of the shopping process, it was decided to maintain the number of factors at the expense of factor precision. Further research endeavors should aim to enhance the precision of factors within the UTAUT2 framework while considering the specificity of mobile shopping as a process that extends beyond mere technology. Some variables from the original factors were substituted as the UTAUT2 model does not perfectly align with the mobile shopping process.

A more thorough examination should be dedicated to the substitutions of variables, especially within the domain of facilitating conditions. While we believe this factor does affect the usage of technology, the research was unable to establish it as reliable enough. Non-users of mobile shopping exhibit a different relationship between factors compared to users. Therefore, further attention should be directed towards researches that differentiate underlying factors based on their impact on the frequency of use (as continuous use) versus the initial adoption of the technology.

Given the broad and diverse nature of the field of mobile shopping, it would be beneficial to analyze the factors for specific product categories (Shen et al., 2016; Sohn, 2017; OECD, 2019). Another significant limitation identified in the research is the unequal sample distribution among age groups, which led to a significant statistical deviation. For example, while the male group showed a higher average estimated monthly expenditure than the female group across the entire dataset, this trend varied when considering age groups with uneven responses or those with three or fewer responses per gender. In such cases, the female group had a slightly higher average estimated expenditure. Therefore, future research exploring sociological effects in connection with technology should ensure equal representation not only by gender but also by age group to produce more reliable statistics.

Furthermore, the relatively small sample size and convenient sampling method (among acquaintances) limit the possibility of the generalization of the results, particularly as the geographical distribution of the sample is unknown. Geographical accessibility, including postal service coverage, could pose a barrier to mobile shopping, regardless of the user's age or gender. However, some barriers as geographical accessibility, could also act as an incentive to use mobile shopping (OECD, 2019), particularly if physical shopping options are limited, and this aspect may strongly influence the underlying factors.

The research also found that the frequency of use of social media apps was almost identical among both genders and had a moderate effect on the frequency of use of mobile shopping. The correlation between mobile shopping and the usage of social apps was based on the idea that increased frequency of social media app utilization exposes users to advertisements (Hajli, 2014; Hossain et al., 2020) and facilitates accessibility to shopping channels (e.g., redirection, fast buy buttons). However, this correlation does not account for the user's skillfulness and their perception of the usefulness of online shopping (performance expectancy). We suggest that further research explore the connection between the accessibility of shopping channels and overall shopping frequency. As suggested by Hure et al. (2017), more studies should focus on the overall effects of omnichannel experience rather than limited retail sections and single-channel studies, such as online retail or mobile shopping.

As even older generations adopt new lifestyles and trends, and technology becomes increasingly pervasive, as well as mobile payments becoming more convenient, conducting a longitudinal study could yield valuable insights into shopping behavior and the evolving underlying factors.

6 CONCLUSIONS

This master's thesis discusses the underlying factors influencing the frequency of mobile shopping usage among Slovenian consumers and presents the results of empirical research. The goal of the empirical research is to expand knowledge about mobile shopping practices among Slovenian consumers by considering the entirety of the mobile shopping process.

This research offers a theoretical generalization of the concept of frequency of technology use about underlying factors that may influence it. Originating from a model that typically measures technology use or adoption from a utilitarian perspective, this study provides an interesting perspective by testing it within the field of shopping, where hedonic motivations also play a significant role. The additional focus was given to the spectrum of factors aiming to inclusively cover the entire mobile shopping process product search to purchase and delivery. The practical value of this study lies in the recommendations presented, which can enhance marketers' or developers' approach to consumers and their frequency of use.

Frequency of use is a leading factor used to explain consumers' purchase behavior, relevant to various domains such as purchase behavior, marketing, and business development. It varies across nations, countries, and regions, influenced by infrastructure, culture, overall development level, general income, and many other factors. Moreover, it is subject to the influence of consumers' demographics and socio-psychological factors, leading to inconsistencies observed across age groups and countries.

Based on the confirmation or refutation of the proposed hypotheses, the conclusions drawn answer the question posed in the introduction of the thesis. Results indicate that mobile shopping users in Slovenia engage in mobile shopping a few times a month, demonstrating a moderate frequency, which corroborates with the statistical research at the national and European level (SURS, 2023; Lone & Weltevreden, 2023). Users in Slovenia strongly perceive m-shopping as useful in their daily lives, with a particularly high perception of the additional flexibility it offers. Research suggests that users in Slovenia have a genuine interest in mobile shopping, rather than engaging in it solely as an unplanned activity during moments of boredom in contrast with DynamicYield (2020). Moreover, the research reveals that mobile shopping habits do not differ significantly between genders but are strongly influenced by the age of consumers. Businesses should make mobile shopping easier throughout the shopping process to attract older generations who are gradually discovering and adopting the possibilities offered by mobile apps and simplified web interfaces.

Results also suggest that factors such as Performance Expectancy, Price Value, and Hedonic Motivation exert the strongest effect on the frequency of use of mobile shopping. Additionally, there was a positive correlation observed between the frequency of use of mobile shopping and the frequency of use of social media applications, with a moderate correlation identified between the former and the level of estimated expenditure on mobile shopping. This insight can be particularly valuable for marketers, as it suggests that active users of social media applications tend to spend more on online shopping and engage more frequently in mobile shopping activities.

While this research has indeed confirmed that mobile shopping users in Slovenia engage with it at a moderate frequency and that this frequency is influenced by factors such as Age, Performance Expectancy, Price Value, and Hedonic Motivation, there remains a need for further exploration, particularly regarding the factors of Facilitating Conditions and Trust. A more extensive investigation into these factors is warranted to gain a deeper understanding of their relationship with mobile shopping behavior.

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APPENDICES

APPENDIX 1: Summary in Slovene

Namen te magistrske naloge je poglobiti znanje na področju vedenja porabnikov, in sicer z raziskovanjem dejavnikov, ki vplivajo na uporabo mobilnega nakupovanja v Sloveniji. S tem nameravam izboljšati razumevanje vedenja porabnikov, ki uporabljajo ta relativno novi način nakupovanja. Ta raziskava odgovarja na naslednja vprašanja: Kako pogosto se v Sloveniji izvaja mobilno nakupovanje? Kako slovenski uporabniki dojemajo mobilno nakupovanje in kateri dejavniki vplivajo na mobilno nakupovanje v Sloveniji ter v kakšnem obsegu?

Za testiranje hipotez sem oblikoval vprašalnik, ki je vseboval vse potrebne spremenljivke. Analiza je bila izvedena z odgovori iz 149 vprašalnikov, ki so bili izpolnjeni med 15. januarjem 2023 in 15. februarjem 2023. Da bi izluščili učinek, ki ga imajo merjene spremenljivke na naše konstrukte, smo najprej uporabili eksplorativno faktorsko analizo (EFA). Nato pa so bile hipoteze preizkušene še s Spearmanovim testom koeficienta korelacije in Mann-Whitneyjevim testom.

Rezultati raziskave kažejo, da večina Slovencev v zajetem vzorcu mobilno nakupovanje uporablja nekajkrat mesečno, mobilno nakupovanje pa dojemajo kot zelo koristno v vsakdanjem življenju. Še bolj pa cenijo dodatno fleksibilnost, ki nam jo mobilno nakupovanje ponuja. Uporabniki mobilnega nakupovanja v vzorcu menijo, da so aplikacije za mobilno nakupovanje enostavne za uporabo, spletna mesta pa so jasna in razumljiva, vendar obstaja prostor za izboljšave pri uporabniških vmesnikih. Na podlagi raziskave lahko sklepamo, da med slovenskimi uporabniki v vzorcu spol nima vpliva na pogostost uporabe mobilnega nakupovanja. Obenem je raziskava pokazala, da starost vpliva na nakupovalne navade, predvsem na pričakovani trud. Z raziskavo nismo uspeli potrditi statistično značajnih vplivov starosti uporabnikov na pogostost uporabe preko sledečih dejavnikov: pričakovani učinek, pričakovan trud, hedonična motivacija, zaupanje, cenovna vrednost ter spodbujevalni pogoji. Smo pa uspeli najti vzorčne povezave med temi dejavniki in pogostostjo mobilnega nakupovanja za vse dejavnike razen za spodbujevalne pogoje, kateri so bili izločeni iz statistične obdelave zaradi slabe konsistence. Raziskava je še pokazala, da je pogostost mobilnega nakupovanja močno povezana z ocenjenimi mesečnimi izdatki za mobilno nakupovanje.

Podjetja bi morala stremeti k poenostavljanju celotnega procesa mobilnega nakupovanja, s čimer bi lahko pritegnili tudi starejše generacije, ki počasi a vztrajno odkrivajo in sprejemajo priložnosti, ki jih mobilne aplikacije omogočajo. Zlasti trgovci s hrano v Sloveniji bi morali več pozornosti posvetiti temu problemu, saj vsakodnevno poslujejo s takšnimi strankami. Podjetja bi si morala prizadevati k povečanju dojemanja koristnosti mobilnega nakupovanja, predvsem z zagotavljanjem boljših uporabniških vmesnikov, bolj personaliziranih storitev in predvsem s povečanjem vsakodnevne fleksibilnosti uporabnikov. Predvsem bi moral biti cilj podjetij približati te nakupovalne kanale tistim, ki jih trenutno ne uporabljajo, saj uporabniki prepoznavajo, da mobilno nakupovanje prihrani čas, omogoča iskanje boljših cen in ponuja večjo vsakodnevno fleksibilnost. Enak pristop bi moral veljati za državo in državne ustanove, saj bi povečana digitalizacija javne uprave prek uporabe mobilnih aplikacij olajšala fizični pritisk na upravne enote, avtomatizacija procesov pa bi lahko prinesla splošne prihranke časa ter denarja obema vpletenima stranema. Uporabniški vmesniki vladnih aplikacij bi morali odražati značilnosti uspešnih mobilnih nakupovalnih aplikacij, zagotavljati zanesljivost, intuitivnost, jasnost, hitrost in varnost.

APPENDIX 2: Overview of scales; Original versus this research in English and translation in Slovene

ORIGINAL	THIS RESEARCH	TRANSLATION (SI) CORRECTED
PE1. I find mobile Internet useful in my daily life. (Venkatesh et al., 2012)	PE1. I find m-shopping useful in my daily life.	PE1. M-nakupovanje vidim kot uporabno v mojem vsakdanjem življenju.
PE3. Using mobile Internet helps me accomplish things more quickly. (Venkatesh et al., 2012)	PE2. Using m-shopping gives me more flexibility (anywhere & anytime).	PE2. Uporaba m-nakupovanja mi omogoča večjo fleksibilnost (kjerkoli in kadarkoli).
EE2. My interaction with mobile Internet is clear and understandable. (Venkatesh et al., 2012)	EE1. My interaction with m-shopping apps or websites is clear and understandable.	EE1. Uporaba aplikacij in web-strani za nakupovanje s telefonom je jasna in razumljiva.
EE3. I find mobile Internet easy to use. (Venkatesh et al., 2012)	EE2. I find mobile payments easy.	EE2. Plačevanje z uporabo mobilnega telefona se mi zdi enostavno.
EE3. I find mobile Internet easy to use. (Venkatesh et al., 2012)	EE3. I find m-shopping easy to use.	EE3. M-nakupovanje je enostavno za uporabo.
EE4. It is easy for me to become skillful at using mobile Internet. (Venkatesh et al., 2012)	EE4. It is easy for me to become skillful at using new apps.	EE4. Hitro osvojim nove aplikacije.
FC1. I have the resources necessary to use mobile Internet. (Venkatesh et al., 2012)	FC1. My phone features fully support m-shopping process (apps, payments, comfortable screen size, etc.).	FC1. Zmogljivosti mojega telefona popolnoma podpirajo proces m-nakupov (aplikacije, plačila, primerna velikost zaslona, ipd.).
FC1. I have the resources necessary to use mobile Internet. (Venkatesh et al., 2012)	FC2. I have the appropriate means of payment for m-shopping (credit cards, Apple Pay, Google Pay, Revolut, etc).	FC2. Imam primerna plačilna sredstva, ki mi omogočajo m-nakupovanje. (kreditne kartice, Apple Pay, Google Pay, Revolut, ipd.).
FC4. I can get help from others when I have difficulties using mobile Internet. (Venkatesh et al., 2012)	FC4. I can get help from customer support when I have difficulties using mobile shopping.	FC4. V primeru težav z mobilnim nakupovanjem, se lahko obrnem na uporabniško pomoč (customer support).
"Mobile shopping gives me something to do." Dynamic Yield (2020)	HM1. Sometimes I do m-shopping when I have nothing better to do.	HM1. Kadar nimam pametnejšega dela, se poslužujem tudi m-nakupovanja.
"ISM. I go shopping to see what new products are available" (Arnold and Reynolds, 2003)	HM2. I use m-shopping to see what new products are available.	HM2. M-nakupovanje uporabljam za odkrivanje novih izdelkov.
HM2. Using mobile Internet is enjoyable. (Venkatesh et al., 2012)	HM3. Using m-shopping is enjoyable.	HM3. Uporaba m-nakupovanja je prijetna.
PV1. Mobile Internet is reasonably priced. (Venkatesh et al., 2012)	PV1. M-shopping allows me to find better deals.	PV1. Z m-nakupovanjem lahko odkrijem boljšo ponudbo.
"Transactions via m-commerce are safe." Liébana-Cabanillas (2016), Chong et al. (2012);	TR1. I feel monetary transactions in m-shopping are safe.	TR1. Denarne transakcije pri m-nakupovanju so varne.
"This Web retailer is trustworthy" (Pavlou, 2003); "This Web retailer is one that keeps promises and commitments" (Pavlou, 2003); "M-commerce transactions are reliable." Liébana-Cabanillas (2016), Chong et al.	TR2. I trust the seller that the items I buy via m-shopping will be the same as presented (picture, size, quality, …).	TR2. Prodajalcu zaupam, da bodo kupljeni izdelki enaki kot v predstavitvi (slika, velikost, kakovost, …)
"TM2: Purchasing on my mobile device involves a time-consuming payment procedure." Marriott et al. (2017)	TR3. I believe that the delivery will be done on time.	TR3. Verjamem, da bo dostava opravljena pravočasno.
"DEC2. The recommendations information was truthful" (Cenfetelli and Schwarz, 2011)	TR4. I trust online reviews of other users (either rating, product photo, video).	TR4. Zaupam spletnim mnenjem ostalih uporabnikov (katerokoli: ocena, slika izdelka, video komentar).

Source: adapted by Venkatesh et al. (2012); Dynamic Yield (2020); Arnold & Reynolds (2003); Liébana-Cabanillas et al. (2017); Chong et al. (2012); Pavlou (2003); Marriott et al. (2017); Cenfetelli & Schwarz (2011).

APPENDIX 3: Questionnaire in English

MOBILE SHOPPING IN SLOVENIA

For the purpose of this questionnaire, m-shopping is conducted using a smartphone, tablet, or voice assistant (such as Siri or Alexa). Please note that the term "m-shopping" refers to the **entire shopping process**, including product search, price comparison, and purchase, and applies to all product categories (IT, groceries, clothing and fashion accessories, furniture, etc.) and all services (web reservations, in-app purchases, food delivery, flights, taxi services, etc.).

FREQUENCY OF USE

Please choose the frequency of use of mobile shopping in the last month (remember m-shopping refers to everything from product search, price comparison, purchasing, … and for all product categories (IT, food, fashion & apparel, furniture & home décor, …) and all services (in-app purchases, food delivery, taxi, etc.):
(The item is measured on a 7-point Likert scale where 0 = never, 1 = once a month, 2 = few times a month, 3 = every week, 4 = several times a week, 5 = every day, 6 = few times a day)

PERFORMANCE EXPECTANCY

(The item is measured on a 5-point Likert scale where (1) Strongly disagree; (2) Disagree; (3) Neither agree nor disagree; (4) Agree; (5) Strongly agree)
PE1. I find m-shopping useful in my daily life.
PE2. Using m-shopping gives me more flexibility (anywhere & anytime).

EFFORT EXPECTANCY

(The item is measured on a 5-point Likert scale where (1) Strongly disagree; (2) Disagree; (3) Neither agree nor disagree; (4) Agree; (5) Strongly agree)
EE1. My interaction with m-shopping apps or m-shopping websites is clear and understandable.
EE2. I find online payments simple.
EE3. I find m-shopping easy to use.
EE4. It is easy for me to become skillful in using new shopping apps.

FACILITATING CONDITIONS

(The item is measured on a 5-point Likert scale where (1) Strongly disagree; (2) Disagree; (3) Neither agree nor disagree; (4) Agree; (5) Strongly agree)
FC1. My phone features can support the m-shopping process (apps, payments, comfortable screen size, etc.).
FC2. I have the appropriate means of payment for m-shopping (credit cards, Apple Pay, Google Pay, Revolut, etc).
FC4. I can get help from customer support when I have difficulties using mobile shopping.

HEDONIC MOTIVATION

(The item is measured on a 5-point Likert scale where (1) Strongly disagree; (2) Disagree; (3) Neither agree nor disagree; (4) Agree; (5) Strongly agree)

HM1. Sometimes, I use m-shopping when I have nothing better to do.

HM2. I use m-shopping to see what new products are available.

HM3. Using m-shopping is enjoyable.

PRICE VALUE

(The item is measured on a 5-point Likert scale where (1) Strongly disagree; (2) Disagree; (3) Neither agree nor disagree; (4) Agree; (5) Strongly agree)

PV1. M-shopping allows me to find good deals.

TRUST

(The item is measured on a 5-point Likert scale where (1) Strongly disagree; (2) Disagree; (3) Neither agree nor disagree; (4) Agree; (5) Strongly agree)

TR1. I feel monetary transactions in m-shopping are safe.

TR2. I trust the seller that the items I buy via m-shopping will be the same as presented (picture, size, quality, …).

TR3. I believe that the delivery will be done on time.

TR4. I trust the online reviews of other users.

Personal data

Estimated Expenditure: "On average, I spend per month using mobile shopping:" 0€, 0-50€, 51-100€, 101-300€, 301-500€, 501-1000€, unknown/I don't track

Frequency of use of social media apps: "I use social networks (FB, Instagram, TikTok, Twitter, etc.):"

(I don't use; a few times a week; every day - one app; every day - several apps)

Gender Male Female

Age 16-24, 25-34, 35-44, 45-55, over 56

APPENDIX 4: Questionnaire in Slovene

MOBILNO NAKUPOVANJE V SLOVENIJI

Tekom ankete prosim imejte v mislih sledeče:
M-nakupovanje se opravlja z uporabo **pametnega telefona, tablice ali pa s pomočjo hišne pomočnice** (Siri, Alexa). Prosimo upoštevajte, da m-nakupovanje **zajema celoten nakupovalni proces** od iskanja izdelkov, primerjanja cen, do samega nakupa in velja za vse katerogije izdelkov (IT, hrana, oblačila in modni dodatki, pohištvo, ...) **ter vse storitve** (spletne rezervacije, nakupi v aplikacijah, dostave hrane, letalski prevozi, taksi, ipd.).

Prosim ocenite pogostost uporabe mobilnega nakupovanja.

M-nakupovanje zajema celoten nakupovalni proces, tudi če ni zaključen, od iskanja izdelkov, primerjanja cen, do samega nakupa in velja za vse katerogije izdelkov ter vse storitve (spletne rezervacije, nakupi v aplikacijah, dostave hrane, letalski prevozi, taksi, ipd.).

	Nikoli	Enkrat mesečno	Nekajkrat mesečno	Vsak teden	Večkrat tedensko	Vsak dan	Večkrat dnevno
m-nakupovanje uporabljam	○	○	○	○	○	○	○

(Ne)uporabnost m-nakupovanja

	Sploh se ne strinjam	Ne strinjam se	Niti se strinjam, niti se ne strinjam	Strinjam se	Popolnoma se strinjam
M-nakupovanje vidim kot uporabno v mojem vsakdanjem življenju.	○	○	○	○	○
Uporaba m-nakupovanja mi omogoča večjo fleksibilnost (kjerkoli in kadarkoli).	○	○	○	○	○

"Brez muje se še čevelj ne obuje."

	Sploh se ne strinjam	Se ne strinjam	Niti se ne strinjam niti se strinjam	Strinjam se	Popolnoma se strinjam
Uporaba aplikacij in web-strani za nakupovanje s telefonom je jasna in razumljiva.	○	○	○	○	○
Plačevanje z uporabo mobilnega telefona se mi zdi enostavno.	○	○	○	○	○
M-nakupovanje je enostavno za uporabo.	○	○	○	○	○
Hitro osvojim nove aplikacije.	○	○	○	○	○

Včasih se pri nakupih lahko zatakne...

	Sploh se ne strinjam	Ne strinjam se	Niti se strinjam, niti se ne strinjam	Strinjam se	Popolnoma se strinjam
Zmogljivosti mojega telefona popolnoma podpirajo proces m-nakupov (aplikacije, plačila, primerna velikost zaslona, ipd.).	○	○	○	○	○
Imam primerna plačilna sredstva, ki mi omogočajo m-nakupovanje. (kreditne kartice, Apple Pay, Google Pay, Revolut, ipd.).	○	○	○	○	○
V primeru težav z mobilnim nakupovanjem, se lahko obrnem na uporabniško pomoč (customer support).	○	○	○	○	○

"Kdor preveč obljublja, zaupanje izgublja."

	Sploh se ne strinjam	Se ne strinjam	Niti se ne strinjam niti se strinjam	Strinjam se	Popolnoma se strinjam
Denarne transakcije pri m-nakupovanju so varne.	○	○	○	○	○
Prodajalcu zaupam, da bodo kupljeni izdelki enaki kot v predstavitvi (slika, velikost, kakovost, …).	○	○	○	○	○
Verjamem, da bo dostava opravljena pravočasno.	○	○	○	○	○
Zaupam spletnim mnenjem ostalih uporabnikov (katerokoli: ocena, slika izdelka, video komentar).	○	○	○	○	○

Nakupovanje je lahko tudi zabavno, ali pač?

	Sploh se ne strinjam	Ne strinjam se	Niti se strinjam, niti se ne strinjam	Strinjam se	Popolnoma se strinjam
Kadar nimam pametnejšega dela, se poslužujem tudi m-nakupovanja.	○	○	○	○	○
M-nakupovanje uporabljam za odkrivanje novih izdelkov.	○	○	○	○	○
Uporaba m-nakupovanja je prijetna.	○	○	○	○	○

Kdor išče, ta najde...

	Sploh se ne strinjam	Ne strinjam se	Niti se strinjam, niti se ne strinjam	Strinjam se	Popolnoma se strinjam
Z m-nakupovanjem lahko odkrijem boljšo ponudbo.	○	○	○	○	○

Ste kdaj računali koliko zapravite?

	0€	do 50€	51€ -100€	101€ -300€	301€ -500€	501-1000€	ne vem/ne spremljan
V povprečju mesečno z uporabo m-nakupovanja zapravim:	○	○	○	○	○	○	○

... saj za prijatelje si je treba čas vzet' ...

	ne uporabljam	večkrat tedensko	vsak dan - ena aplikacija	vsak dan - več aplikacij
Socialna omrežja (FB, IG, TikTok, Twitter, ipd.) uporabljam:	○	○	○	○

Še vaš spol:

- ○ Moški
- ○ Ženski

in starost:

- ○ Manj kot 18 let
- ○ Od 18 do 24 let
- ○ Od 25 do 34 let
- ○ Od 35 do 44 let
- ○ Od 45 do 54 let
- ○ Od 55 do 64 let
- ○ 65 let ali več

APPENDIX 5: Hypotheses output

- **H1: Performance expectancy will positively influence customers' frequency of mobile shopping.**
- **H2: Effort expectancy will positively influence customers' frequency of mobile shopping.**
- **H3: Facilitating conditions will positively influence customers' frequency of mobile shopping.**
- **H4: Hedonic motivation will positively influence customers' frequency of mobile shopping.**
- **H5: Price value will positively influence customers' frequency of mobile shopping.**
- **H6: Trust will positively influence customers' frequency of mobile shopping.**

Appendix Table 1: Hypotheses H1-H6 output, correlation coefficients and significance

Correlations

			PE	EE	FC	TR	HM	PV1 Z m-nakupovanjem lahko odkrijem boljšo ponudbo.	Fq m-nakupovanje uporabljam
Spearman's rho	PE	Correlation Coefficient	1,000	,460**	,340**	,340**	,399**	,375**	,537**
		Sig. (2-tailed)	.	,000	,000	,000	,000	,000	,000
		N	149	149	149	149	149	149	149
	EE	Correlation Coefficient	,460**	1,000	,656**	,422**	,368**	,318**	,250**
		Sig. (2-tailed)	,000	.	,000	,000	,000	,000	,002
		N	149	149	149	149	149	149	149
	FC	Correlation Coefficient	,340**	,656**	1,000	,248**	,291**	,321**	,299**
		Sig. (2-tailed)	,000	,000	.	,002	,000	,000	,000
		N	149	149	149	149	149	149	149
	TR	Correlation Coefficient	,340**	,422**	,248**	1,000	,295**	,298**	,166*
		Sig. (2-tailed)	,000	,000	,002	.	,000	,000	,043
		N	149	149	149	149	149	149	149
	HM	Correlation Coefficient	,399**	,368**	,291**	,295**	1,000	,445**	,345**
		Sig. (2-tailed)	,000	,000	,000	,000	.	,000	,000
		N	149	149	149	149	149	149	149
	PV1 Z m-nakupovanjem lahko odkrijem boljšo ponudbo.	Correlation Coefficient	,375**	,318**	,321**	,298**	,445**	1,000	,347**
		Sig. (2-tailed)	,000	,000	,000	,000	,000	.	,000
		N	149	149	149	149	149	149	149
	Fq m-nakupovanje uporabljam	Correlation Coefficient	,537**	,250**	,299**	,166*	,345**	,347**	1,000
		Sig. (2-tailed)	,000	,002	,000	,043	,000	,000	.
		N	149	149	149	149	149	149	149

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Source: own work.

- **H7: A higher age will negatively influence the frequency of mobile shopping.**

Appendix Table 2: H7 output, linear regression analysis, model summary

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,966	1	13,966	9,824	,002[b]
	Residual	208,974	147	1,422		
	Total	222,940	148			

a. Dependent Variable: Fq m-nakupovanje uporabljam

b. Predictors: (Constant), Age

Source: own work.

Appendix Table 3: H7 output, linear regression analysis, factor significance

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3,868	,300		12,905	,000		
	Age	-,234	,075	-,250	-3,134	,002	1,000	1,000

a. Dependent Variable: Fq m-nakupovanje uporabljam

Source: own work.

- **H8: Gender influences the frequency of mobile shopping; female users will have a higher frequency of use than male users.**

Appendix Table 4: H8 output, Mann-Whitney test, nonsignificant

	Frequency
Mann-Whitney U	2599,000
Wilcoxon W	4615,000
Z	-0,442
Asymp. Sig. (1-tailed)	0,329

a. Grouping Variable: gender

Source: own work.

APPENDIX 6: Results of additional tests

Additional test: The effect of PE on the frequency of use of mobile shopping.

Appendix Table 5: PE output, regression analysis, model summary

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	,517[a]	,267	,262	1,054	,267	53,631	1	147	,000
2	,549[b]	,301	,292	1,033	,034	7,125	1	146	,008

a. Predictors: (Constant), cenPE

b. Predictors: (Constant), cenPE, Age

Source: own work.

Appendix Table 6: PE output, regression analysis, coefficients PE, Age

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,980	,086		34,506	,000		
	cenPE	,870	,119	,517	7,323	,000	1,000	1,000
2	(Constant)	3,641	,262		13,915	,000		
	cenPE	,829	,117	,493	7,064	,000	,983	1,017
	Age	-,174	,065	-,186	-2,669	,008	,983	1,017

a. Dependent Variable: Fq m-nakupovanje uporabljam

Source: own work.

Additional test: The effect of EE on the frequency of use of mobile shopping.

Appendix Table 7: EE output, regression analysis, model summary

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	,247[a]	,061	,055	1,193	,061	9,552	1	147	,002
2	,317[b]	,100	,088	1,172	,039	6,396	1	146	,013

a. Predictors: (Constant), cenEE

b. Predictors: (Constant), cenEE, Age

Source: own work.

Appendix Table 8: EE output, regression analysis, coefficients EE, Age

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,980	,098		30,481	,000		
	cenEE	,507	,164	,247	3,091	,002	1,000	1,000
2	(Constant)	3,704	,302		12,265	,000		
	cenEE	,410	,166	,200	2,476	,014	,946	1,057
	Age	-,191	,076	-,204	-2,529	,013	,946	1,057

a. Dependent Variable: Fq m-nakupovanje uporabljam

Source: own work.

Additional test: The effect of HM on the frequency of use of mobile shopping.

Appendix Table 9: HM output, regression analysis, model summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	,311[a]	,097	,091	1,170	,097	15,754	1	147	,000
2	,378[b]	,143	,131	1,144	,046	7,830	1	146	,006

a. Predictors: (Constant), cenHM

b. Predictors: (Constant), cenHM, Age

Source: own work.

Appendix Table 10: HM output, regression analysis, coefficients HM, Age

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,980	,096		31,079	,000		
	cenHM	,439	,111	,311	3,969	,000	1,000	1,000
2	(Constant)	3,746	,290		12,940	,000		
	cenHM	,403	,109	,285	3,694	,000	,986	1,015
	Age	-,202	,072	-,216	-2,798	,006	,986	1,015

a. Dependent Variable: Fq m-nakupovanje uporabljam

Source: own work.

Additional test: The effect of PV on the frequency of use of mobile shopping.

Appendix Table 11: PV output, regression analysis, model summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,338[a]	,114	,108	1,159	,114	18,953	1	147	,000
2	,405[b]	,164	,152	1,130	,049	8,629	1	146	,004

a. Predictors: (Constant), cenPV1a

b. Predictors: (Constant), cenPV1a, Age

Source: own work.

Appendix Table 12: PV output, regression analysis, coefficients PV, Age

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2,980	,095		31,383	,000		
	cenPV1a	,600	,138	,338	4,353	,000	1,000	1,000
2	(Constant)	3,772	,285		13,233	,000		
	cenPV1a	,566	,135	,319	4,199	,000	,993	1,007
	Age	-,209	,071	-,223	-2,938	,004	,993	1,007

a. Dependent Variable: Fq m-nakupovanje uporabljam

Source: own work.

Additional test: The effect of TR on the frequency of use of mobile shopping.

Appendix Table 13: TR output, regression analysis, model summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,135[a]	,018	,011	1,220	,018	2,710	1	147	,102
2	,274[b]	,075	,062	1,189	,057	8,967	1	146	,003

a. Predictors: (Constant), cenTR

b. Predictors: (Constant), cenTR, Age

Source: own work.

Appendix Table 14: TR output, regression analysis, coefficients TR, Age

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,980	,100		29,807	,000		
	cenTR	,313	,190	,135	1,646	,102	1,000	1,000
2	(Constant)	3,830	,300		12,764	,000		
	cenTR	,259	,186	,111	1,392	,166	,991	1,009
	Age	-,224	,075	-,239	-2,995	,003	,991	1,009

a. Dependent Variable: Fq m-nakupovanje uporabljam

Source: own work.

Additional test: The effect of Social media usage and Age on Frequency of Use

Appendix Table 15: Social media, regression analysis, model summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	,198[a]	,039	,033	1,207	,039	6,026	1	147	,015
2	,268[b]	,072	,059	1,191	,032	5,073	1	146	,026

a. Predictors: (Constant), SI1 Socialna omrežja (FB, IG, TikTok, Twitter, ipd.) uporabljam:

b. Predictors: (Constant), SI1 Socialna omrežja (FB, IG, TikTok, Twitter, ipd.) uporabljam:, Age

Source: own work.

Appendix Table 16 : Social media, regression analysis, coefficients

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,235	,319		7,001	,000		
	SI1 Socialna omrežja (FB, IG, TikTok, Twitter, ipd.) uporabljam:	,234	,095	,198	2,455	,015	1,000	1,000
2	(Constant)	3,296	,567		5,816	,000		
	SI1 Socialna omrežja (FB, IG, TikTok, Twitter, ipd.) uporabljam:	,125	,106	,106	1,189	,236	,792	1,262
	Age	-,189	,084	-,202	-2,252	,026	,792	1,262

a. Dependent Variable: Fq m-nakupovanje uporabljam

Source: own work.

Additional test: Effect of Facilitating Conditions and Age on Frequency of Use

Appendix Table 17: FC output, regression analysis, model summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,290[a]	,084	,078	1,179	,084	13,462	1	147	,000
2	,344[b]	,118	,106	1,160	,035	5,720	1	146	,018

a. Predictors: (Constant), FC

b. Predictors: (Constant), FC, Age

Source: own work.

Appendix Table 18: FC output, regression analysis, coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1,023	,542		1,887	,061		
	FC	,507	,138	,290	3,669	,000	1,000	1,000
2	(Constant)	2,015	,676		2,981	,003		
	FC	,426	,140	,243	3,040	,003	,942	1,062
	Age	-,179	,075	-,192	-2,392	,018	,942	1,062

a. Dependent Variable: Fq m-nakupovanje uporabljam

Source: own work.

Additional test: Correlation of Age and Factors (PE, EE, TR, HM, PV)

Appendix table 19: Correlation of Age and Factors

			Age
Spearman's rho coef.	Age	Correlation Coefficient	1,000
		Sig. (1-tailed)	
		N	*149*
	PE	Correlation Coefficient	-0,096
		Sig. (1-tailed)	0,121
		N	*149*
	EE	Correlation Coefficient	-0,263
		Sig. (1-tailed)	**0,001**
		N	*149*
	TR	Correlation Coefficient	-0,037
		Sig. (1-tailed)	0,326
		N	*149*
	HM	Correlation Coefficient	-0,113
		Sig. (1-tailed)	0,085
		N	*149*
	PV	Correlation Coefficient	-0,087
		Sig. (1-tailed)	0,145
		N	*149*

Source: own work.

Additional test: Effects of age on Estimated expenditure

Appendix Table 20: Age on Expenditure output, regression analysis, model summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,129[a]	,017	,009	1,138	,017	2,081	1	123	,152

a. Predictors: (Constant), Age

Source: own work.

Appendix Table 21: Age on Expenditure output, regression analysis, coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3,424	,311		11,007	,000		
	Age	-,112	,078	-,129	-1,443	,152	1,000	1,000

a. Dependent Variable: Exp V povprečju mesečno z uporabo m-nakupovanja zapravim:

Source: own work.

Additional test: Moderating effects of age on Effort expectancy and Frequency of use

Appendix Table 22: Moderated regression analysis, effects of age on EE and Frequency of use; model summary

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,603	1	13,603	9,552	,002[b]
	Residual	209,337	147	1,424		
	Total	222,940	148			
2	Regression	22,388	2	11,194	8,149	,000[c]
	Residual	200,551	146	1,374		
	Total	222,940	148			
3	Regression	32,455	3	10,818	8,235	,000[d]
	Residual	190,485	145	1,314		
	Total	222,940	148			

a. Dependent Variable: Fq m-nakupovanje uporabljam

b. Predictors: (Constant), Zscore(cenEE)

c. Predictors: (Constant), Zscore(cenEE), Age

d. Predictors: (Constant), Zscore(cenEE), Age, intZEExAge

Source: own work.

Appendix Table 23: Moderated regression analysis, effects of age on EE and Frequency of use; factor significance

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2,980	,098		30,481	,000		
	Zscore(cenEE)	,303	,098	,247	3,091	,002	1,000	1,000
2	(Constant)	3,704	,302		12,265	,000		
	Zscore(cenEE)	,245	,099	,200	2,476	,014	,946	1,057
	Age	-,191	,076	-,204	-2,529	,013	,946	1,057
3	(Constant)	3,657	,296		12,361	,000		
	Zscore(cenEE)	-,668	,344	-,544	-1,943	,054	,075	13,325
	Age	-,160	,075	-,170	-2,135	,034	,925	1,082
	intZEExAge	,239	,086	,782	2,768	,006	,074	13,549

a. Dependent Variable: Fq m-nakupovanje uporabljam

Source: own work.

Additional test: Effects of gender on factors (PE, EE, FC, HM, PV, TR) and Frequency of Use

Appendix Table 24: Testing the impact of gender on six factors and Frequency of use

Independent Samples Test

		Levene's Test for Equality of Variances F	Levene's Test for Equality of Variances Sig.	t-test for Equality of Means t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	95% Confidence Interval of the Difference Upper
Fq	Equal variances assumed	,036	,850	-,368	147	,713	-,075	,204	-,479	,328
	Equal variances not assumed			-,368	133,890	,713	-,075	,204	-,479	,329
PV	Equal variances assumed	,339	,561	,406	147	,685	,047	,115	-,181	,274
	Equal variances not assumed			,404	130,896	,687	,047	,116	-,182	,275
PE	Equal variances assumed	2,566	,111	-1,336	147	,184	-,16113	,12063	-,39952	,07726
	Equal variances not assumed			-1,352	139,121	,179	-,16113	,11920	-,39680	,07454
EE	Equal variances assumed	,227	,635	-,359	147	,720	-,03567	,09948	-,23226	,16092
	Equal variances not assumed			-,358	133,203	,721	-,03567	,09959	-,23265	,16131
FC	Equal variances assumed	,147	,702	,849	147	,397	,098929	,116491	-,131284	,329143
	Equal variances not assumed			,852	135,140	,396	,098929	,116154	-,130786	,328645
TR	Equal variances assumed	2,092	,150	-,681	147	,497	-,05971	,08771	-,23304	,11362
	Equal variances not assumed			-,703	145,382	,483	-,05971	,08496	-,22762	,10820
HM	Equal variances assumed	,246	,621	-2,890	147	,004	-,40648	,14063	-,68440	-,12857
	Equal variances not assumed			-2,860	128,365	,005	-,40648	,14212	-,68769	-,12528

Source: own work.

Additional test: Do factors (PE, EE, FC, HM, PV, TR) and Age differ between users and non-users of mobile shopping?

Appendix Table 25: Testing the difference between users and non-users by 5 factors and age

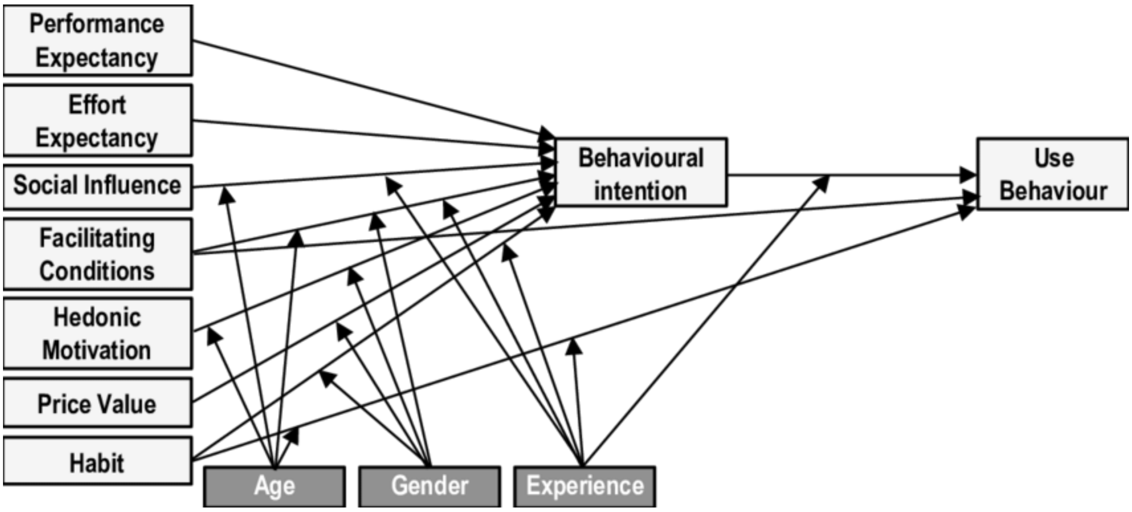
Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Age	Equal variances assumed	4,034	,046	2,148	147	,033	,781	,364	,063	1,500
	Equal variances not assumed			1,597	14,323	,132	,781	,489	-,266	1,829
PE	Equal variances assumed	,321	,572	-7,612	147	,000	-1,32460	,17402	-1,66850	-,98070
	Equal variances not assumed			-6,428	14,835	,000	-1,32460	,20605	-1,76422	-,88498
EE	Equal variances assumed	,685	,409	-4,433	147	,000	-,70159	,15825	-1,01433	-,38884
	Equal variances not assumed			-3,863	14,987	,002	-,70159	,18161	-1,08871	-,31446
FC	Equal variances assumed	,294	,589	-3,952	147	,000	-,742857	,187984	-1,114357	-,371358
	Equal variances not assumed			-4,297	16,495	,001	-,742857	,172884	-1,108463	-,377252
TR	Equal variances assumed	2,310	,131	-2,407	147	,017	-,35119	,14588	-,63949	-,06289
	Equal variances not assumed			-3,115	18,541	,006	-,35119	,11273	-,58753	-,11485
HM	Equal variances assumed	3,151	,078	-3,390	147	,001	-,79912	,23574	-1,26499	-,33325
	Equal variances not assumed			-4,490	18,906	,000	-,79912	,17797	-1,17173	-,42650

Source: own work.

APPENDIX 7*: UTAUT2 model*

Figure 1: UTAUT2 model



Source: V. Venkatesh, J. Thong, X. Xu; Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology; 2012.