St. Petersburg University
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THE IMPACT OF CONSUMER DIGITAL COMPETENCE ON ACCEPTANCE OF DIGITAL ECOSYSTEM SOLUTIONS: THE CASE OF SBER.

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ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПОЛНЕНИЯ ВЫПУСКНОЙ КВАЛИФИКАЦИОННОЙ РАБОТЫ

Я, Саакян Ануш Гайковна, студент второго курса магистратуры направления «Менеджмент», заявляю, что в моей магистерской диссертации на тему **«Влияние цифровой компетентности потребителей на принятие цифровых экосистем (на примере Сбера)»**, представленной в службу обеспечения программ магистратуры для последующей передачи в государственную аттестационную комиссию для публичной защиты, не содержится элементов плагиата.

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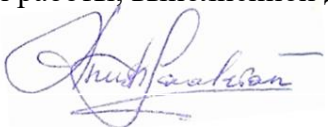
Саакян А. Г.  (Подпись студента)

6.06.2021 (Дата)

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I, Saakian Anush Gaikovna, (second) year master student, program «Management», state that my master thesis on the topic **« The Impact of Consumer Digital Competence on Acceptance of Digital Ecosystem Solutions: the Case of Sber»**, which is presented to the Master Office to be submitted to the Official Defense Committee for the public defense, does not contain any elements of plagiarism.

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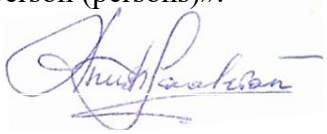
Saakian A. G.  (Student's signature)

6.06.2021 (Date)

АННОТАЦИЯ

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Название ВКР	Влияние цифровой компетентности потребителей на принятие цифровых экосистем (на примере Сбера)
Образовательная программа	Менеджмент
Направление подготовки	Менеджмент (Master in Management – MiM)
Год	2019–2021
Научный руководитель	Алканова Ольга Николаевна, Кандидат экономических наук
Описание цели, задач и основных результатов	Цель: исследовательская работа направлена на выяснение роли цифровых компетенций в поведении потребителей в контексте моделей принятия технологий. Задачи (сформулированы как исследовательские вопросы): • Какова роль цифровой компетенции в процессе принятия решений цифровой экосистемы? • Насколько конкретно цифровая компетенция участвует в процессе принятия решений цифровой экосистемы? Результаты: • Доказано, что уровень цифровой компетентности потребителей влияет на такие конструкции, как ожидаемая производительность, ожидаемая работа, предполагаемый риск и благоприятные условия, что позволяет получить ответы на поставленные вопросы исследования. • Доверие и безопасность вместе с ожидаемой производительностью были определены как наиболее влиятельные движущие силы для поведенческого намерения использовать технологическое решение, добавляя существенный эффект посредничества отношения к бренду. • На основе результатов эмпирических исследований были разработаны и рассмотрены дальнейшие теоретические и практические выводы
Ключевые слова	Цифровая компетенция, экосистема цифрового бизнеса, экосистема Сбер, UTAUT, принятие технологий

ABSTRACT

Master Student's Name	Saakian Anush Gaikovna
Master Thesis Title	The Impact of Consumer Digital Competence on Acceptance of Digital Ecosystem Solutions: the Case of Sber
Educational Program	Master in Management Program
Main field of study	Management
Year	2019–2021
Academic Advisor's Name	Alkanova Olga Nikolaevna, Candidate of Economic Sciences
Description of the goal, tasks, and main results	Goal: the research paper aims to find out the role of digital competence on consumer behavior in the context of the technology acceptance models. Tasks (formulated as research questions): • What is the role of digital competence in the digital ecosystem solutions acceptance process? • How specifically does digital competence participate in the digital ecosystem solutions acceptance process? Main result: • The level of consumer digital competence proved to have effects on such constructs as Performance Expectancy, Effort Expectancy, Perceived Risk, and Facilitating conditions, thus, answering the stated research questions. • Trust and Security together with the Performance Expectancy were defined as the most influential drivers to Behavioral intention to use, adding the substantial effect of the Brand Attitude mediation. • Based on the empirical research results, further theoretical and practical implications were developed and addressed
Keywords	digital competence, digital business ecosystem, Sber ecosystem, UTAUT, technology acceptance

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INTRODUCTION

Research gap

Consumer behavior is a widely studied topic in the marketing area since the 1930s. It is defined as the study of individuals, groups of people, or organizations and the activities associated with the purchase, use, and elimination of goods and services. This study includes consumers' emotional, mental, and behavioral responses (Fullerton, 2013). So, consumer behavior is a concept that provides for different aspects and theories.

With the advancement of technologies, the business map has inevitably been changed. The introduction of the Internet has impacted the process of decision-making by consumers. The buying process has changed, pushing back the face-to-face communication with sellers, and replacing it with dynamic information presentation through digital channels (Suleman, et al., 2019). What is more important, recent events show how fast the traditional ways of doing business are replaced with new digital solutions (McKinsey & Co., 2020). These changes have dramatically affected both businesses and customers. Thus, consumer behavior has also changed, and new models for predicting consumer behavior have appeared since then.

Moreover, there are several models for understanding and predicting consumer behavior. Most of the studies of the use of technological products are based on several theories. The Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) are the most popular of them. Thus, it is vital to investigate these models to choose the most appropriate one for further research.

Furthermore, consumer behavior differs in different contexts. Such variables as age, gender, and nationality play a significant role in making decisions (Williams, et al., 2015). On the other hand, the variables mentioned are not the only influencers. There are many factors affecting decision-making by target consumers, such as the confident usage of digital technologies for information, communication, and basic problem-solving in different aspects of real life. From this point, this research suggests investigating the role of one of the eight key competencies, according to The European Parliament and the Council as of December 30, 2006, on the technology acceptance by consumers – digital competence.

Digital competence is often described as *"a set of knowledge, skills, and attitudes associated with the use of digital technology in individual's goals fulfillment"* (Baartman & de Bruijn, 2011; Ferrari et al., 2012). It is significant to focus on the current continuously changing digital environment and learn to choose and use technological solutions appropriately. Different

researchers insist that ICT skills are the basic need to function in society, the crucial condition for life, and even substantial background to survive (Ferrari, 2012).

Currently, there is a lack of investigations on the impact of the individual level of digital competence on consumer acceptance of digital solutions. The research mainly focused on the influence of personal innovativeness, digital self-efficacy, or digital savviness (Jin, 2013; Sell et al., 2014; McDonald, Uncles, 2007). Therefore, the possible impact of digital competence on the overall model of technology acceptance has to be investigated. Existent literature lacks the possible linkage between digital competence and any of the technology acceptance models. Thus, the lack of knowledge on the relationships between digital competence and the consumers' digital technology acceptance represents this master's thesis research gap.

Research problem

Nowadays technology is rapidly evolving bringing up new innovative solutions for everyday interactions. Businesses do not only compete with each other but cooperate and share customers to provide greater value in the end (Tikhonova, 2019; Zakharov, et al., 2019; Dneprov & Mikhaylyuk, 2019; RBC Trends, 2021). Therefore, the phenomenon of business ecosystems appeared. The business ecosystem was defined as *"a network of organizations and individuals in the business community which together create a system of mutual support as well as evolve together"* (Moore, 1993).

There are a lot of notions and concepts the business ecosystem phenomenon contains (Rong, et al., 2017; Wulf & Butel, 2017; Iansiti & Levien, 2004; Kapoor & Agarwal, 2017; Lee, et al., 2017; Joo, et al., 2017; Valkokari, 2015; Gomes, et al., 2018; Attour & Lazaric, 2020). What is more, due to the global transition towards the digital economy, the phenomenon changed its paradigm. Digital intelligence along with the support of big data becomes the central factor of production fostering the switch from traditional resources to intellectual ones (Dneprov & Mikhaylyuk, 2019). Digital platforms became the core for the development of digital business ecosystems. Various industries' organizational forms are digital platforms (Faik & Asadullah, 2018).

What is more, the financial industry is one of the first industries affected by new technology because of rapidly developing non-financial platforms (Bubnova, 2020; RBC Trends, 2021). These platforms forced banks to rethink their core businesses. Currently, banks are on the way to change their business model offering not only financial services but extending their operations to adjacent industries and far more (Kleiner, et al., 2020; Bubnova, 2020).

Sber is the largest Russian financial institution that historically offered mainly banking services. However, it has recently transformed into a huge ecosystem with more than fifty non-financial companies included in it (RBC Trends, 2021; Sberbank.ru). Sber's case is considered special because it is the only banking company that offers such a huge and complex business ecosystem solution extending its operations to food delivery, entertainment offering, and more other services consolidated under the brand of Sber (RBC Trends, 2021).

As the user's level of digital competence is expected to affect consumer perception of highly technological goods and services, the recently formed digital business ecosystem solution provided by Sber is the most appealing case to study. Therefore, the research problem of this master's thesis is investigating the impact of consumer digital competence on acceptance of digital ecosystem solutions using the case of Sber.

Research questions

As this paper aims to find out the role of digital competence on consumer behavior in the context of the technology acceptance models, the following **research questions** are set:

RQ1: What is the *role* of digital competence in the digital ecosystem solutions acceptance process?

RQ2: How specifically does digital competence participate in the digital ecosystem solutions acceptance process?

The study investigates the digital competence effect on the technology acceptance model by investigating Sber's digital ecosystem solutions acceptance. Moreover, the research integrates digital competence with the technology acceptance model to explore the area of interest. Therefore, the findings expected as the result of the study are of exploratory type.

CHAPTER 1. ECOSYSTEM PHENOMENON IN BUSINESS.

The business ecosystem is a very complex phenomenon that must be specified and defined in the context of the master's thesis. The chapter starts with the research on the business ecosystem definition offering different cases of current ecosystems to dive into a better understanding of the phenomenon. Then, the technology acceptance models are reviewed. Finally, the digital competence phenomenon is investigated to get the construct and initiate the development of the theoretical research framework.

1.1 Defining the digital business ecosystem phenomenon.

Business ecosystem evolution

The business ecosystem concept was first introduced by Moore (1993) who was inspired by biological ecosystems and co-evolution concepts in both natural and social systems. The business ecosystem was defined as *"a network of organizations and individuals in the business community which together create a system of mutual support as well as evolve together"* (Moore, 1993). The logic behind this approach is clear – companies work together with several firms and compete with other companies to find solutions to fulfill customer needs. Ultimately, these actions trigger the next innovation round. So, the concept identifies key categories of the business ecosystem: the central firm around which the ecosystem is built, various economic agents who do not participate in a given business ecosystem, different links within a given business ecosystem, and the unique jointly created value. (Moore, 1993)

Moreover, Moore (1993) explored the business ecosystem from its life cycle point of view. The author figured out four stages for ecosystem development – birth, expansion, leadership, and self-renewal or, otherwise, death. So, the firm should follow particular steps depending on the life cycle stage (Table 1). One should keep in mind that the first group of actions aims to form and support the interconnections within the ecosystem, whereas the other actions aim to prevent the formation of alternative business ecosystems.

Table 1. The evolutionary stages of a Business Ecosystem (Moore, 1993)

Stages/Challenges	**Cooperative Challenges**	**Competitive Challenges**
Birth	Cooperation with customers and suppliers in order to identify the new value proposition to foster innovation	Advocate unique ideas from external players. Create strong connections with critical lead customers, key suppliers, and protect important channels.
Expansion	Bring the new offer to a large market	Defeat alternative implementations of

	by working with suppliers and partners to scale up supply and to achieve maximum market coverage.	similar ideas. Ensure that your approach is the market standard in its class through dominating key market segments
Leadership	Provide a compelling vision for the future that encourages suppliers and customers to work together to continue improving the complete offer.	Maintain strong bargaining power concerning other players in the ecosystem, including key customers and valued suppliers.
Self-Renewal	Work with innovators to bring new ideas to the existing ecosystem.	Maintain high entry barriers to prevent the creation of alternative ecosystems. Maintain high customer switching costs to buy time to incorporate new ideas into your products and services.

Afterward, the studies of business ecosystems evolved, and three approaches were developed to study the subject. The representatives of the first approach of studies of a business ecosystem focused their attention on one of the components of business ecosystems striving for a thorough investigation (Vasilenko, 2020). The compiled summaries of the research results can be observed in Table 2. The authors from different perspectives studied the phenomenon of business ecosystem starting from defining the components and investigating the multi-level relationships between the central firm and other players of the ecosystem (Rong, et al., 2017), following with the communication and knowledge sharing within the business ecosystem (Wulf & Butel, 2017), moving to the strategy development issues in the context of the business ecosystem (Iansiti & Levien, 2004), and finishing with the studies of relationships between the platform-based firms and the complementary firms, their roles and experiences in the platform-based business ecosystems (Kapoor & Agarwal, 2017).

Table 2. Summary of the first approach (compiled by the author)

Authors	**Research results summary**
Rong, Shi, Shang, Chen, and Hao (Rong, et al., 2017)	Focus on the supply chain in the context of the business ecosystem (BE) by diving into the integration of supply side, demand side, its intermediaries, and working mechanisms between them using cases from electric car producers in China and the EU. Define BE as an interdependent community that attracts a large number of different stakeholders into its ecosystem allowing the expansion of the traditional supply chain.

Wulf and Butel (Wulf & Butel, 2017)	Focus on how interfirm relationships are established and maintained, how firms establish trust among themselves and foster knowledge sharing, forming the basis of organizational learning. Authors argue that the BE consists of several different network structures, each of which forms a different group of organizations, and the relationship between them can be both formalized and informal.
Iansiti and Levien (Iansiti & Levien, 2004)	Focus on the issue of strategy development, considering its development in the context of the BE, including the interests of firms that make up this BE, and the role of the organization in this BE (identify four possible strategies for the business ecosystem: niche, core firm (value dominator), physical dominator, and product). Authors write that BE can expand the boundaries of the company. The BE includes resource providers, compliment producers, consumers, and various firms that influence the firm's operations. At the same time, it is emphasized that the boundaries of a firm are difficult to define since often an organization can simultaneously be a member of several BEs.
Kapoor and Agarwal (Kapoor & Agarwal, 2017)	Focus on how the structural and evolutionary features of the BE affect the performance indicators of firms that produce additional goods and services and are part of the BE; on the other hand, how the unique, accumulated experience of the latter can have a beneficial effect on the entire business ecosystem. Define a BE as a structure in which a platform company coordinates the functioning of an entire BE, providing a platform for firms that produce complementary goods and services, and setting rules for participation in it.

The researchers from the second approach of the studies focused on the influence the business ecosystem might have to foster innovation and the creation of new products and services (Vasilenko, 2020). Lee and his colleagues (2017) focused their research on applying ideas of the business ecosystem to the high-tech industry and startups investigating cases from Korean, Chinese, and Japanese start-up markets. They found out that firms develop their innovative potential by interacting within the business ecosystem, thus, creating new innovative products and services (Lee, et al., 2017). On the contrary, Joo and his colleagues (2017) approach to the study of business ecosystems from the corporate social responsibility point of view. They believe that corporate social responsibility can act as an investment in creating a

sustainable business ecosystem and may lead to an increase in the competitiveness of participants in the business ecosystem (Joo, et al., 2017). The compiled summaries of the research can be seen in Table 3.

Table 3. Summary of the second approach (compiled by the author)

Authors	**Research results summary**
Lee, Lee, and Kim (Lee, et al., 2017)	Focus on the role of the BE in the context of the startup lifecycle, viewing the BE as a general driving force for developing a favorable environment, and launching startups based on it. Define BE as an economic environment that is created and exists through the interaction of such stakeholders as organizations and individuals.
Joo, Eom, and Shin (Joo, et al., 2017)	Focus on corporate social responsibility's impact on the business ecosystem. Under the BE authors mean the system which consists of different members of the BE that recognize a common goal, and function on the common platform coordinated by the central firm and other key participants of the BE.

Finally, the third approach representatives focus their research on such close to business ecosystem notions as knowledge ecosystem and innovation ecosystem identifying their differences and relations. Thus, Valkokari (2015) studies three concepts which are a business ecosystem, innovation ecosystem, and knowledge ecosystem. The research aimed to define what is meant by these concepts and to describe their relationships and specifics. As a result, the business ecosystem focuses on the value creation for consumers; the knowledge ecosystem concentrates on generating new knowledge and technologies; and the innovation ecosystem is an integration of the business ecosystem and knowledge ecosystem (Valkokari, 2015). Practically, the study sheds light on the differences in the logic of action and the rules of the game within each concept emphasizing the idea that different ecosystems require the development of different models of behavior (Valkokari, 2015).

Unlike Valkokari, Gomes and his colleagues (2018) focused their research deeply on the relationships between the business ecosystem and the innovation ecosystem. The authors suggest that the innovation ecosystem is the next stage in the business ecosystem development process. The main difference between these two concepts is that the business ecosystem mainly centers around the obtaining of value, while the transition to an innovation ecosystem involves the search and creation of new value (Gomes, et al., 2018). According to the idea of the research,

entities are advised to build the business ecosystem the members of which operate in the relatively long-lasting industries, however, do not work on explicitly innovative activities (Gomes, et al., 2018).

In contrast, other authors established the relationships between the business ecosystem and knowledge ecosystem considering the business ecosystem to be the result of knowledge ecosystem transformation (Attour & Lazaric, 2020). At the core of such a business ecosystem is the technology platform that provides academic actors and other stakeholders with additional opportunities, which gives them not only additional motivation to expand their field of activity, but also real opportunities to commercialize their innovative ideas (Attour & Lazaric, 2020).

The summaries of the third approach research results can be observed in Table 4.

Table 4. Summary of the third approach (compiled by the author)

Authors	**Research results summary**
Valkokari (Valkokari, 2015)	Focus on the definition and interrelations of the three closely related concepts: business ecosystem (BE), knowledge ecosystem (KE), and innovation ecosystem (IE). The BE implies a central player acting as a platform and providing shared resources for other participants in the network to create value. The KE is a large number of actors grouped around a knowledge exchange center to discover new areas of knowledge. The IE implies geographically close actors that interact around a specific center of activity with the assistance of intermediaries to create innovations.
Gomes, Facin, Salerno, and Ikenami (Gomes, et al., 2018)	Focus on the idea that IE is the next stage in BE development process. BE concentrate on the value capture, whereas IE focuses on the value creation
Attour and Lazaric (Attour & Lazaric, 2020)	Focus on the relationships between KE and BE testing the approach in the university environment to show how the KE transforms into the BE. The BEs are the complex form of organization of exchange, structure, or institutional structure that governs relationships between several actors, more or less sharing the idea of an open, collective process for creating innovation.

An overview of the approaches above shows how many notions and concepts the business ecosystem phenomenon contains. What is more, due to the global transition towards the digital economy, the phenomenon changed its paradigm. Digital intelligence along with the support of big data becomes the central factor of production fostering the switch from traditional resources to intellectual ones (Dneprov & Mikhaylyuk, 2019). Thus, it is crucial to define the digital business ecosystem term as well.

Digital business ecosystem

In the digital era, companies should interact with a wider range of partners to foster integrated solutions on innovations, applications, software platforms, and services. The growing demand for personalized offers and rapidly changing technology intensify the need for partnerships. To manage the company's value chain at every stage of the development intangible assets and information software tools are required (Babina, 2019). Therefore, digital ecosystems come to the stage and redefine traditional companies' operations through breaking down industry barriers, opening up opportunities for cross-functional products and services, and mixing previously segregated markets (Zakharov, et al., 2019).

So, a digital ecosystem is an interdependent group of businesses, people, and objects that share digital platforms for mutually beneficial purposes, such as commercial gain, innovation, or common interests. Additionally, the digital ecosystem has a wide variety of autonomous actors that are linked through resource sharing and expertise to collectively deliver products of greater economic value than would otherwise be possible outside the functioning of the digital ecosystem (Tikhonova, 2019).

According to the European Commission (2008), *"a Digital Business Ecosystem results from the structurally coupled and co-evolving digital ecosystem and business ecosystem."* So, in this master's thesis, the digital business ecosystem will be viewed as *"a loosely coupled, demand-driven collaborative environment where each digital species is proactive and responsive for its benefit or profit"* (Chang, et al., 2006, p.2).

Non-financial industries form ecosystems

Digital platforms became the core for the development of digital business ecosystems. Various industries' organizational forms are digital platforms (Faik & Asadullah, 2018)

To start with, the IT industry ecosystem solutions are among the most successful and profound. Talking on this issue, electronic device producers create and develop their ecosystems creating hubs and offering complimentary services. Apple formed the unified use network for gadget owners by offering access to various services like Apple TV or iTunes. The other

example is Yandex. Within Yandex's ecosystem, one may access such services as taxi ordering, car sharing, food delivery, music listening, and a lot of other services including financial. Alibaba Group, a Chinese multinational technology company, incorporated retail, payments, and even credit scoring in its ecosystem (RBC Trends, 2021). One must consider such multinational digital ecosystems as Alphabet (Google ecosystem), Amazon (from e-commerce to cloud solutions), Microsoft (from software to hardware), and Facebook (global social network). These ecosystems form a substantial share of the global market (Morozov, & Morozova, 2020).

Following the representatives from the IT industry, car manufacturer giants Daimler and BMW launched the joint project "You Now" together with startups. It aims to develop urban mobility services including car-sharing, parking, taxi ordering, charging electronic vehicles, and a multimodal transportation app (AG Daimler Mobility, 2021).

Moving further, digitalization fostered the formation of ecosystems in the hospitality industry as well. Booking.com and Airbnb, exiting platforms for accommodation booking services, are already connected with AviaSales and Skyscanner.ru, platforms for booking plane tickets (Morozov & Morozova, 2020).

Inside a successful ecosystem, the company gains much more clients, thus, selling more goods and services. What is more, the ecosystems offer companies a wide pool of data to better satisfy customer needs. Therefore, the other trend emerged in the development of ecosystems the super apps, when IT corporations merge their services into one app. With the emergence of the trend, the non-financial platforms start offering financial services. The examples of such super apps are WeChat (a Chinese platform that offers financial, consumer, and governmental services), Alipay (a Chinese platform that offers payment system and different financial services), Line Corporation (a Japanese platform that offers food delivery, logistics for restaurants, and payment system), and Vkontakte (a Russian social network that offers payment system VK Pay and mini-apps offering food delivery, music, video and movie streams, and games) (RBC Trends, 2021).

Summing up, the development of business ecosystems changed the market paradigm. Instead of standing alone against the competitors firms form the business ecosystems where the digital platform is the core. In turn, these ecosystems seize the market share (Tikhonova, 2019; Zakharov, et al., 2019; Dneprov & Mikhaylyuk, 2019; RBC Trends, 2021). Therefore, it is important to understand how consumers regard such novation and study consumer behavior in this context.

1.2 Technology acceptance models' overview.

To begin with, it is essential to understand the term "consumer behavior." According to the Cambridge dictionary, consumer behavior, or "customer behavior', is the choice people make to buy or not to buy a good, and everything that influences people's choices. Thus, consumer behavior is the decision-making process of consumers affected by different factors and conditions.

In the marketing world, consumer behavior is the study of how people make their decisions about the goods and services they want, need, or buy (2016). It is a crucial aspect of marketing because companies can increase their market share and identify other opportunities for the long-run perspective.

Moreover, there are three main factors influencing consumer behavior. They are psychological, personal, and social factors (Fullerton, 2013). All the models of consumer behavior are, hence, built around the idea of these factors.

As this study aims to understand the prominent role of digital competence on technology acceptance (TA), one should consider the models of online consumer behavior.

Many theoretical frameworks have been proposed and empirically tested regarding the explanation of online consumer behavior in different conditions. Several studies connect the theory of planned behavior, introduced by Ajzen and Fishbein (1975), to understand consumer behavior during searching for goods. The other theory – the theory of reasoned action (Ajzen & Fishbein, 1980) – mainly covers apparel purchasing (Yoh, Damhorst, Snapp, & Laczniak, 2018). Regarding usage and adoption of mobile services, especially the e-payments and other banking services, the Technology Acceptance Model (Davis, 1986) and the Unified Theory of Acceptance and Usage of Technology (Venkatesh, Morris, Davis, & Davis, 2003) are widely used.

With regards to this study, the leading models under consideration are the ones that explain consumer behavior in the context of accepting and adopting new technology in the retail banking industry. Further paragraphs will highlight and compare the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Usage of Technology (UTAUT).

The Technology Acceptance Model (TAM) overview

Technology Acceptance Model (TAM) is widely used in explaining the attitude towards technology usage. At first, it was introduced by Davis (1986) as a modified Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980) specified for modeling the user acceptance of

information systems. Its overall goal was to predict consumer behavior and explain it (Davis F., 1986). Therefore, managers can use the model to understand the reasons behind the rejection of the particular system and urge necessary corrective steps based on the knowledge gained.

Figure 1 below shows the variables used to form the theory. The two beliefs are of the most relevance for technology acceptance behavior – perceived usefulness and perceived ease of use. These beliefs strongly affect attitude toward using. Then the behavioral intention to use is also affected. (Davis, Bagozzi, & Warshaw, 1989)

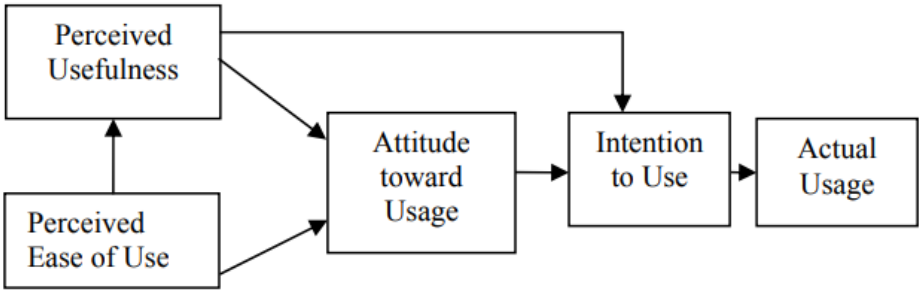


Figure 1. *Original Technology Acceptance Model (Davis, 1986)*

Perceived usefulness is the degree to which an individual believes that the technology used will improve his or her performance. Perceived ease of use is defined as a level at which an individual believes that the technology will be effortless (Swanson, 1987). These two believes can be considered as two different dimensions. So, the technology acceptance is predicted by the prediction of the attitude to use.

A considerable number of researches have replicated TAM and provided empirical evidence on the relations between perceived usefulness, perceived ease of use, and system usage (Adams, Nelson & Todd 1992; Davis 1989; Hendrickson, Massey & Cronan 1993; Segars & Grover 1993; Subramanian 1994; Szajna 1994). Moreover, TAM is used in most contexts, both geographic and technological, like rapidly growing healthcare.

On the other hand, the original model has several limitations because it does not consider several important aspects. Thus, Venkatesh and Davis (2000) extended it considering the social influence and cognitive instrumental processes (Figure 2).

TAM 2 was constructed to predict the adoption of information technology. The model considers two contexts for social influence – mandatory and voluntary. Moreover, the social factors considered in this model are the subjective norm, voluntariness, and image (Venkatesh & Davis, 2000). Consequently, the subjective standard directly influences the intention to use in the

mandatory context. Alternatively, the subjective standard indirectly affects the intention to use in the voluntary context.

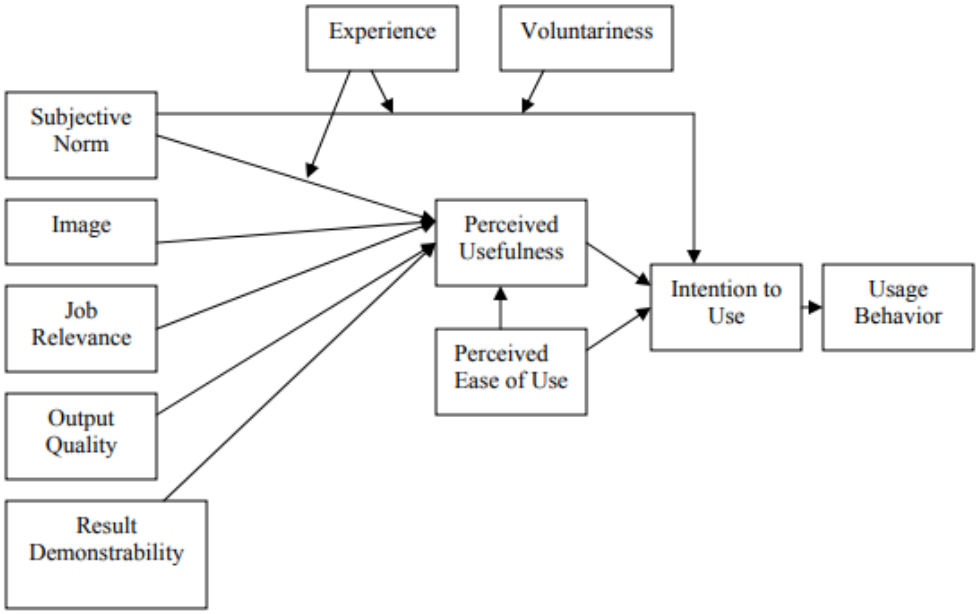


Figure 2. *The Extended TAM 2 (Venkatesh & Davis, 2000)*

Furthermore, TAM 2 introduces four cognitive instruments affecting the perceived usefulness: job relevance, output quality, result demonstrability, and perceived ease of use (Venkatesh & Davis, 2000). So, with these extensions, TAM 2 was supposed to predict if the information technology would be adopted or not.

What is more, the TAM 2 is not the only modification of the TA model. Several studies extended the original TAM by adding additional external variables and exploring its influence on the model in general.

However, the TAM has limitations due to behavioral complexity. Ultimately, TAM has been criticized for its questionable value, limited explanatory power, and limited predictive power despite its frequent usage. Moreover, perceived ease of use is doubted to be a determinant of attitude and usage intention following the studies of telemedicine (Hu, Chau, & Sheng, 1999), mobile commerce (Wu & Wang, 2005), and online banking (Pikkarainen, Pikkarainen, Karjaluoto, & Pahnila, 2004).

Therefore, the influence factors cannot be covered by only one theory (Xu, Li, & Hao, 2019). With this regard, the following model was developed.

The Unified Theory of Acceptance and Usage of Technology (UTAUT) overview

The other model under consideration is the UTAUT model. This model was developed by Venkantesh et al. (2003) for redefining the technology acceptance theories. Among such approaches were Theory of Reasoned Action, Theory of Planned Behaviour, and Technology Acceptance Model. (Venkatesh, Morris, Davis, & Davis, 2003). The new model was advanced with considerations of individual perspectives and social and environmental factors on technology acceptance.

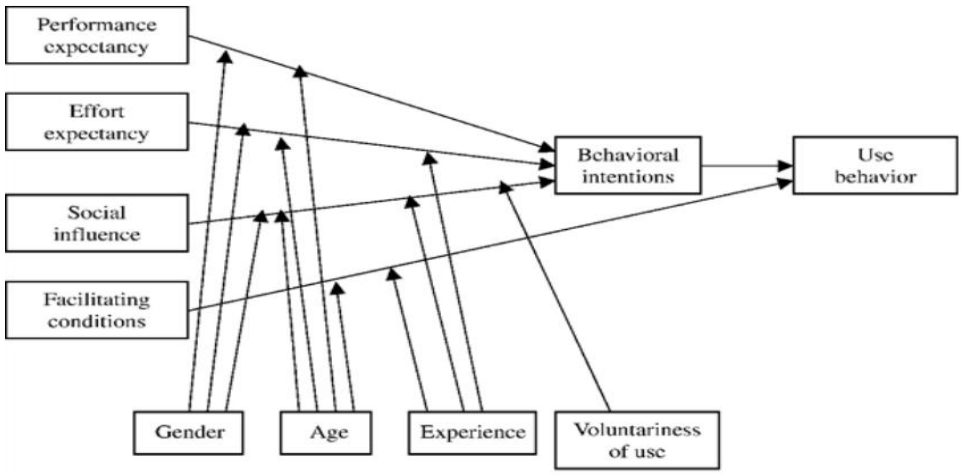


Figure 3. *UTAUT by Venkantesh et al. (2003)*

The UTAUT model consists of four major determinants that are performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). These constructs are the direct determinants of behavioral intention and, eventually, user behavior. In the model, age, gender, experience, and voluntariness are moderators that directly influence every determinant (Williams, Rana, & Dwivedi, 2015).

This model is widely applied in various technology adoption researches as the theory base for further empirical studies. There was a lot of research on a different range of technologies with multiple control factors while analyzing multiple user groups (Williams, Rana, & Dwivedi, 2015).

What is more critical, Venkatesh, Thong, & Xu (2012) introduced an extended UTAUT model – UTAUT 2 (Figure 4) – that includes hedonic motivation, price value, and habit as determinants of the model. The research showed that the original model of technology acceptance is more useful in the organizational context, while for the consumer behavior studies, the UTAUT 2 is essential (Venkatesh, Thong, & Xu, 2012). For this purpose, other drivers come to the first place: hedonic motivation, the fun or pleasure derived from using technology, and price value, being a predictor of behavioral intention.

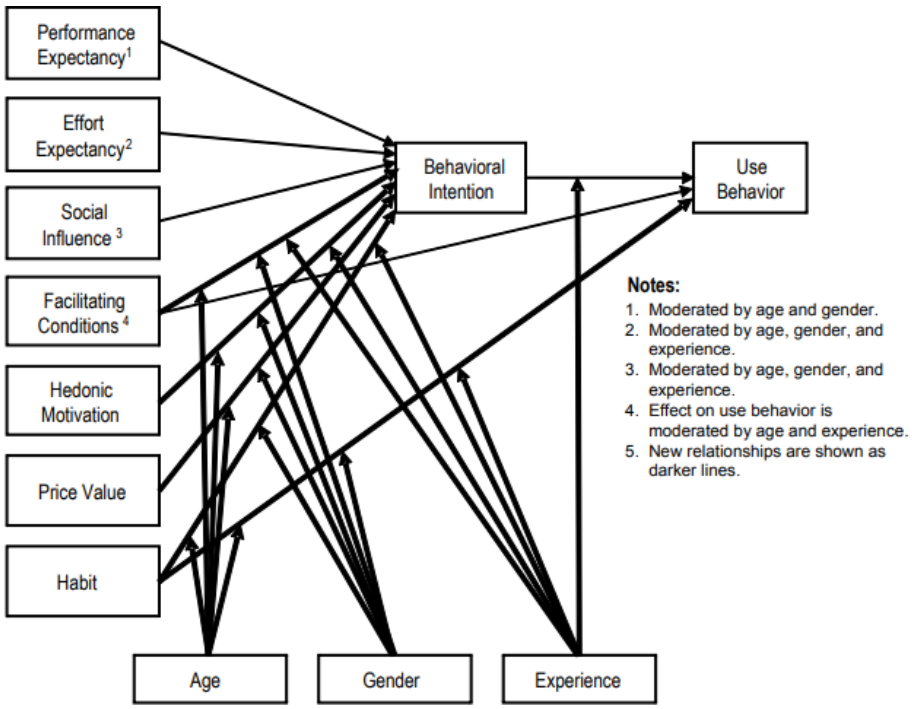


Figure 4. *UTAUT 2 Venkatesh, Thong, & Xu (2012)*

Despite being widely spread, UTAUT has several limitations one must consider. The most significant is that the focus was only on a single subject across the studies, limiting the potential generalization of the results (Williams, Rana, & Dwivedi, 2015).

Finally, the UTAUT model is widely adopted in many cultures and has empirically been validated, revealing the whole model to explain almost 70% of the variance in the behavioral intentions (Im et al., 2011; Venkatesh & Zhang, 2010; Min et al., 2008).

Summing up, it is essential to mention that all these models are widely used in researches despite limitations. In this research, the UTAUT 2 model will be considered the basis for further analysis. It is regarded as the most complete by now and is designed to predict consumer behavior in particular.

1.3 Digital Competence.

This sub-chapter will shed light on the term “digital competence” in the context of consumer behavior.

To start with, technological advancement has impacted a lot of the everyday routine of people. Technology is being used everywhere, thus transforming how people study, work, communicate, and access information. People from all age groups are affected by these changes (Ala-Mutka, 2008). Therefore, it is crucial to understand these transformations and, hence, develop digital competencies.

According to Ala-Mutka (2011), digital competence is defined as "involving the confident and critical use of Information Society Technology (IST) for work, leisure, and communication." On the other hand, digital consumer competence is "defined as the competence consumers need to function actively, safely and assertively in the digital marketplace" (Brečko & Ferrari, 2016).

According to European Commission (2006), digital competence is acknowledged as one of the eight critical competencies of Lifelong Learning. The table below summarizes the areas covered with the Digital Competence Framework for Consumers proposed by the European Commission (Brečko & Ferrari, 2016).

Table 5. Digital Competence Reference Framework for Consumers (Brečko & Ferrari, 2016)

Competence areas	**Competences**
Pre-purchase	Browsing, searching, and filtering information on goods and services Evaluating and comparing information on goods and services Recognizing and evaluating commercial communication and advertisement Managing digital identity and profile in the digital marketplace Considering responsible and sustainable consumption in digital markets
Purchase	Interacting in the digital marketplace to buy and sell Participating in collaborative economy platforms Managing payments and finances through digital means Understanding copyrights, licenses, and contracts of digital goods and services Managing personal data and privacy Protecting health and safety
Post-purchase	Sharing information with other consumers in the digital marketplace Asserting consumer rights in the digital marketplace Identifying digital consumer competence gaps and limits

Thus, following the consumers' logic, there are three competence areas that consumers need to act assertively and reasonably: pre-purchase, purchase, and post-purchase. Every competence area is filled with competencies that consumers must develop to be confident in the digital marketplace (Brečko & Ferrari, 2016). However, this framework is more descriptive, showing the required knowledge for being digitally competent in the online market.

With this regard, Ala-Mutka (2011) developed other conceptual understanding models and the framework linked to the European Qualification Framework (EQF). So, the conceptual model of Digital Competence was formulated (Figure 5).

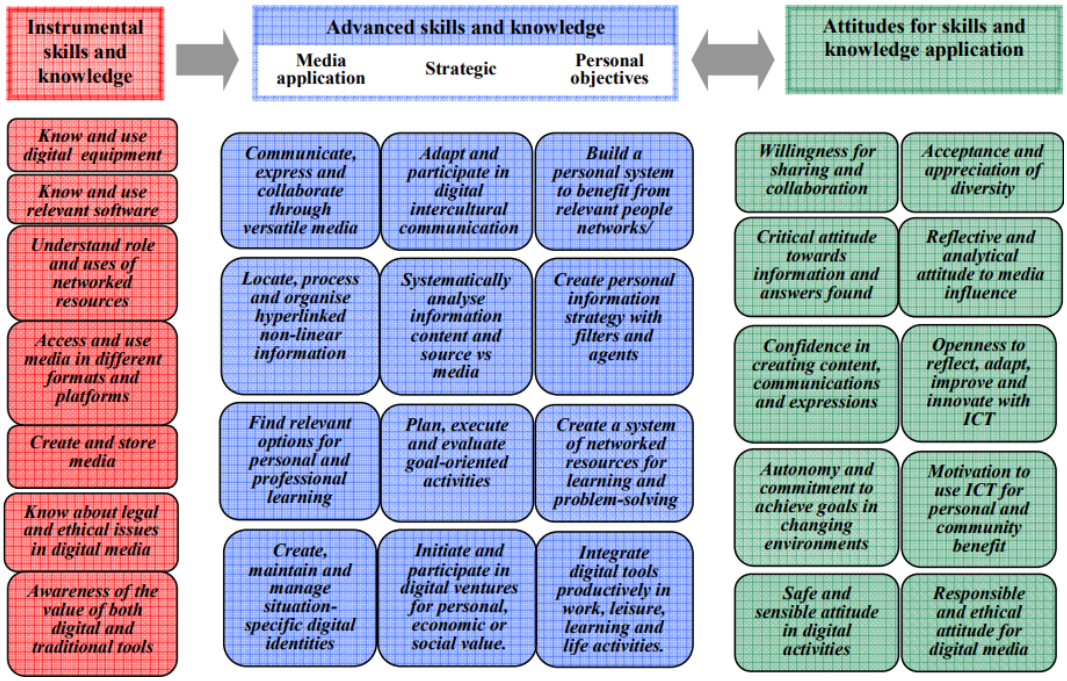


Figure 5. *Knowledge, skills, and attitude items contributing to Digital Competence (Ala-Mutka, 2011)*

The proposed model further was grouped into significant clusters composed logically with several elements as digital competence areas. These areas denote topics that should be elaborated on in detail while doing the in-depth research (Ala-Mutka, 2011).

What is more, three types of research influenced the structure of the model mentioned above. Bawden (2008) composed a model that includes four main elements of digital literacy: underpinnings that give the basic set of skill presented and background knowledge, which provides a basic understanding of both digital and nondigital sources information other forms.

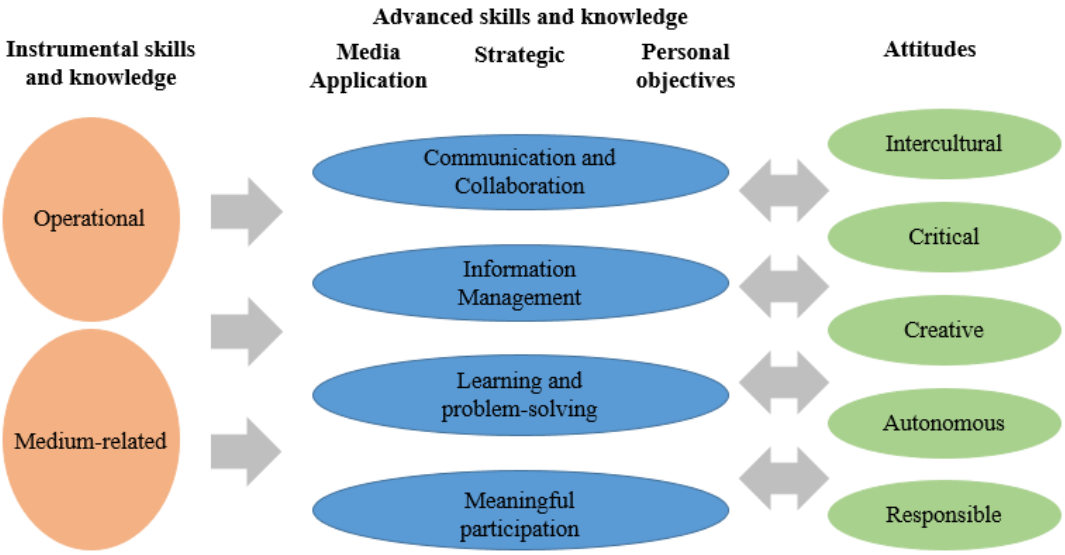


Figure 6. *Proposed Digital Competence conceptual model (Ala-Mutka, 2011)*

Furthermore, central competencies denote the elements of digital literacy proposed by Glister (1997). The attitudes and perspectives represent the main goal of digital literacy as an understanding of sensible and correct behavior in the digital marketplace (Bawden, 2008). Figure 7 below summarizes this research.

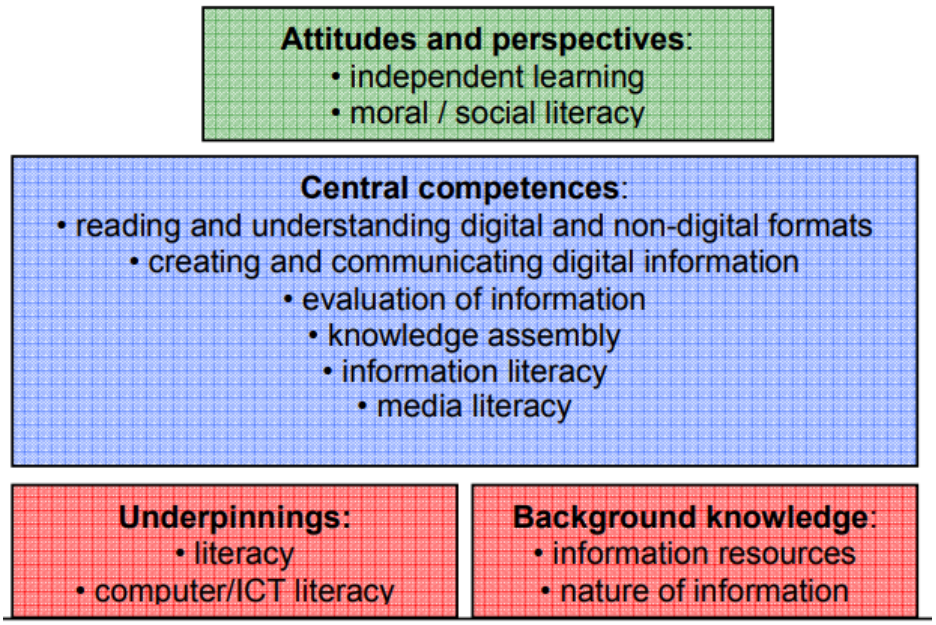


Figure 7. *Digital literacy elements from Bawden (2008)*

Moving further, Martin & Grudziecki, 2006) introduced three stages to develop digital literacy: digital competence, digital usage, and digital transformation as the last one (Figure 8). The authors suggested that digital literacy had to be applied to individuals using a persona development profile.

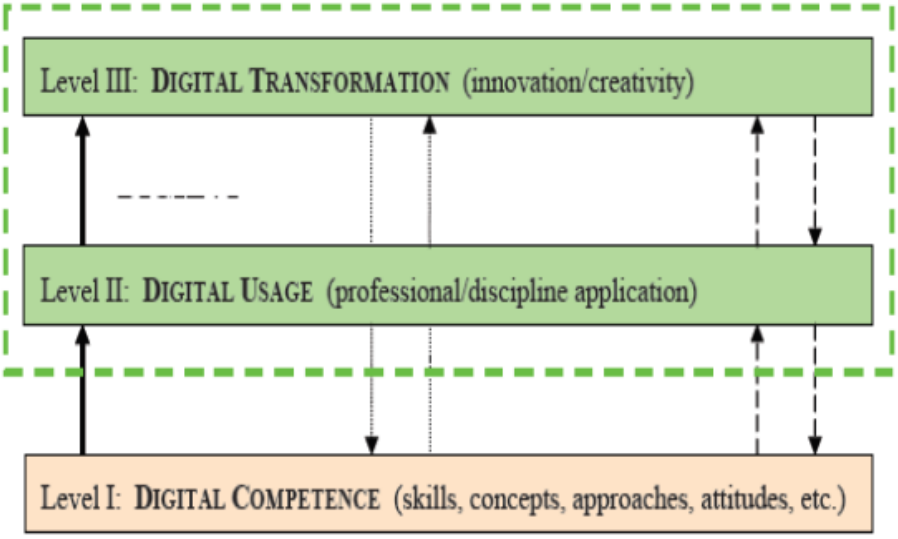


Figure 8. *Digital literacy stages by Martin & Grudzieck (2006)*

Finally, the last research was developed by van Deursen (2010) to validate the model for internet skills. The model lists four major categories in the order of increasing complexity – from operational skills to strategic information skills (Figure 9). This model cannot be compared with the whole digital competence one because of lacking some crucial points like media creation. On the other hand, it proposes one critical element – the differentiation between medium-related and content-related skills.

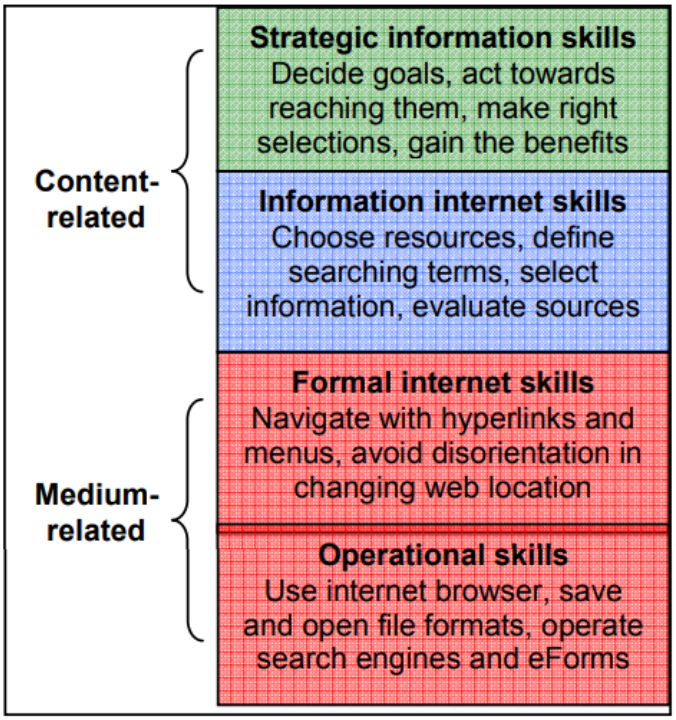


Figure 9. *Summary of the Internet skills definition of van Deursen (2010)*

Despite the thing that the previously mentioned framework is complete, it is very complicated for further analysis. Thus, it is crucial to consider the integrative framework of consumers' digital competencies developed by Golovacheva and Smirnova (2019).

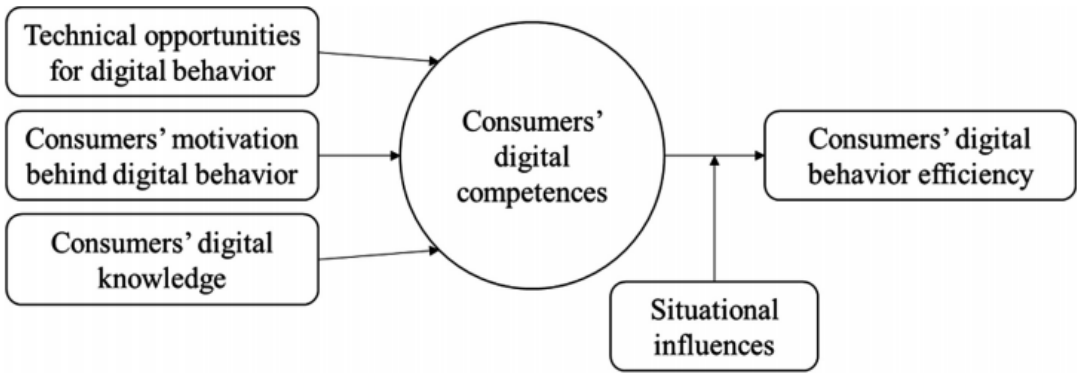


Figure 10. *An integrative framework of consumers' digital competencies (Golovacheva & Smirnova, 2019)*

The framework mentioned above considers Consumers' digital competencies as the main driver of efficient consumer digital behavior. Moreover, it also considers the various situational influences as constraints to translation into efficient digital behavior (Golovacheva & Smirnova, 2019). However, the research conducted by Golovacheva and Smirnova (2019) showed a strong bias towards a behavior-based approach that lacked attention to motivation and perceived opportunities according to the motivation – opportunity – ability (MOA) framework. Therefore, the next model was considered as the basis for further research.

The last framework to consider is the Digital Competence Research (DCR) model developed by Labazanov (2020). The model was developed based on Digital Competence Framework for Citizens (Dig Comp), developed by European Commission's Joint Research Centre, and Digital Literacy Global Framework (DLGF), developed by UNESCO's Institute for Statistics (Labazanov, 2020). The author supplemented the initial Dig Comp model with "Devices and software operations" from the DLGF framework so that it will consider appropriately the operational skills, knowledge, and attitudes (Labazanov, 2020).

The model contains six competence areas as the main components of digital competence. These competence areas are subdivided into more specific competencies presented in Table 6.

Table 6. Competences in DCR (Labazanov, 2020)

Competence area	**Competences**
Information and data literacy	Browsing, searching, filtering data, information, and digital content Evaluating data, information, and digital content Managing data, information, and digital content
Communication and collaboration	Interacting through digital technologies Sharing through digital technologies Engaging in citizenship through digital technologies Collaborating through digital technologies Netiquette Managing digital identity
Digital content creation	Developing digital content Integrating and re-elaborating digital content Copyright and licenses Programming
Safety	Protecting devices Protecting personal data and privacy

	Protecting health and well-being Protecting the environment
Problem-solving	Solving technical problems Identifying needs and technological responses Creatively using digital technologies Identifying digital competence gaps
Devices and software operations	Physical operations of digital devices Software operations in digital devices

This model will be considered for further investigation in the context of this master's thesis for several reasons. Firstly, it was successfully implemented on the Russian market previously. Moreover, it contains a relatively small number of components that fully describe digital competence areas. Finally, the components are suitable for consumer behavior research due to their comprehension and application on the individual level (Labazanov, 2020).

Summary of Chapter 1

The digital business ecosystem phenomenon involves an interdependent group of businesses, people, and objects that share digital platforms for mutually beneficial purposes to create greater value for customers. It consists of a wide variety of autonomous actors that are linked through resource sharing and expertise to collectively deliver products of greater economic value than would otherwise be possible outside the functioning of the digital ecosystem (Tikhonova, 2019).

Inside a successful ecosystem, the company gains much more clients, thus, selling more goods and services. With the emergence of the trend, the non-financial platforms extended their operations by offering financial services (Google, Apple, Samsung, VK, etc.) forcing banks to change and adapt to the current reality (Kleiner, et al., 2020; Bubnova, 2020). Sber is the example of the most developed digital business ecosystem consisting of more than fifty different companies, offering a wide range of non-financial services, and unifying all these services under one brand (RBC Trends, 2021; Sberbank.ru; Morozov & Morozova, 2020). In the further chapter, it will be discussed as a unique phenomenon in the banking industry.

Moving further, based on the analysis of the existing research frameworks of consumer behavior studies the initial integrated model was developed. The UTAUT 2 model was used as the base for the study as the aim of the research is to study consumer behavior in the context of the technology acceptance process (Venkatesh, Thong, & Xu, 2012).

Since the research aims at investigating the acceptance of the digital business ecosystem solutions using the case of Sber, it is essential to expand the initial model with variables considering security issues, as we are dealing with the banking industry, and remove the price value variable from the initial framework, as the technology offered is free of charge. Therefore, the initial framework was extended with perceived risk, trust, and security variables as the security and privacy concerns may affect the adoption of this type of technology, and exclude price value due to its uselessness (Voronenko, 2018; Khalilzadeh, et al., 2017; Morosan & DeFranco, 2016). The model summary can be seen in Figure 11. The "security" variable is defined as an individual's belief that a particular procedure would be secure affecting directly the intention to use. The "trust " variable denotes a person who believes that a mobile application or another kind of service would work as intended predicting the intention to use as well. The "perceived risk" variable depicts the person's fear that usage of service will lead to losses and unexpected barriers for intended activity, thus, affecting the intention to use (Voronenko, 2018; Khalilzadeh, et al., 2017).

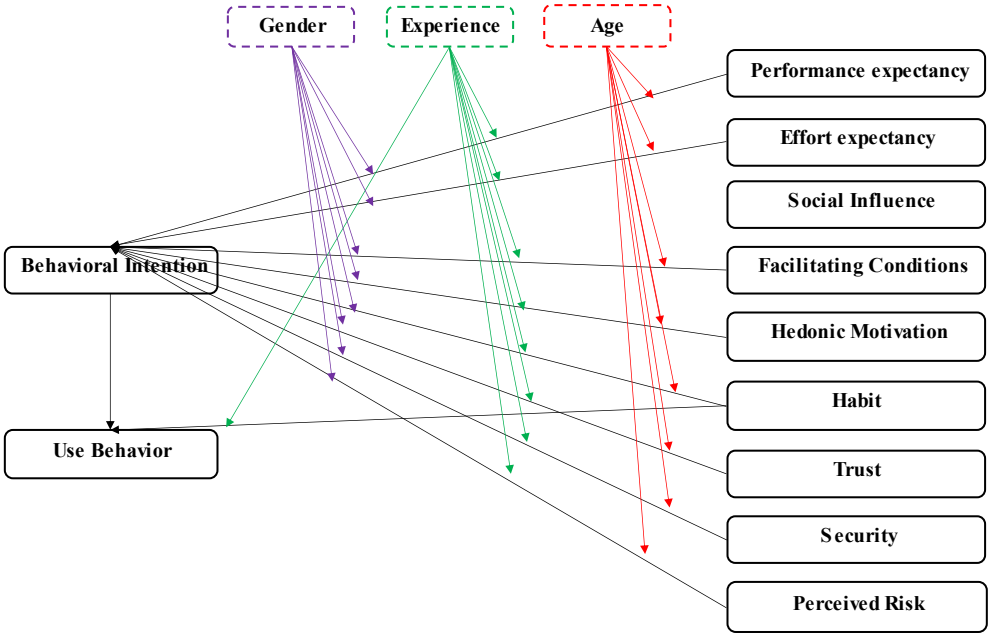


Figure 11. *UTAUT2 (without Price value) extended with Trust, Security, and Perceived Risk (Voronenko, 2018)*

The model was designed to provide maximum explanatory power taking into consideration the additional concerns that might arise when consumers adopting any digital solutions, especially, the ones that are based on banking platforms (Voronenko, 2018; Khalilzadeh, et al., 2017; Gharaibeh, 2018).

Based on the theoretical review in Chapter 1 considering the research questions of this mater's thesis, the initial theoretical framework was developed (Figure 12).

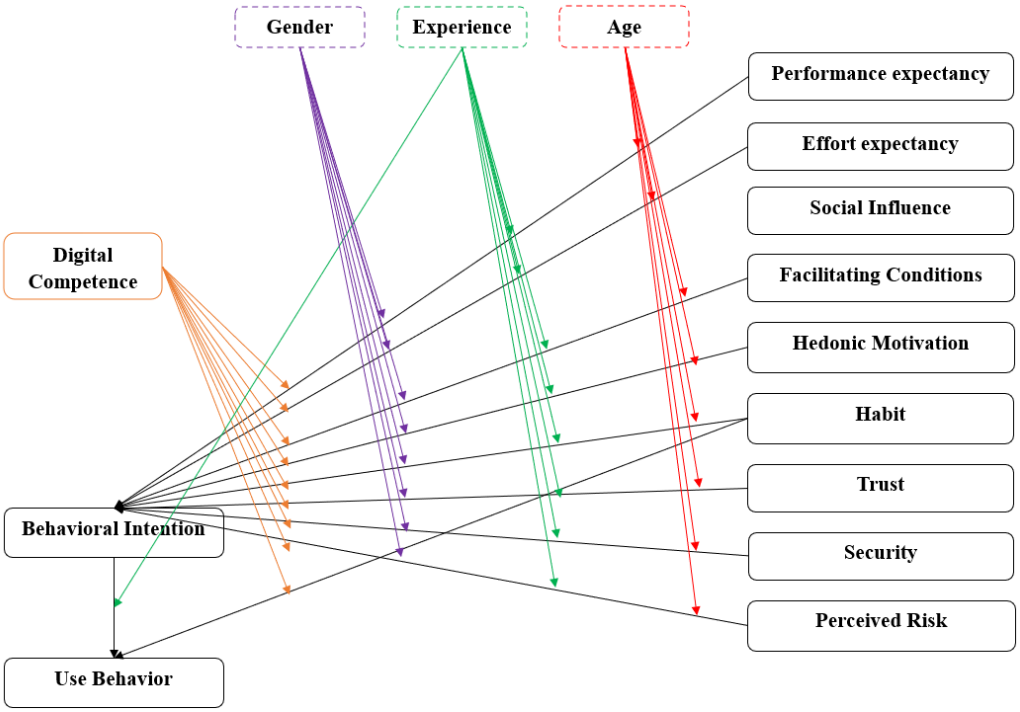


Figure 12. *Initial theoretical framework (compiled by the author)*

The initial theoretical framework demonstrates the components of the UTAUT2 model integrated with the digital competence variable assuming its impact on the behavioral intention and use behavior. Therefore, Chapter 2 is going to shed light on the further development of the research.

CHAPTER 2. DEVELOPMENT OF THE RESEARCH MODEL.

The chapter is going to develop the research model for assessment of the impact the consumer digital competence has on the process of Sber digital ecosystem solution acceptance.

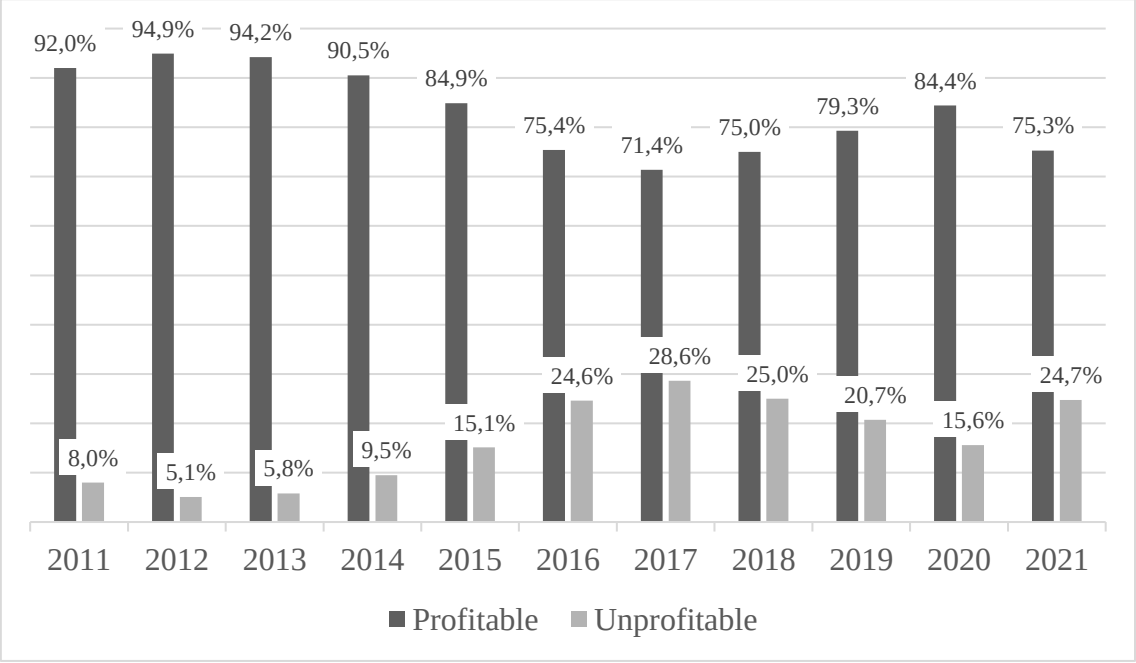
Therefore, the chapter will start with the description of the Sber ecosystem extending the current research model with additional moderating variables connected to the brand image.

Furthermore, it will open the discussion of the variables' measurement and develop the research propositions on the role of digital competence in the technology acceptance process.

Finally, the chapter will highlight the chosen methodology providing the assessment techniques, questionnaire development, and specified data collection and analysis approach.

Sber ecosystem as a phenomenon in the banking industry

The main driver for the creation of business ecosystems and development of the partnerships with organizations in the financial industry was the decrease in sales volume and the slowdown profit growth rate. In the past decade, the number of credit organizations three times decreased leaving the share of unprofitable credit organizations on a relatively similar level (Cbr.ru., 2021).



Graph 1. *The ratio of profitable and unprofitable financial organizations in Russia in 2010-2020, % (Cbr.ru., 2021)*

There are several reasons for such dynamics. One of the main reasons is the high level of formed reserves to cover possible losses due to the increase of credit risks caused by the economic situation in Russia. Moreover, the implementation of the international financial

reporting standards in banking practices forcing banks to increase their expenses for creating reserves. The other reason to consider is the decline in traditional interest income as the result of decreasing lending volumes. The relatively high level of fee and commission income does not allow to compensate for losses and significantly affects the overall financial result (Bubnova, 2020). Finally, the general trend towards digitalization and business ecosystem creation made it nearly impossible to develop and compete alone (Tikhonova, 2019; Kleiner, et al., 2020).

Historically, the financial industry led in the adoption of innovative technologies and their large-scale use. In recent years, fintech developments are driving a fundamental transformation of the entire financial services industry and the business models of traditional banks (EY, 2019). Over the past years, the fintech industry has grown rapidly (CBInsights, 2020). Investors are investing heavily in the fintech segment assessing the size and potential of the financial services transformation market as significant. Fintech companies can take out any process from banking and simplify its provision to customers. The main areas of use of innovative digital technologies in the financial sector are lending (including microlending), peer-to-peer (P2P) platforms for lending (crowdlending) and fundraising (crowdfunding and crowd investing), payment systems, internet banking, big data, blockchain, machine learning (Schueffel, 2016; Bofondi, Gobbi, 2017; Chen, Wu, Yang, 2019).

These factors forced banks to consider new models for value creation and customer interaction to generate innovative services and increase the additional income. The emergence of digital ecosystem partnerships became the main solution to the current business reality. Thus, the formation of alliances of traditional banks with fintech organizations in the context of digitalization serves as a powerful factor in the formation of ecosystems at the intersection of the financial and non-financial sectors in Russia.

Sber is one of the biggest ecosystems in the Russian financial sector. Since 2016 Sber has been moving from a traditional services provider model to a diversified digital ecosystem. The bank unites partners based on a platform that provides both financial and non-financial services to expand the possibilities of offering complex products to customers (Sberbank, 2019).

Its digital ecosystem includes such partners as Domclick, Yandex.Money, Sbermobile, ‘Beru!’, Okko, Citymobil, Delivery Club, DocDoc. The Domclick portal provides services for the search and purchase of apartments on a mortgage. The Yandex.Money service provides electronic transfer services. The virtual operator "Sbermobile" provides mobile communication services. Thanks to the online marketplace "Beru!" Sberbank customers can order goods at a discount. Online cinema services are provided by Okko, and taxi services are provided by

Citymobil. Using the Delivery Club, customers can order food, and medical services can be ordered through the DocDoc service (Kleiner, et al., 2020; Bubnova, 2020; RBC Trends, 2021).

Nowadays, Sber digital ecosystem consists of at least 50 companies that are not directly related to the banking business. Moreover, most of them are not purchased but developed in-house (RBC Trends, 2021).

Since the elements of the digital ecosystem under analysis are united under one unified brand of Sber, it is crucial to add the analysis of the attitude towards Sber that will measure the ideas and beliefs associated with the brand and, consequently, with the product (Fishbein & Ajzen, 1975).

So, the next subchapter will provide the further development of the initial research model and provide substantial measurement.

2.1 Development of the theoretical framework and research propositions.

Dimensions of UTAUT 2

The research logic follows the research questions presented earlier in this Master Thesis:

RQ1: What is the *role* of digital competence in the digital ecosystem solutions acceptance process?

RQ2: How specifically does digital competence participate in the digital ecosystem solutions acceptance process?

However, to integrate the UTAUT2 model with the DCR model the development of research hypotheses is required, which will serve as a basis for the inclusion of potential factors of adoption to the measurement model. Therefore, a set of research hypotheses were developed following the previous research both on UTAUT2 and Digital Competence based on the set of statistical hypotheses typical for UTAUT2 (Venkatesh et al., 2012; Labazanov, 2020; Voronenko, 2018). For the simplicity of analysis, the variable Use behavior was removed, leaving the Behavioural Intention (BI) to use as the only outcome of the integrated model. A brief explanation is provided before every stated proposition.

Effort expectancy

The effort expectancy (EE) variable denotes the degree of ease of use, which is associated with the usage of new technology or a technology product (Venkatesh et al., 2012). According to the previous studies, the greater the EE, the more rapid will the rate of adoption for products or innovations be, thus, positively affect the Behavioral Intention (BI) to use (Lin et al., 2014;

Okumus, et al., 2018). Therefore, in this research, it is considered to be positively influenced by the level of individuals' digital competence (DC) meaning that the higher the individual's digital competence level the easier the person will adapt to the new technological solution, thus, arising the research hypotheses:

***P1.1*:** DC positively influences the EE in the process of digital ecosystem solutions' acceptance.

***P1.2*:** EE positively influences the BI to use digital ecosystem solutions.

Performance expectancy

Performance expectancy (PE) in the UTAUT2 model is defined as the extent to which the usage of new technology or a new technology product can provide consumers the benefits in performing specific activities (Venkatesh et al., 2012). According to the theory, clients who expect the technology to perform well are more inclined to BI use this technology. Therefore, the variable is considered to be positively affected by DC either. Following the definition, the second set of hypotheses is developed:

***P2.1*:** DC positively influences the PE in the process of digital ecosystem solutions' acceptance.

***P2.2*:** PE positively influences the BI to use digital ecosystem solutions.

Facilitating condition

Facilitating condition (FC) is the degree to which a person believes that an organization and a technical infrastructure exist to support the usage of a system (Venkatesh et al., 2012). It plays one of the crucial roles in the UTAUT2 model due to its direct influence on BI use (Jawad, & Hassan, 2015). Therefore, it is considered to be also positively influenced by the level of individual's digital competence, allowing to provide the third set of research hypotheses:

***P3.1*:** DC positively influences the FC in the process of digital ecosystem acceptance.

***P3.2*:** FC positively influences the BI to use digital ecosystem solutions.

Social influence

Social influence (SI) is the degree of importance being recognized by others to use a novel technology (Venkatesh et al., 2012). In other words, it is directly correlated to the degree to which outcomes from using innovations are noticeable to friends and relatives (Eneizan, et al., 2019). Researches propose that SI has an impact on the BI. In this research it is expected to be

influenced by the individual's digital competence level as the higher level of digital competence is supposed to alter the social influence. Therefore, the next hypotheses are set:

***P4.1*:** DC influences the SI in the process of digital ecosystem solutions' acceptance.

***P4.2*:** SI positively influences the BI to use digital ecosystem solutions.

Hedonic motivation

Hedonic motivation (HM) is defined as the motivation to do something due to internal satisfaction (Venkatesh et al., 2012). The recent studies showed evidence on the fact that perceived enjoyment directly influences the intention to use the Internet and mobile banking (Venkatesh et al., 2012). This master's thesis is considered to be positively affected by the individual's digital competence level resulting in higher motivation to use technology. So, the next research hypotheses are developed:

***P5.1*:** DC positively influences the HM in the process of digital ecosystem solutions' acceptance.

***P5.2*:** HM positively influences the BI to use digital ecosystem solutions.

Habit

Habit (H) defines the degree to which consumers tend to perform the usage of technologies or the usage of technology products behaviors automatically because of learning, thus, adopting the technology at a faster rate (Venkatesh et al., 2012; Bere, 2014). This master's thesis is considered to be positively affected by DC resulting in faster adoption of the new technology. So, the sixth set of hypotheses are developed:

***P6.1*:** DC positively influences the H in the process of digital ecosystem solutions' acceptance.

***P6.2*:** H positively influences the BI to use the digital ecosystem solutions.

Trust

Trust (T) denotes a person's beliefs that mobile application or other kinds of service would work as intended establishing the positive influence on BI to use (Eneizan, et al., 2019; Voronenko, 2018). In the current research, it is as well expected to be positively affected by the individual's digital competence level, thus, bringing up the next research hypotheses:

***P7.1*:** DC positively influences the T in the process of digital ecosystem solutions' acceptance.

***P7.2*:** T positively influences the BI to use the Sber' digital ecosystem solutions.

Security

Security (S) is defined as an individual's belief that a particular procedure would be secure (Voronenko, 2018). The individual's digital competence level, in this case, is also considered to positively affect the variable and, thus, the BI to use new technology. So, the next hypotheses are stated:

***P8.1*:** DC positively influences the S in the process of digital ecosystem acceptance.

***P8.2*:** S positively influences the BI to use digital ecosystem solutions.

Perceived risk

Perceived risk (PR) depicts the person's fear that the usage of service will lead to losses and unexpected barriers for intended activity (Eneizan, et al., 2019; Voronenko, 2018). In the previous studies, it had a negative effect on BI use (Eneizan, et al., 2019; Voronenko, 2018). Nowadays, privacy issues force people to carefully deploy personal information in the digital world. Therefore, the variable PR is complemented with privacy risk concerns because it is also associated with risks (Voronenko, 2018). Therefore, in this research, it is considered to be negatively impacted by the individual's digital competence level. DC is considered to lower the perceived risk by the consumer. So, the next hypotheses are stated as:

***P9.1*:** DC influences the PR in the process of digital ecosystem solutions' acceptance.

***P9.2*:** PR influences the BI to use digital ecosystem solutions.

Generally, it is supposed that the individual's level of digital competence has an impact on the Behavioral Intention (BI) to use the technology. So, the effect by the individual's level of digital competence is supposed to influence the UTAUT2 constructs, thus, affecting BI to use.

The classical model also highlights the importance of the behavioral features of respondents into account, when analyzing the adoption of technology. Therefore, the model states that age, gender, and the previously accumulated experience of using technology might affect and change the effects of factors on intention to use technology. So, a set of hypotheses are added in addition to the previously stated ones.

H1-H9: Age of respondents mediates the effect of effort expectancy (H1), performance expectancy (H2), facilitating conditions (H3), social influence (H4), hedonic motivation (H5),

habit (H6), trust (H7), security (H8), and perceived risk (H9) on the behavioral intention to use digital ecosystem solutions.

H10-H18: Gender of respondents mediates the effect of effort expectancy (H10), performance expectancy (H11), facilitating conditions (H12), social influence (H13), hedonic motivation (H14), habit (H15), trust (H16), security (H17), and perceived risk (H18) on the behavioral intention to use digital ecosystem solutions.

H19-H27: Experience of respondents mediates the effect of effort expectancy (H19), performance expectancy (H20), facilitating conditions (H21), social influence (H22), hedonic motivation (H23), habit (H24), trust (H25), security (H26), and perceived risk (H27) on the behavioral intention to use digital ecosystem solutions.

Additional factors influencing the Sber's digital ecosystem acceptance.

Following the previous research done, it seemed crucial to extend the empirical model with an additional mediating variable – brand attitude. The reason to extend the model is that the research problem involves investigation of the phenomenon using the case of Sber. Thus, there is the possibility that the Behavioral Intention to use the new technology will be affected by the consumer brand attitude towards Sber.

The brand attitude is defined as the buyer's evaluation of the brand concerning its expected capacity to deliver on a currently relevant buying motive (Rossiter & Percy, 1987; Rossiter, 2014). Brand attitude is basically what customers think and how they feel towards the brand (Sauro, 2021). The existent studies on brand attitude and brand image show that it directly influences consumer behavior (Okazaki, 2006; Christodoulides, et al., 2006; Christodoulides & de Chernatony, 2004). Moreover, Hoffman and Novak (1996; 2009) studied online brands viewing them as augmented products or services which meet customer needs through interaction in computer-mediated environments.

In this research, the brand attitude is considered as a mediating factor influencing the UTAUT2 model variables affecting and changing the impact of factors on intention to use technology. Therefore, an additional list of hypotheses is developed.

H28-H36: Brand attitude towards Sber mediates the effect of effort expectancy (H287), performance expectancy (H29), facilitating conditions (H30), social influence (H31), hedonic motivation (H32), habit (H323, trust (H34), security (H35), and perceived risk (H36) on the behavioral intention to use digital ecosystem solutions.

The final theoretical framework for this research is depicted in Figure 13 featuring all eighteen direct research hypotheses together with thirty-six moderating research hypotheses, combining all theorized elements of digital competence and the UTAUT2 model described previously.

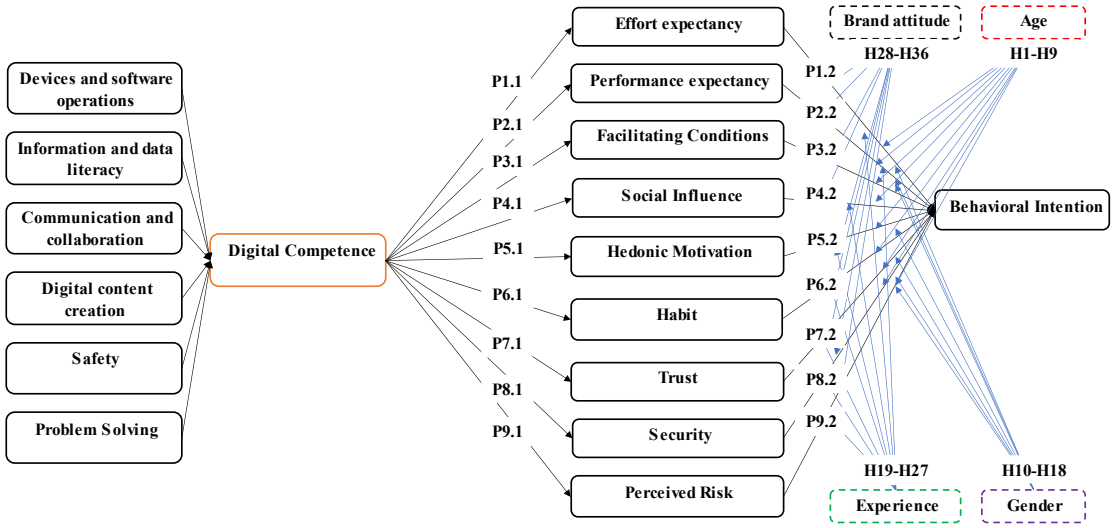


Figure 13. *Final theoretical framework (compiled by the author)*

The extended list of hypotheses is presented in the appendices. The further subchapter will highlight the methodology used in this master's thesis.

2.3 Methodology.

Research design and development

The research design of this master's thesis is aimed at combining the previously conducted research with empirical research methods. The theoretical framework developed in the literature review has to be explored on empirical evidence to test the stated research hypotheses.

Comparative analysis of existing studies on the adoption of electronic banking channels revealed that studies under comparison can be split into qualitative, quantitative, and mixed methods of research (Hanafizadeh et al., 2014). As quantitative studies estimate and assess relationships among factors connected to the adoption or rejection of advanced technology, the quantitative research methods are applied to test the research propositions in this master's thesis. Quantitative methods allow using numerical data as a basis for statistical analysis and approval or rejection of statistical hypotheses. This type of study allows to potentially extrapolate the results obtained on a sample to the entire investigated population. The two main types of design for such study are survey and observation (Malhotra, et. al., 2012).

Since the survey is a more targeted and convenient way of obtaining quantitative information, it was decided to use this type of data collection method. The advantage of an online over an offline survey is its cost-effectiveness and better potential geographical reach. Therefore, in this master's thesis, an online survey tool is applied (Malhotra, et al., 2012).

Choice of assessment technique

To proceed with further development of the research design, a technique has to be chosen for digital competence and UTAUT 2 assessment. Regarding digital competence, three main types of assessment techniques are usually applied in academic research and commercial sector: self-assessment (individuals evaluate their knowledge and skills with questionnaires that range from structured scales to free-form reflection), knowledge-based assessment (individuals are asked to respond to carefully designed test items that measure both declarative and procedural knowledge), and performance assessment (human observers or software monitor individuals when they are being engaged in solving authentic, real-life problems by using common software tools) (Kluze, Pujol Priego, 2018; Laanpere, 2019).

Based on overviews of digital competence assessment techniques (Deursen, 2017; Kluze, Pujol Priego, 2018; Laanpere, 2019) and theory on consumer and market research (Malhotra, et al., 2012), the chosen technique for this research is the self-assessment technique. Although the self-assessment technique tends to be subjective, as it relies on the respondent's self-perception, it is the optimal choice given the context of the research and available resources due to this technique being the least time-consuming and easy to implement (Labazanov, 2020).

The subjective factor of self-assessment is reduced by the development of an appropriate questionnaire, with items describing specific knowledge, skills, and attitudes connected with digital competence, in the next paragraph of this chapter.

Questionnaire development

The survey's questionnaire includes several blocks of questions: digital competence assessment, technology acceptance assessment (including trust, security, and perceived risk), questions regarding individual digital tools usage, and individual electronic payment usage experience. The questionnaire also includes the attitude towards the brand as the specific technology is used in this study, as well as the attitude to shopping to provide a more extended analysis. Sociodemographic questions have also been added to the questionnaire. They include gender, age group, city of the living, education level, area of employment, and income level.

From the previously obtained research on Digital Competence, the listed below competence areas were included in the questionnaire. Some competencies were excluded because of their complexity and applicability to the narrow group of respondents (Labazanov, 2020).

Table 7. Competences in DCR (Labazanov, 2020)

Competence area	**Competences**
Information and data literacy	Browsing, searching, filtering data, information, and digital content Evaluating data, information, and digital content Managing data, information, and digital content
Communication and collaboration	Interacting through digital technologies Sharing through digital technologies Collaborating through digital technologies Netiquette
Digital content creation	Developing digital content Integrating and re-elaborating digital content Copyright and licenses
Safety	Protecting devices Protecting personal data and privacy Protecting health and well-being
Problem-solving	Solving technical problems Identifying needs and technological responses Identifying digital competence gaps
Devices and software operations	Physical operations of digital devices Software operations in digital devices

Each competence area must be assessed not only through skills and knowledge items but also through at least one attitude item, as the competence is a combination of all three components (Fielder et al., 2016). As defined in the previous paragraph of this master's thesis, a self-assessment technique is being used. For each competence, the respondent is suggested to express the level of agreement with a specific statement describing the developed level of competence. Formulations of the statement were adapted from the research developed by Labazanov (2020). Statements are positively worded and express a 'proficient' digital competence level, so that less digitally competent respondents could define their level of agreement according to their level of digital competence. The assessment is conducted on a

widely used 5-point Likert scale indicating from1 – strongly disagree to 5 – strongly agree (Van Deursen, 2014).

Table 8. Digital competencies for self-assessment (Labazanov, 2020)

Competence area	**Component**	**Competence**	**Scale**
Devices and software operations	Skills, knowledge	Shortcuts and hotkey usage	5-point Likert scale *1 – strongly disagree* *…* *5 – strongly agree*
		Settings personification in software	
		Knowledge of basic device specifications	
	Attitude	Love for installing and trying new software	
Information and data literacy	Skills, knowledge	Search operators and filters usage	
		Smart storage and organization of data	
	Attitude	Critical outlook on online information	
Communication and collaboration	Skills, knowledge	Various communication tools usage	
		Various collaboration tools knowledge	
	Attitude	Respect towards netiquette	
Digital content creation	Skills, knowledge	Simple content for self-expression creation	
		Complex multimedia content creation	
	Attitude	Respect towards intellectual property	
Safety	Skills, knowledge	Safety settings periodical checks	
		Information encoding and protection skills	
	Attitude	Attention to not share sensitive info online	
Problem-solving	Skills, knowledge	Task-appropriate digital tools knowledge	
		Ability to receive help or information	
	Attitude	Love for renewal and increasing of digital competence	

For the UTAUT2 assessment a similar questionnaire was conducted using the 5-point Likert scale indicating from 1 – strongly disagree to 5 – strongly agree. Questions were developed using the previously conducted research on factors of adoption of digital device wallets by Russian consumers by Voronenko (2018).

Finally, a special welcoming window was prepared by the author, which explained the purposes of the research to invite people to take part in it. The goal of this text is to increase the proportion of people, who fill in the questionnaire after opening it. Moreover, for the same goal, the survey was declared anonymous in the beginning. In addition, a brief description of the term digital competence, the electronic payment system, and Sber ID was presented. It stated the main features of technology to explain the scope of the study to respondents. It was particularly

important because respondents are not required to have used a technology to participate in the survey, as reasons for the absence of technology use are also important in the UTAUT2 model (Venkatesh et al., 2012). Nevertheless, the description was brief and stated in neutral tones, to avoid bias in respondents by trying to sell the advantages or disadvantages of technology. The questionnaire is attached to the appendices.

Sampling method and sample size

The general population of the research is Russian citizens 15-49 years of age who use any digital devices in their daily life. According to the research conducted by Beeline in 2018, the largest percentage of all iPhone users was 25-44 years old – more than 61% (iGuides, 2018). In the research on the consumption of the Internet, Mediascope identified that in the 12-24 age group 93% of Russian respondents surfed the Internet on their smartphone; the analogical percentage was 89% for the 25-34 age group and 79% for the 35-44 age group. For the next age group of 45-54 years, the number decreased dramatically to 60% of respondents (Mediascope, 2019). However, for this research people of the 15-49 age group are considered due to the recent events connected to COVID-19 that forced more people to start using digital devices.

As the research is conducted in Russia, the Russian population aged 15-49 is almost 69 million people and 97% of them do use digital devices (World bank, 2019; Statista, 2021). It means that around 66 million people could potentially be investigated for this research.

Restrictions on the level of income, educational level, and other characteristics of the respondent are not set. However, to ensure sample representativeness, it is necessary to set quotas on the main demographic characteristics of respondents, which in this research include age group and gender. Quotas are used to guarantee that representatives of both genders (male, female) and all age sub-groups (15-19, 20-29, 30-39, 40-49 years) are presented in the collected numerical data. Therefore, a non-probability quota sampling is used in this research.

Once the quotas are specified, sampling selection is done through convenience sampling (Semiz, 2016). For the simplification of the data collection process, the data is collected through convenience and snowball sampling methods. This means that initially the respondents are attracted from a group of people easy to contact or to reach (convenience sampling), but they are also stimulated to recruit other participants to take part in the survey (snowball sampling).

The size of each quota was set at 35 respondents. The quota size was chosen to exceed the ‘small sample’ size, which is usually set at 30 observations (Sergeant, Bock, 2002). Moreover, PLS data analysis requires from 40 and even 30 observations, according to academic research (Goodhue, et al., 2012), the same type of analysis that is going to be used in this

research design. Equal quotas were set, and the sample structure is not aimed at replication of the demographic structure of the general population. This done is for wider applicability of the study results.

Table 9. Minimal quotas (compiled by author)

	Gender		
Age group	Male	Female	Total
15-19	35	35	70
20-29	35	35	70
30-39	35	35	70
40-49	35	35	70
Total	140	140	280

The total sample size is 280 respondents, which has to comply with the minimum for the chosen statistical methods of analysis. The appropriate data analysis method for this type of research is PLS-SEM (the choice of data analysis method is specified in the following paragraph). The statistically determined minimum sample size for PLS-SEM is 160. Additionally, a '10-times rule-of-thumb' is widely used, which implies that the 'sample size should be greater than 10 times the maximum number of inner or outer model links pointing at any latent variable in the model' (Kock, 2018). The maximum number of links connected to the integrated digital competence and UTAUT2 variables in the theoretical model is 18, therefore, according to the '10-times rule,' the minimum sample size should be 180.

Consequently, the minimum sample size for the 'problem or phenomenon exploration' research is 200 respondents as the sample size should correspond with the chosen research objectives (Malhotra, et al. 2012).

Data collection and analysis

To start with, it is essential to discuss the data collection methods used. Because the study population may be difficult to access, it was decided to conduct an online survey. The advantages of an online survey are its cost-effectiveness and the possibility of general population analysis through the collection of a sample of an appropriate size (Malhotra, et al., 2012).

The survey was distributed through social networks Vkontakte, Telegram, and WhatsApp via private messages and post sharing. The initial distribution was conducted through convenience sampling. Moreover, the respondents were stimulated to further share the

questionnaire. For that purpose, a prize lottery was held among the respondents to encourage more answers to the questionnaire.

Moving to the data analysis methods, the major method of data analysis applied is PLS-SEM (partial least squares structural equation modeling). Structural equation modeling is a statistical analysis technique used to analyze structural relationships. This technique is a combination of factor analysis and regression analysis, and it is used to analyze the structural relationship between measured variables and latent constructs (Statistics Solutions, 2020). PLS-SEM resolves important concerns, which usually arise while dealing with the research in the fields of social sciences and related. Moreover, the PLS-SEM method can transform non-normal data following the central limit theorem to minimize errors.

The appropriate application of SEM allows understanding relationships between the studied constructs – digital competence and technology acceptance. In the context of this master's thesis, PLS-based SEM will be used as it is utmost suitable for an exploratory study, where the theoretical knowledge is relatively limited (Chin, 2010). This type of analysis is distribution-free and able to handle data from non-normal or unknown distributions. Finally, PLS-SEM aims to test predictive relationships between constructs by looking at whether there is a relationship or influence between them or not. It is widely used in studies of the technology adoption (Ramirez-Correa, et al., 2015; Eneizan, et al., 2019; Berlilana et al., 2017) and in examining digital literacy (Muthupoltotage, Gardner, 2018; Seufert, Guggemos, Tarantini, 2019) due to its ease and explanatory power.

Summary of Chapter 2

Summing up Chapter 2, the final theoretical framework (Figure 13) was developed for uncovering drivers of the adoption of Sber's digital ecosystem solutions.

Sber ID was chosen since the elements of the digital ecosystem under analysis are united under one unified brand of Sber. Therefore, the analysis of the attitude towards Sber is added, thus, extending the initial theoretical framework with the moderating effects of Brand Attitude.

A research design was developed to facilitate the appropriate testing of the hypotheses in the research model. The quantitative method in form of a survey questionnaire was proved to comply with the requirements of research questions. Then a questionnaire was developed by combining and adjusting scales from classical papers on the topic. The self-assessment technique was chosen for the measurement of individual digital competence, because of its timeliness and ease of implementation, and the subjectivity of self-assessment is reduced by the appropriate item design of the questionnaire.

The questionnaire applied for data collection can be found in Appendix 1. For the most part, it features positively expressed statements on digital competence and technology acceptance. The agreement with the statements is assessed on a 5-point Likert scale with descriptors from ‘strongly disagree’ to ‘strongly agree’. Snowball and convenience sampling are applied, with quotas based on age group and gender, with each quota amounting to 35 respondents and a total sample of 280 respondents.

For data analysis, the partial least squares structural equation modeling is applied. The method applied to investigate the relationships between studied constructs and test the research hypotheses.

CHAPTER 3. DATA ANALYSIS AND PRACTICAL IMPLICATIONS.

The chapter presents the results of obtained data analysis. First of all, an obtained sample analysis will be presented denoting sample size and characteristics.

Then, the research hypotheses will be tested based on statistical testing. Modeling will be performed in WarpPLS 7.0 software, and statistical checks will be performed based on its comprehensive user guide, which summarizes all the necessary statistical information for the PLS-SEM method (Kock, 2020).

The discussion of the results presents the most important part of the study. First, new databased models will be developed if the initial research model is not approved. Finally, the chapter concludes with theoretical and practical implications made on the quantitative research results.

3.1 Data analysis

Obtained sample.

All in all, 374 responses to the questionnaire were obtained. The answers were filtered with the age of respondents (15-49) since there were answers from not defined age group (from 50 years old).

However, the quotas were not met properly. In some demographic groups, the number of responses exceeded minimum quotas (Male, 20-29; Female, 20-29), whereas, in other demographic groups the number of respondents barely reached the required minimum number (Male, 40-49; Female, 40-49; Male, 15-19). Therefore, the final sample size was decided to be reduced to 280 respondents by applying random selection to exceeding demographic groups.

Table 10. Final sample (collected data)

	Gender		
Age group	Male	Female	Total
15-19	35	35	70
20-29	35	35	70
30-39	35	35	70
40-49	35	35	70
Total	140	140	280

The majority of the respondents are from Saint Petersburg (53%) and Moscow (19%). So, there is a skew in the sample towards residents of big cities. While this may be considered as a

slight limitation, it is important to mention that if residents of big cities will adopt new technology, then a wave of adoption across the country is expected.

We can conclude that the respondents mostly have the high and moderate perceived level of digital competence, however, respondents were denoting their level of digital competence to be very high or low. Interestingly, the perceived level of digital competence was not significantly affected by age or income level. Moreover, the majority of the respondents are students of master's and bachelor's degrees with an average level of income. This can explain the high level of perceived digital competence by respondents.

34% of respondents claimed that they have never used Sber ID and 22% said that they always use it. This shows that the sample consisted of both those, who have only perceptions about features of the Sber digital ecosystem, and those, who have tried using it and have formed an opinion. According to the UTAUT2 methodology, the respondents don't need to have prior experience in using technology, still not being prohibited.

Finally, collected sample size allows for reliable calculation of the measurement model in special statistical software WarpPLS 7.0 as it exceeds the minimal sample size according to the rule of thumb (180) and it is higher than the required minimum number for problem or phenomenon exploration (Malhotra, et al. 2012).

Descriptive statistics

Before running PLS-SEM analysis, the average descriptive analysis was run with DCR and UTAUT2 constructs. Each theoretical construct is reflected in the questionnaire by a set of 5-point Likert scales. The average level of agreement with each question associated with a scale was calculated. Then average score was calculated for each set of scales to represent the level of agreement with the overall statement about the importance of particular factors in the opinion of respondents. A 5-point scale means that an average score of 3,0 lies exactly in the middle of the scale representing a neutral opinion. The summarizing tables with average scores of agreements for each construct are presented below.

Table 11. Average scores for DCR scales (collected data)

Competence area	**Score**
Devices and software operations	3,8
Information and data literacy	3,7
Communication and collaboration	3,4
Digital content creation	3,3

Safety	4,0
Problem-solving	3,9

To start with, the average agreement of respondents with the questions about digital competence areas is quite high. Respondents mostly agreed with the questions connected to such areas as Safety, Problem-solving, and Devices and software operations indicating their overall high level of skills, knowledge, and attitude.

Furthermore, the average agreement of respondents with the questions about Performance Expectancy, Hedonic motivation, and Habit is a little bit more than neutral indicating the features and issues connected with Sber ID. Moreover, the average agreement of respondents with the questions about Effort Expectancy, Facilitating Conditions, Trust, and Security is high indicating the level of agreement with questions connected with Sber ID. Finally, the average agreement of respondents with the questions about Social Influence, Perceived Risk, and Behavioral Intention is average indicating the relatively small level of agreement with issues connected with Sber ID. The summarized scores are depicted in Table 11.

Table 12. Average scores for UTAUT2 constructs (collected data)

Construct	**Score**
Performance Expectancy	3,4
Effort Expectancy	4,0
Social Influence	2,9
Facilitating Conditions	3,8
Hedonic Motivation	3,3
Habit	3,3
Trust	3,6
Security	3,5
Perceived Risk	3,0
Behavioral Intention	3,1

In the next section, results are analyzed with PLS-SEM techniques to investigate, how the abovementioned scales can be used to derive factors affection adoption of digital ecosystem solutions.

3.2 Research model and hypothesis testing

As it was stated previously, the research model analysis was conducted using WarpPLS 7.0 software. General model fit and quality indices were calculated assuring the necessary values to prove the quality. However, the first trials showed low Average R-square and Average

adjusted R-square which means the lower overall predictive and explanatory power of the model. As a result, the model was modified several times during the process of modeling.

Statistical hypotheses formed in the previous chapter and the relationships between investigated variables were calculated by the applied software. Three indicators concerning path coefficients of the model were taken into consideration when testing the hypotheses – the significance of path coefficients, effect sizes of path coefficients, and the value of path coefficients (for comparative purposes). All size coefficients must be significant. As per Chin (1998), Path coefficients 'should be at least 0.20 to be considered meaningful'. However, valid effect sizes start from 0.10. The significant small effect size in the PLS-SEM method usually starts at the value of 0.02 (Cohen, 1988), but such threshold is considered too low by the author to be applied in this research and make substantiated conclusions.

At the first step of the calculation, the software runs the collinearity analysis between all constructs in the model. Therefore, once the collinearity appears to be too high, the scales must be recombined to make the model reliable and valid. During the first run, the variables showed multicollinearity. Therefore, actions were taken to decrease its level.

First of all, the correlation constructs with too high (>0,6) correlation were combined. Thus, Trust and Security constructs were combined due to this issue. These two constructs are tightly connected making it possible to use one unified Trust and Security construct, thus, combining P7.1, P7.2, H7, H16, H25, H34 with P8.1, P8.2, H8, H17, H26, H35 hypotheses respectively. Moreover, Hedonic Motivation was removed from the analysis since it was correlated with more than two constructs, thus, dropping P5.1, P5.2, H5, H14, H23, H32 hypotheses from the list.

Thus, the new model was run in the software showing the absence of multicollinearity issues. With several trials and failures, the final model was developed. During the trial process, several variables were removed due to a negative effect on the model's explanatory power and hypotheses dropped. So, hypotheses H19 – H27 were dropped, because the variable Experience showed insignificant moderating effects on the model constructs' connection to Behavioral intention to use, thus, removing it from the model. Then, hypotheses H1 – H5 and H7 – H9 were rejected because the variable Age showed insignificant moderating effects on every construct's connection to Behavioral intention to use, except for Habit. Furthermore, the variable Gender showed almost the same insignificant moderating effects as Age, thus, rejecting hypotheses H10 – H12 and H14 – H18. Finally, hypotheses H29, H30, and H36 were rejected due to the same reasons indicating the Brand Attitude moderating effect to be insignificant. The last point to be

mentioned is that the connection between Facilitating condition and Behavioral intention was removed due to its high insignificant value, which negatively affected the overall model, so, hypothesis P3.2 was rejected as well.

Thus, the final model was adjusted so that the software calculated the final model's coefficients which will be discussed further.

Model fit and quality indexes.

WarpPLS software provides 10 different indices, which describe the statistical quality of the calculated model: average path coefficient (APC), Average R-squared (ARS), Average adjusted R-squared (AARS), Average block VIF (AVIF), Average full collinearity VIF (AFVIF), Tenenhaus GoF (GoF), Sympson's paradox ration (SPR), R-squared contribution ratio (RSCR), Statistical suppression ratio (SSR), and Nonlinear bivariate causality direction ration (NLBCDR). The software automatically calculates all of these indices providing recommended values. Generally, all of these indices show the degree to which collected data fits with the proposed model.

WarpPLS recommends that P-values associated with APC, ARS, and AARS are less than 0,05 to be significant (Kock, 2020). In the case of this research P-value for APC is less than 0,001 (<0,05); for ARS is less than 0,001 (<0,05); for AARS is less than 0,001 (<0,05). As it can be seen all three P-values associated with quality indices are less than recommended 0,05. This indicates that on average coefficients of the internal model are significant.

WarpPLS states that AVIF and AFVIF indexes are acceptable if their values are less or equal than 5, and perfect if they are less or equal to 3.3 (Cock, 2020). In the case of this research, the resulting AVIF is 2,671 and AFVIF is 2,718, which falls into the ideal range. This index shows that the model has good overall predictive and explanatory power due to an acceptable level of collinearity in the model. It means that the hypothesized constructs in the model do not overlap in their meaning and reflect different factors.

The next index GoF is recommended to be as high as possible, with small GoF > 0.1; medium >= 0.25; and large >= 0.36 (Kock, 2020). GoF calculated based on primary data equals 0.380, which is higher, than the cutoff for large GoF. This index is a measure of the model's explanatory power, which is quite high in this case.

According to the software, the SPR index should be at least higher than 0.7 and should equal 1 in a perfect case (Kock, 2020). In this research, SPR equals 0.813, which is higher, than the accepted cutoff value. This index measures to which extent a model is free of Simpson's

paradox instances when a path coefficient and a correlation associated with a pair of linked variables have different signs. Acceptable SPR shows that there are no casualty problems in the model, and the pre-defined paths truly reflect effects in the direction proposed by the researcher.

RSCR should be acceptable if higher than 0.9 and perfect if equal to 1 (Kock, 2020). In this case, RSCR equals 0.856, which is slightly lower for being acceptable. However, with the rough estimation, it may be accepted due to low deviation from the acceptable term. RSCR is another index, which proves the absence of instances of Simpson's paradox described earlier. However, in this case, the predictor reduces the percentage variance explained by criterion (Kock, 2020).

According to WarpPLS SSR index is acceptable, if higher or equal to 0.7 (Kock, 2020). SSR equals 1.000, which is much higher, than the required minimum. This index is a measure of the extent to which a model is free from statistical suppression indexes. Statistical suppression occurs when a path coefficient in absolute terms is greater than the corresponding correlation associated with a pair of linked variables. Therefore, acceptable SSR proves that a model does not have casualty problems.

NLBCDR index is acceptable, when higher or equal to 0.7 (Kock, 2020). In the calculated model NLBCDR equals 0.688, which is slightly lower, than the required value. However, with the rough estimation, it may be accepted due to low deviation from the acceptable term. NLBCDR is an index, which proves that non-linear paths reflect effects in the direction proposed by a researcher.

Furthermore, the program calculates according to statistical procedures, whether separate constructs may be derived based on several underlying scales. The program provides four types of output to check the reliability of derived constructs/factors of the model. The first one is a classical coefficient called Cronbach's alpha, which should be equal to or greater than 0.7 for a construct to be reliable. WarpPLS 7.0 supplements Cronbach's alpha with another more recent coefficient called composite reliability, which also should be equal or greater than 0.7 for a construct to be reliable. Another important indicator is the Average Variance Extracted (AVE) for each construct. This indicator proves the validity of a construct and is recommended to be 0.5 and higher for each reflective construct (reflective constructs are constructs, which are derived based on a set of scales close in meaning; formative constructs are constructs, which are derived based on a set of scales with potentially not overlapping meaning). The last indicator recommended for analysis of results of Factor Analysis is Full collinearity VIF, which is used for common method bias tests to check for the absence of multicollinearity. According to the

developer of WarpPLS (Kock, 2020), VIF should be lower than 3.3. However, VIFs lower than 5 are also acceptable. Eventually, the WarpPLS 7.0 manual states that a more relaxed criterion of 10 is also acceptable, while not an ideal, threshold for VIF. Further a table with the results of these four tests for each construct in the extended UTAUT2 model is presented.

Table 13. Reliability and Validity Indicators (collected data)

	Composite reliability	**Cronbach's alpha**	**Average variances extracted**	**Full collinearity VIFs**
DC	0.884	0.863	0.309	1.278
BI	0.947	0.926	0.818	3.157
PE	0.946	0.938	0.577	2.347
EE	0.953	0.934	0.834	3.610
SI	0.964	0.943	0.899	2.525
H	0.938	0.911	0.792	3.101
T&S	0.947	0.933	0.718	4.301
PR	0.928	0.907	0.683	1.540
FC	0.890	0.835	0.670	3.780

All the constructs are proved to be reliable based on Cronbach's alpha and Composite Reliability coefficients. However, Digital Competence constructs have a too low level of AVE. Therefore, the validity of Digital competence is questionable in this research, which is considered a limitation.

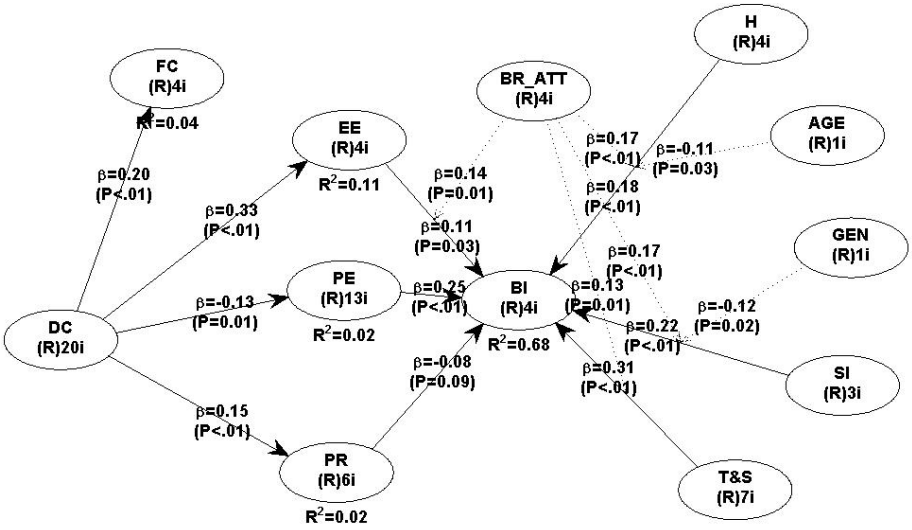


Figure 14. *A data-based model on technology acceptance (compiled by the author)*

Moving further, the structural model was successfully developed based on the questionnaire response (Figure 14). The model provided the calculations for path coefficients, associated p-values, and effect sizes. A certain path coefficient value means that if certain independent variable changes by 1 standard deviation, then a dependent variable changes by the portion of its standard deviation equal to the path coefficient. Path coefficients are statistically significant and show a real dependency relationship in a model if p-values associated with them are lower than 0.1. Effect size shows the strength of the effect of an independent/predictor variable on a dependent/endogenous variable. Based on commonly accepted thresholds (Kock, 2020) effect size can be weak (<0.02); small (0.02<x<0.15); medium (0.15<x<0.35); or large (>0.35).

Table 14. Outputs for main variables of the internal model (collected data)

Path	Path coefficients	P values	Effect sizes for path coefficients	Hypotheses, strength
DC->PE	-0.132	0.012	0,02	P2.1: supported, weak
DC->EE	0.331	<0.001	0,11	P1.1: supported, small
DC->PR	0.147	0.006	0,02	P9.1: supported, weak
DC->FC	0.197	<0.001	0,04	P3.1: supported, small
PE->BI	0.246	<0.001	0,16	P2.2: supported, medium
EE->BI	0.111	0.030	0,04	P1.2: supported, weak
SI->BI	0.224	<0.001	0,15	P4.2: supported, medium
H->BI	0.175	0.001	0,13	P6.2: supported, small
T&S->BI	0.310	<0.001	0,22	P7.2: supported, medium
PR->BI	-0.078	0.094	0,04	P9.2: supported, small

Table 15. Outputs for mediating variables of internal model (collected data)

Path	Path coefficients	P values	Effect sizes for path coefficients	Hypotheses Supported
AGE*H->BI	-0.113	0.028	0,03	H6: supported, small
GEN*SI->BI	-0.119	0.022	0,02	H13: supported, weak
BR_ATT*EE->BI	0.136	0.010	0,06	H28: supported, small
BR_ATT*H->BI	0.171	0.002	0,07	H31: supported, small
BR_ATT*SI->BI	0.166	0.002	0,07	H33: supported, small
BR_ATT*T&S->BI	0.132	0.012	0,05	H34: supported, small

The research model supported the effects of the Digital competence variable on Performance Expectancy, Effort Expectancy, Perceived Risk, and Facilitating conditions. What is more, the impact of digital competence level is positive in most cases as was expected. Interestingly, the level of an individual's digital competence negatively impacts performance expectancy. So, it means that the increase in the level of an individual's digital competence deviation decreases the performance expectancy.

Moreover, the effects of Performance Expectancy, Effort Expectancy, Social Influence, Habit, Trust and Security, and Perceived risk on Behavioral Intention to use technology were proved. As it was supposed, most of the constructs have a positive effect on the Behavioral Intention to use, except for Perceived Risk which was considered to have a negative effect.

Finally, all other supporting statistical hypotheses for this study were not supported by the results of the PLS-SEM analysis. Summing up, the quality of the model proved to be high despite small deviations of RSCR and NLBDR indexes. Thus, the model proves the high reliability of received results, which will be described further. An output summary with the calculated model fit and quality indices is attached to the appendices.

3.3 Discussion of the results

Data-based model and its interpretation

Average R-squared of 0.68 means that the model explains 68% of the total variance in consumer's intention to adopt Sber's digital ecosystem solutions. The value is significant, which indicates that the model is reliable and can be used for practical implementation. It can be observed in Figure 15.

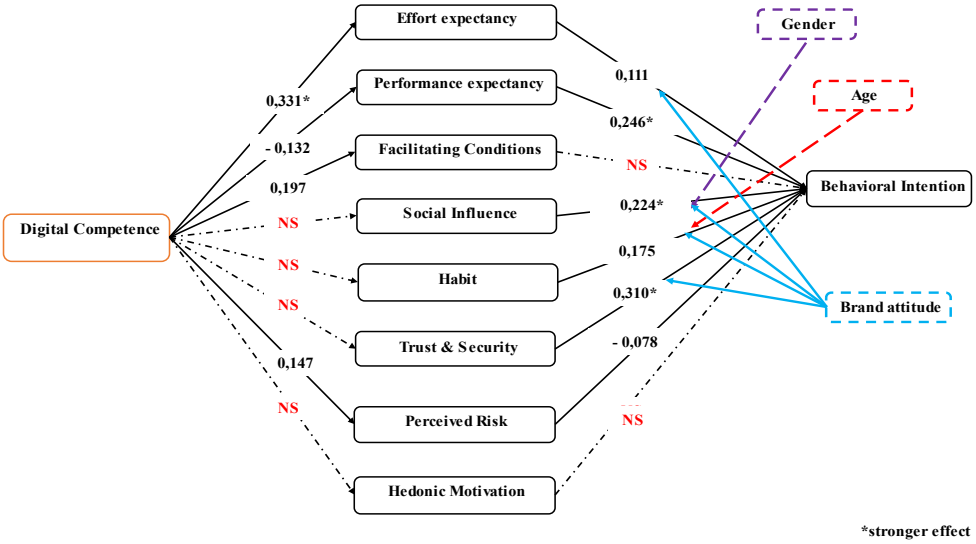


Figure 15. *A modified model on technology acceptance (compiled by the author)*

The results of the analysis can be divided into two groups: the effect of Digital competence on the UTAUT2 constructs and the impact of the UTAUT2 constructs on the Behavioral intention to Sber ID technology.

To start with, Digital competence has effects on such constructs as Performance Expectancy, Effort Expectancy, Perceived Risk, and Facilitating conditions, as was mentioned previously. The model proved that a higher individual's level of digital competence leads to the easier adaptation to new technology for consumers. It was expected as the more people know about Sber ID the easier it is to start using it on an everyday basis. Moreover, the increase in the level of an individual's digital competence, surprisingly, leads to a decrease in the level of an individual's performance expectancy. It could be understood as the more people know about the Sber ID the fewer benefits they expect from its usage in performing specific activities. Following this, the model predicted that the level of digital competence positively impacts the person's fear of barriers and losses associated with technology usage. Unexpectedly, the results show that the risks associated with the usage of Sber ID increase following the increase in the level of digital competence which is another discussion point. Finally, the model predicts that the higher the level of digital competence leads to a higher degree of a person's belief towards technical infrastructure support when using Sber ID. It means that the digitally competent person would likely ask for help from the support organization rather than from peers.

Moving to the factors affecting Behavioral intention to use, it is crucial to mention that Performance Expectancy, Effort Expectancy, Social Influence, Habit, Trust and Security, and Perceived risk on Behavioral Intention to use technology was proved to be significant. The most influential drivers to Behavioral Intention to use in this case are Trust and Security, which is expected because Sber is a financial institution, and security connected issues often arise. The other driver is Performance Expectancy, which is also expected since the benefits connected with the usage of Sber ID directly affect the outcome.

So, the model predicts that if consumers believe Sber ID will perform as intended and will help to achieve their goals during the use period, then they will intend to use Sber ID in the future. Talking about the rest of the constructs, the analysis shows the positive influence of almost all the constructs on the behavioral intention to use Sber ID, as was expected previously. The negative effect of risk factors was also expected based on the literature review. If consumers believe that Sber ID might collect their data, which they would not like to disclose, or that it might fail during the use process, then it would decrease their intention to use Sber ID in the future

Another considerable finding is that the age, gender, and brand attitude toward Sber showed an interesting result. The final model assumes that age affects the relationships between behavioral intention and habit; gender heavily impacts the relations between social influence and behavioral intention; and, finally, the brand attitude affects relationships of Trust and Security, Effort Expectancy, Habit, and Social Influence constructs with Behavioral Intention to use Sber ID. What is more, the experience might be of no relevance, because of the relative simplicity of Sber ID usage and consumer's general familiarity with Sber's Internet banking or mobile banking applications.

Based on model modification and the information discussed previously, theoretical and practical recommendations were developed.

Further theoretical implication

One of the important contributions of this master's thesis is developing the link between the technology acceptance model and the digital competence framework. The results show that, in general, the digital competence level of an individual affects the person's intention to use particular technology by affecting such constructs as Performance Expectancy, Effort Expectancy, Perceived Risk, and Facilitating conditions.

Therefore, the theoretical contribution of the research is the following. First of all, the research provides the answers to the research questions on the role of digital competence in the technology acceptance process of Sber's digital ecosystem solution. Thus, it generates new knowledge regarding the list of factors and the unique acceptance model.

Moreover, the research lays the foundation for subsequent studies on this topic. The research has developed and verified the linkage between the level of an individual's digital competence and the acceptance model, and it has comprehensively described the methodology used. Thus, the research has provided the model and methodology, which can be further adjusted and extended, to perform similar researches.

Finally, the research has generated new relevant knowledge and has created the foundation for further studies on the topics of technology acceptance and digital competence in the context of digital business ecosystems.

Further practical implication

The results of the current research can be useful for practitioners as well. This study would be helpful for marketing managers responsible for developing promotional campaigns in

particular. It would be most appropriate to use the results in two different categories discussed further.

First of all, targeting should be based on the consumer's level of digital competence and focus mainly on influential drivers that proved to affect the Behavioral intention to use the technological solutions. Thus, one of the prominent results of the study is the negative impact of the digital competence level on the degree to which consumers expect benefits in using a particular technology, which in turn, affects negatively the intention to use it. So, the consumers with a high level of digital competence expect fewer benefits connected with the usage of new technology, and, therefore, do not intend to use it. Consequently, this group of consumers has to be treated differently so that the potential market share will not be missed.

Finally, it is recommended to educate consumers regarding the new technology to increase the level of their digital competence so that it would be easier for consumers to adopt it, and, thus, to use it.

Limitations and further research

This research is associated with three main limitations. First of all, the sample collected for the study consists primarily of citizens from Saint Petersburg and Moscow, which might introduce bias while being represented to the entire population. Quota sampling allowed to include representatives of all demographic groups of interest into the sample, however, the sampling method remained of convenience and snowball nature, which may introduce bias to the data. Even though the sample is a good representation of only the segment of the entire population, it is not representative of the whole population. So, the results should not be generalized to the country level.

Furthermore, the sample consisted primarily of people with prior experience who have already used Sber services or have is familiar with it, which might be a reason why the FC factor has not been treated statistically as internally valid.

Finally, the sample size was sufficient but was limited by 280 respondents using four quotas of 35 people in each, so it can lead to the situation that to a certain extent the results do not reflect the true effect of a larger population. It is specifically recommended to test significant paths with weak-moderate path effects on larger samples. Consequently, the limitations should be taken into consideration by further studies relying on the obtained insights.

Summary of Chapter 3

In Chapter 3 the process of data analysis was described in detail. As a result, the research questions were addressed. Based on the results of the data analysis, recommendations for both practitioners and academics were provided. Finally, some limitations of the current research were also discussed.

CONCLUSION

The study was dedicated to investigating the possible linkage between the technology acceptance by consumers and their digital competence level using the case of the highly innovative banking company – Sber.

The existing literature and concept analysis defined the research gap as the lack of knowledge on the relationships between digital competence and consumers' digital technology acceptance. Therefore, research questions “What is the role of digital competence in the digital ecosystem solutions acceptance process?” and “How specifically does digital competence participate in the digital ecosystem solutions acceptance process?” were addressed with the empirical research.

The main concepts used in the research together with the recent phenomenon investigation were highlighted. Based on the analysis of the existing research frameworks of consumer behavior studies the initial integrated model was developed based on the UTAUT2 model extending it with additional variables addressed by the stated research problem.

Moving on, the context of the study was explained. Thus, the reasons for choosing Sber digital ecosystem solutions (the unique representative of complex digital solutions in the banking industry) were provided and a research design was developed to facilitate the appropriate testing of the hypotheses in the research model. The choice of methodology (quantitative approach via questionnaire) was justified. The design of the questionnaire and data collection process was given. A particular analysis method (PLS-SEM) via specific software (WarpPLS 7.0.) was explained.

Finally, the results of the analysis can be divided into two groups: the effect of Digital competence on the UTAUT2 constructs and the impact of the UTAUT2 constructs on the Behavioral intention to use Sber ID technology. The level of consumer digital competence proved to have effects on such constructs as Performance Expectancy, Effort Expectancy, Perceived Risk, and Facilitating conditions, thus, answering the stated research questions. Furthermore, Trust and Security together with the Performance Expectancy were defined as the most influential drivers to intention to use, adding the substantial effect of the Brand Attitude mediation.

Based on the empirical research results, further theoretical and practical implications were developed and addressed together with the limitations and further research suggestions.

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APPENDICES

Appendix 1. Questionnaire

Исследование опыта использования новых цифровых сервисов

Здравствуйте!

Благодарю за согласие принять участие в нашем исследовании, посвященном отношению к новым цифровым сервисам и опыту их использования. Все полученные ответы будут использованы только в анонимном обобщенном виде в исследовательских целях.

Время заполнения опроса - примерно 10-15 минут.Все участники опроса могут принять участие в розыгрыше сертификатов на совершение покупки на ozon.ru - для этого оставьте свои контактные данные (электронный адрес) после заполнения анкеты.

С уважением, Ануш Саакян,

Студентка программы магистратуры Master in Management Высшая школа менеджмента СПбГУ

Уровень цифровой компетентности (часть 1)

1. Как бы Вы оценили Ваш уровень цифровой компетентности?
   a. Очень высокий
   b. Высокий
   c. Средний
   d. Низкий
   e. Очень низкий
2. Какими цифровыми устройствами Вы пользуетесь?
   a. Персональный компьютер
   b. Ноутбук
   c. Планшет
   d. Мобильный телефон
   e. Электронная книга
   f. Цифровой фотоаппарат
   g. Цифровой плеер
   h. Умные часы
   i. Фитнес-трекер
   j. Другое: _____
3. Для каких целей чаще всего Вы используете ваши устройства?
   a. Использую базовые функции цифровых устройств (звонки и SMS, электронная почта, хранение файлов и т.д.)
   b. Использую в личных целях (общение с друзьями, поиск информации, покупки и т.д.)
   c. Использую в развлекательных целях (просмотр онлайн-контента, игры и т.д.)

d. Использую для учёбы/работы в качестве вспомогательного инструмента (применение «офисных» и интернет-приложений и т.д.)

e. Использую для учёбы/работы в качестве основного инструмента (профессиональное создание сложного цифрового контента, программирование и т.д.)

f. Другое: _____

Цифровая компетентность (часть 2)

Что такое цифровой контент:

Цифровой контент — это информационные и развлекательные материалы, которые распространяются в электронном виде и используются на цифровых устройствах: компьютерах, планшетах, смартфонах, электронных книгах и т.д.

Оцените, насколько Вы согласны со следующими утверждениями:

Полностью не согласен / Полностью согласен (1-5)

Competence area	Component	Competence	Question translated
Devices and software operations	Skills, knowledge	Shortcuts and hotkey usage	Я применяю разнообразные быстрые сочетания клавиш (также называются «горячие клавиши» и hot keys) в программах, которые я использую на персональном компьютере/ноутбуке
		Settings personification in software	Я всегда изменяю настройки своих цифровых устройств и приложений, чтобы адаптировать их под себя
		Knowledge of basic device specifications	Я знаю мощность, объем памяти и размер хранилища, разрешение экрана и другие общие технические характеристики моих устройств
	Attitude	Love for installing and trying new software	Мне нравится устанавливать и пробовать новые приложения и программное обеспечение на моих устройствах
Information and data literacy	Skills, knowledge	Search operators and filters usage	Я умею использовать поисковые фильтры и различные поисковые операторы, чтобы найти нужную мне информацию
		Smart storage and organization of data	Я использую различные методы для хранения и организации данных (физические и облачные хранилища,

			классификация по папкам и т. д.)
	Attitude	Critical outlook on online information	Я критически воспринимаю информацию в Интернете и предпочитаю перепроверять достоверность получаемых данных и их источников
Communication and collaboration	Skills, knowledge	Various communication tools usage	Я активно использую широкий спектр цифровых инструментов (электронную почту, чаты, SMS, социальные сети, блоги и т. д.) для общения
		Various collaboration tools knowledge	Я владею инструментами совместной работы в Интернете (общие календари, системы управления проектами, видеоконференции, приложения по управлению задачами, файлы с общим доступом и т. д.).
	Attitude	Respect towards netiquette	Я соблюдаю правила понятного и уважительного общения онлайн (также называют «сетевой этикет»)
Digital content creation	Skills, knowledge	Simple content for self-expression creation	Я создаю простой цифровой контент с целью самовыражения (фотографии, видео, записи в социальных сетях и т. д.)
		Complex multimedia content creation	Я умею создавать сложный контент из разных мультимедийных материалов (текст, фотографии, видео, музыка и т. д.) в разных цифровых форматах
	Attitude	Respect towards intellectual property	Я стараюсь уважать цифровую интеллектуальную собственность, авторские права и лицензии
			Я пользуюсь только лицензионным контентом и программным обеспечением
Safety	Skills, knowledge	Safety settings periodical checks	Я периодически проверяю настройки безопасности

			на своих устройствах, в приложениях и в социальных сетях, а также меняю пароли моих личных профилей и устройств
		Information encoding and protection skills	Я знаю различные способы шифрования или защиты информации при ее передаче
	Attitude	Attention to not share sensitive info online	Я внимательно отношусь к тому, чтобы не передавать и не распространять свои конфиденциальные данные в Интернете
Problem-solving	Skills, knowledge	Task-appropriate digital tools knowledge	Я всегда понимаю, какой цифровой инструмент лучше всего подходит для моих потребностей и целей в каждом конкретном случае.
		Ability to receive help or information	Когда при использовании цифровых технологий возникает проблема или вопрос (не связанные с техническими неполадками), я всегда знаю, куда обратиться за помощью и где найти необходимую информацию
	Attitude	Love for renewal and increasing of digital competence	Я люблю приобретать новые знания и навыки в сфере информационных технологий, а также искать возможности для повышения своей цифровой компетентности.

Пользовательский опыт (часть 1)

Что такое Система электронных платежей:

Система электронных платежей, или электронная платёжная система, — система расчётов между финансовыми организациями, бизнес-организациями и интернет-пользователями при покупке-продаже товаров и услуг через Интернет

1. У вас есть смарт фон?
    a. Да
    b. Нет
2. Пользуетесь ли Вы системой электронных платежей?
    a. Да

b. Нет

3. Для каких целей Вы используете систему электронных платежей?
    a. Онлайн шоппинг (одежда, электроника, аксессуары, т.д.)
    b. Доставка продуктов
    c. Доставка готовой еды
    d. Оплата коммунальных платежей
    e. Другое:_____
4. Как часто Вы используете систему электронных платежей?
    a. Никогда
    b. Раз в месяц
    c. Несколько раз в месяц
    d. Раз в неделю
    e. Несколько раз в неделю
    f. Раз в день
    g. Несколько раз в день
5. Пользуетесь ли Вы сервисами Сбер ID?
    a. Да, пользуюсь постоянно.
    b. Да, пользуюсь иногда.
    c. Да, пользуюсь редко.
    d. Нет, не пользуюсь.
    e. Нет, а что это?

Пользовательский опыт (часть 2)

Что такое СберID:

Сбер ID — это единый вход в сервисы экосистемы Сбербанка и партнеров (https://www.sberbank.ru/ru/person/dist_services/sberbankid?tab=partners). В Сбер ID используются технологические решения (например, протокол OpenID Connect) для обеспечения должного уровня безопасности.

Пожалуйста, ознакомьтесь с рекламой Сбер ID (ссылка https://www.youtube.com/watch?v=ImNOC5fMz7M) и ответьте на следующие вопросы.

Вопросы по видео

1. Какая песня В. Брежневой была адаптирована для данной рекламы?
    a. Любовь спасёт мир
    b. Хороший день
    c. Я не святая
    d. Любите друг друга
2. Исходя из видео, какие сервисы доступны для входа по Сбер ID?

a. Сервисы для доставки продуктов
b. Сервисы для просмотра кино
c. Сервисы для покупки одежды, обуви и аксессуаров
d. Сервисы для доставки готовой еды

3. Насколько полезным Вы считаете данное видео?
    a. Очень полезное
    b. Полезное
    c. Нейтральное
    d. Бесполезное

Далее мы просим Вас ответить на вопросы о Вашем потенциальном опыте использования Сбер ID. Пожалуйста, отметьте, насколько Вы согласны с каждым из перечисленных утверждений (1 – полностью не согласны, 5 –полностью согласны)

Performance Expectancy (Adapted from Venkatesh et al., 2012)	Использование Сбер ID во время покупки продуктов или услуг улучшит эффективность моего взаимодействия с продавцом (например, при онлайн шоппинге)
	Использование Сбер ID увеличит эффективность процесса моей покупки
	Использование Сбер ID во время моей покупки улучшит качество процесса покупки
	Использование Сбер ID позволит мне быстрее получать доступ к продуктам/услугам во время покупки
	Использование Сбер ID позволит мне более точно отслеживать процесс моей покупки
	Использование Сбер ID позволит мне увеличить общую получаемую мной ценность от приобретения продуктов/услуг
	Использование Сбер ID позволит мне лучше управлять моими денежными средствами во время покупок
	Использование Сбер ID позволит мне лучше контролировать мои расходы во время покупок
	Использование Сбер ID даст мне улучшенное представление о моей истории покупок
	Использование Сбер ID предоставит мне более защищенный способ оплаты покупок
	Использование Сбер ID позволит мне более эффективно выбирать между способами оплаты (например, между различными Вашими картами)
	Использование Сбер ID позволит мне получить другие преимущества, помимо оплаты (например, единный вход для различных сервисов)
	В целом я считаю, что Сбер ID полезен во время совершения покупок
Effort Expectancy (Adapted from Venkatesh et al., 2012)	Мне легко научиться пользоваться Сбер ID
	Мое взаимодействие с Сбер ID будет ясным и понятным
	Я считаю, что Сбер ID легко использовать
	Мне будет легко развить навыки уверенного использования Сбер ID
Social Influence (Adapted from Venkatesh et al., 2012)	Люди, которые важны для меня, считают, что мне следует использовать Сбер ID
	Люди, которые влияют на мое поведение, думают, что мне следует пользоваться Сбер ID

	Люди, которые влияют на мое поведение, думают, что мне следует пользоваться Сбер ID
Facilitating Conditions (Adapted from Venkatesh et al., 2012)	У меня есть все необходимые средства для использования Сбер ID
	У меня есть необходимые знания для использования Сбер ID
	Сбер ID совместим с другими технологиями, которые я использую
	Я смогу получить помощь от других людей, если у меня возникнут проблемы с использованием Сбер ID
Hedonic Motivation (Adapted from Venkatesh et al., 2012)	Пользоваться Сбер ID весело
	Пользоваться Сбер ID приятно
	Пользоваться Сбер ID очень увлекательно
Habit (Adapted from Venkatesh et al., 2012)	Использование Сбер ID стало для меня привычным
	Я пристрастился к использованию Сбер ID
	Мне необходимо использовать Сбер ID
	Использование Сбер ID стало для меня естественным
Trust (Adapted from Khalilzadeh et al., 2017)	Я верю, что Сбер держит в уме интересы своих клиентов
	Я верю, что Сберу можно доверять
	Я верю, что Сбер сделает все возможное для защиты транзакций пользователей
Security (Adapted from Khalilzadeh et al., 2017)	Я бы чувствовал себя спокойно при использовании Сбер ID
	Сбер ID – это безопасная система для отправки/использования конфиденциальной информации
	Я бы чувствовал себя в полной безопасности, если бы предоставил конфиденциальную информацию о себе через Сбер ID
	В целом Сбер ID – это безопасная система для передачи конфиденциальной информации
Performance Risk (Adapted from Khalilzadeh et al., 2017)	Высока вероятность того, что что-то пойдет не так во время работы Сбер ID
	Сбер ID может начать неправильно работать и создать проблемы во время оплаты моих покупок
	Учитывая ожидаемый мной уровень работы Сбер ID, для меня будет рискованно в нем зарегистрироваться и использовать его
Privacy Risk (Adapted from Khalilzadeh et al., 2017)	Существует высокая вероятность потерять контроль над конфиденциальной личной информацией из-за использования Сбер ID
	Регистрация в Сбер ID и его дальнейшее использование негативно повлияют на неприкосновенность моей частной жизни, так как моя личная информация будет использоваться без моего ведома
	Я думаю, что использование Сбер ID не поможет сохранить мою конфиденциальную информацию от разглашения
Behavioral Intention ((Adapted from Morosan and DeFranco, 2016)	Я собираюсь использовать Сбер ID для оплаты в будущем
	Я буду пытаться всегда использовать Сбер ID для оплаты моих покупок
	Я буду рекомендовать другим людям использовать Сбер ID для оплаты покупок
	Сбер ID станет одной из главных технологий оплаты для меня

Являетесь ли Вы клиентом Сбера

a. Да
b. Нет

Являлись ли вы раньше клиентом Сбера/Сбербанка?

a. Да
b. Нет

Почему вы отказались от пользования услугами Сбера/Сбербанка?

c. Непредвиденные расходы

d. Сомнения в безопасности организации

e. Нашли более выгодные предложения для Ваших целей

f. Постоянные сбои системы

g. Other

Пожалуйста, отметьте, насколько Вы согласны с каждым из перечисленных утверждений (1 – полностью не согласны, 5 –полностью согласны) – brand attitude (

Opinion: У меня сформировалось положительное мнение о Сбере.

Association: У меня позитивные ассоциации со Сбером

Loyalty: Я предпочитаю Сбер другим банковским сервисам

Trust: Я доверяю Сберу и его сервисам

Пожалуйста, отметьте, насколько Вы согласны с каждым из перечисленных утверждений (1 – полностью не согласны, 5 –полностью согласны)

1. Я люблю онлайн шоппинг
2. Как часто Вы покупаете продукты и товары онлайн?
    a. Никогда
    b. Раз в месяц
    c. Несколько раз в месяц
    d. Раз в неделю
    e. Несколько раз в неделю
    f. Раз в день
    g. Несколько раз в день
3. Какие типы продуктов Вы обычно покупаете онлайн?
    a. Продукты питания
    b. Товары для личной гигиены
    c. Одежду, обувь и аксессуары
    d. Книги и товары для досуга и творчества
    e. Другое:_____

Немного о Вас

1. Укажите свой пол:

    a. Мужской

    b. Женский

2. Укажите свой возраст:

    a. Младше 15

    b. 15-19

    c. 20-29

    d. 30-39

    e. 40-49

    f. 50-59

    g. 60-69

    h. 70 и старше

3. Где Вы сейчас живете?
    a. Санкт-Петербург
    b. Москва
    c. Другое: _____
4. Какое у вас образование:
    a. Незаконченное среднее образование
    b. Полное среднее (11 классов)
    c. Среднее специальное (техникум, колледж и т.д.)
    d. Высшее: Бакалавриат/специалитет (неоконченное или получен диплом)
    e. Высшее: Магистратура (неоконченное или получен диплом)
    f. Высшее: Докторантура и аспирантура (неоконченная или присвоена степень)
    g. Другое: _____
5. Выберите свою сферу занятости:
    a. Безработный/безработная, домохозяин/домохозяйка
    b. Студент/студентка
    c. Рабочий или сотрудник обслуживающего персонала (в компании)
    d. Специалист (в компании)
    e. Руководитель среднего звена (в компании)
    f. Руководитель высшего звена (в компании), управляющий компании
    g. Фрилансер, самозанятый
    h. Собственный бизнес (собственная компания)
    i. Пенсионер/пенсионерка
    j. Другое: _____
6. Какой Ваш уровень дохода?
    a. Моего дохода не хватает даже на приобретение продуктов питания
    b. Моего дохода хватает только на приобретение продуктов питания
    c. Моего дохода достаточно для приобретения необходимых продуктов питания и одежды, но на более крупные покупки приходится откладывать
    d. Покупка большинства товаров длительного пользования (холодильник, телевизор) не вызывает трудностей, однако приобрести автомобиль или квартиру мы не можем
    e. Мы можем позволить себе приобрести автомобиль или квартиру
    f. Моего дохода достаточно, чтобы вообще ни в чем себе не отказывать

Спасибо за Ваше время! В поле ниже Вы можете указать свой электронный адрес для участия в розыгрыше или оставить его пустым.

Если у Вас остались вопросы, Вы можете связаться со мной по адресу: saakiananush96@gmail.com

Ваш e-mail:

Appendix 2. List of Hypotheses.

Direct link P1.1 -9.2; Mediating link H1-36.

P1.1**:** DC positively influences the EE in the process of digital ecosystem solutions' acceptance.
P1.2**:** EE positively influences the BI to use digital ecosystem solutions.
P2.1**:** DC positively influences the PE in the process of digital ecosystem solutions' acceptance.
P2.2**:** PE positively influences the BI to use digital ecosystem solutions.
P3.1**:** DC positively influences the FC in the process of digital ecosystem acceptance.
P3.2**:** FC positively influences the BI to use digital ecosystem solutions.
P4.1**:** DC influences the SI in the process of digital ecosystem solutions' acceptance.
P4.2**:** SI positively influences the BI to use digital ecosystem solutions.
P5.1**:** DC positively influences the HM in the process of digital ecosystem solutions' acceptance.
P5.2**:** HM positively influences the BI to use digital ecosystem solutions.
P6.1**:** DC positively influences the H in the process of digital ecosystem solutions' acceptance.
P6.2**:** H positively influences the BI to use the digital ecosystem solutions.
P7.1**:** DC positively influences the T in the process of digital ecosystem solutions' acceptance.
P7.2**:** T positively influences the BI to use the digital ecosystem solutions.
P8.1**:** DC positively influences the S in the process of digital ecosystem acceptance.
P8.2**:** S positively influences the BI to use digital ecosystem solutions.
P9.1**:** DC negatively influences the PR in the process of digital ecosystem solutions' acceptance.
P9.2**:** PR negatively influences the BI to use digital ecosystem solutions.
H1. Age of respondents mediates the effect of effort expectancy on the behavioral intention to use digital ecosystem solutions.
H2. Age of respondents mediates the effect of performance expectancy on the behavioral intention to use digital ecosystem solutions.
H3. Age of respondents mediates the effect of facilitating conditions on the behavioral intention to use digital ecosystem solutions.
H4. Age of respondents mediates the effect of social influence on the behavioral intention to use digital ecosystem solutions.
H5. Age of respondents mediates the effect of hedonic motivation on the behavioral intention to use digital ecosystem solutions.
H6. Age of respondents mediates the effect of habit on the behavioral intention to use digital ecosystem solutions.
H7. Age of respondents mediates the effect of trust on the behavioral intention to use digital ecosystem

solutions.
H8. Age of respondents mediates the effect of security on the behavioral intention to use digital ecosystem solutions.
H9. Age of respondents mediates the effect of perceived risk on the behavioral intention to use digital ecosystem solutions.
H10. Gender of respondents mediates the effect of effort expectancy on the behavioral intention to use digital ecosystem solutions.
H11. Gender of respondents mediates the effect of performance expectancy on the behavioral intention to use digital ecosystem solutions.
H12. Gender of respondents mediates the effect of facilitating conditions on the behavioral intention to use digital ecosystem solutions.
H13. Gender of respondents mediates the effect of social influence on the behavioral intention to use digital ecosystem solutions.
H14. Gender of respondents mediates the effect of hedonic motivation on the behavioral intention to use digital ecosystem solutions.
H15. Gender of respondents mediates the effect of habit on the behavioral intention to use digital ecosystem solutions.
H16. Gender of respondents mediates the effect of trust on the behavioral intention to use digital ecosystem solutions.
H17. Gender of respondents mediates the effect of security on the behavioral intention to use digital ecosystem solutions.
H18. Gender of respondents mediates the effect of perceived risk on the behavioral intention to use digital ecosystem solutions.
H19. Experience of respondents mediates the effect of effort expectancy on the behavioral intention to use digital ecosystem solutions.
H20. Experience of respondents mediates the effect of performance expectancy on the behavioral intention to use digital ecosystem solutions.
H21. Experience of respondents mediates the effect of facilitating conditions on the behavioral intention to use digital ecosystem solutions.
H22. Experience of respondents mediates the effect of social influence on the behavioral intention to use digital ecosystem solutions.
H23. Experience of respondents mediates the effect of hedonic motivation on the behavioral intention to use digital ecosystem solutions.
H24. Experience of respondents mediates the effect of habit on the behavioral intention to use digital ecosystem solutions.
H25. Experience of respondents mediates the effect of trust on the behavioral intention to use digital ecosystem solutions.

H26. Experience of respondents mediates the effect of security on the behavioral intention to use digital ecosystem solutions.
H27. Experience of respondents mediates the effect of perceived risk on the behavioral intention to use digital ecosystem solutions.
H28. Brand attitude towards Sber mediates the effect of effort expectancy on the behavioral intention to use digital ecosystem solutions.
H29. Brand attitude towards Sber mediates the effect of performance expectancy on the behavioral intention to use digital ecosystem solutions.
H30. Brand attitude towards Sber mediates the effect of facilitating conditions on the behavioral intention to use digital ecosystem solutions.
H31. Brand attitude towards Sber mediates the effect of social influence on the behavioral intention to use digital ecosystem solutions.
H32. Brand attitude towards Sber mediates the effect of hedonic motivation on the behavioral intention to use digital ecosystem solutions.
H33. Brand attitude towards Sber mediates the effect of habit on the behavioral intention to use digital ecosystem solutions.
H34. Brand attitude towards Sber mediates the effect of trust on the behavioral intention to use digital ecosystem solutions.
H35. Brand attitude towards Sber mediates the effect of security on the behavioral intention to use digital ecosystem solutions.
H36. Brand attitude towards Sber mediates the effect of perceived risk on the behavioral intention to use digital ecosystem solutions.

Appendix 3. Descriptive statistics

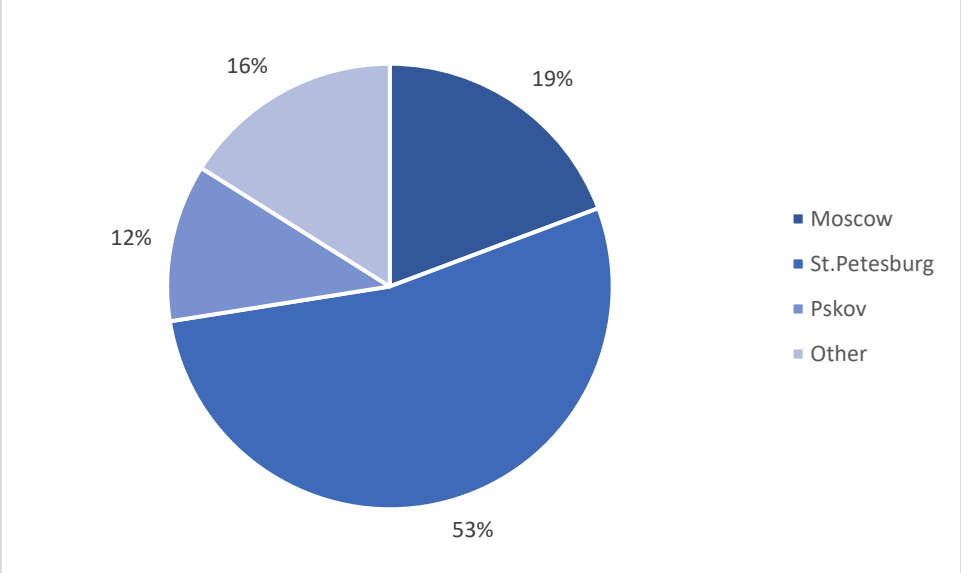

Figure 16. *Summary of places of living (compiled by the author)*

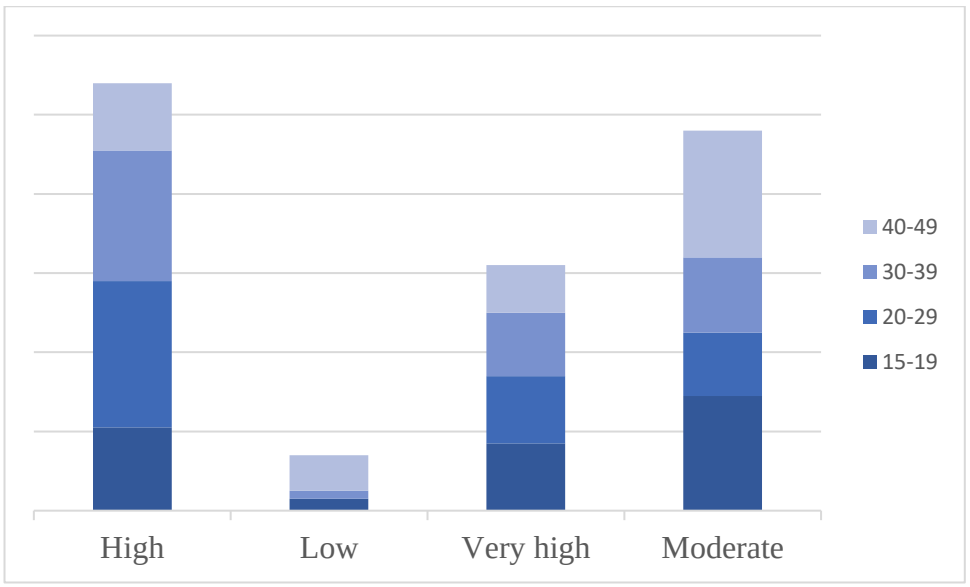

Figure 17. *The level of digital competence in respect to the age groups*

(compiled by the author)

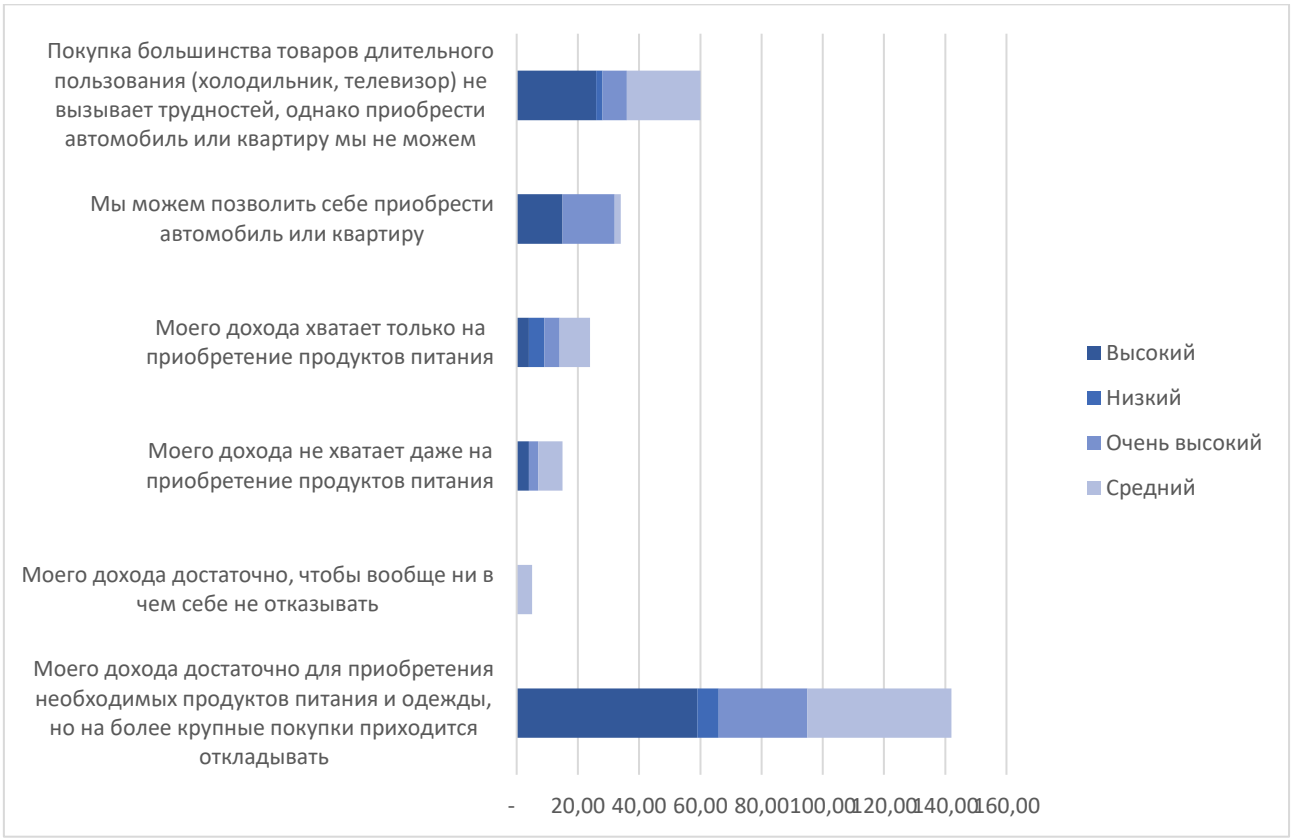

Figure 18. *The level of digital competence in respect to the income level*

(compiled by the author)

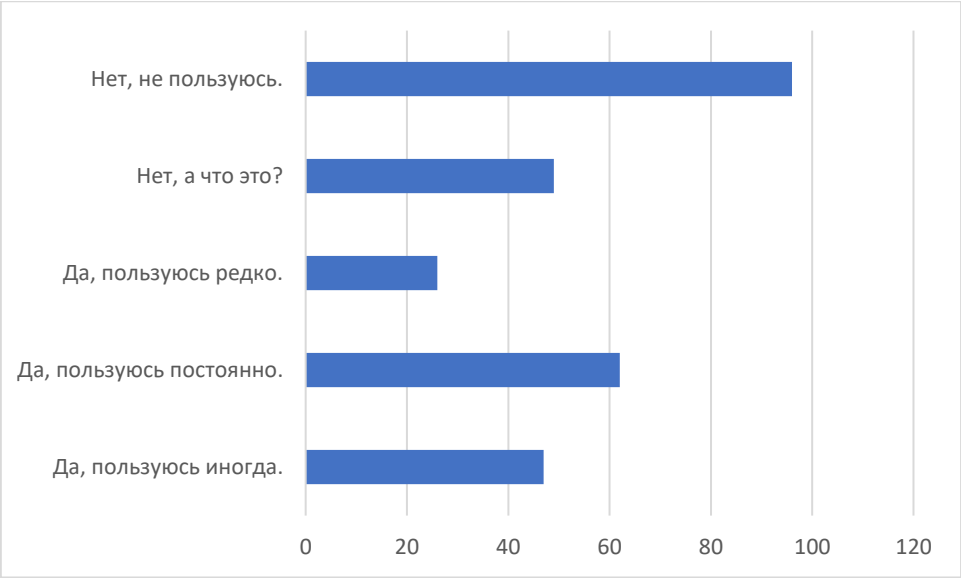

Figure 19. *The Sber ID experience (compiled by the author)*

Appendix 4. Correlation matrix

	DC	BI	PE	EE	SI	H	T&S	PR	EXP	AGE	BR_ATT	GEN	HM
BI	-0.038												
PE	0.058	0.643											
EE	0.338	0.379	0.505										
SI	0.038	0.668	0.497	0.308									
H	0.030	0.662	0.529	0.551	0.622								
T&S	0.017	0.675	0.621	0.500	0.534	0.655							
PR	-0.030	-0.277	-0.390	-0.283	-0.243	-0.100	-0.381						
EXP	-0.010	-0.285	-0.316	-0.334	-0.207	-0.263	-0.264	0.120					
AGE	-0.092	-0.124	-0.146	-0.132	-0.089	-0.138	-0.092	-0.150	0.198				
BR_ATT	0.067	0.505	0.493	0.380	0.450	0.486	0.702	-0.295	-0.472	-0.084			
GEN	0.085	-0.037	-0.103	0.014	-0.049	-0.041	-0.053	-0.007	-0.110	-0.000	-0.046		
HM	0.005	0.708	0.669	0.441	0.656	0.684	0.713	-0.192	-0.273	-0.128	0.485	-0.048	
FC	0.238	0.528	0.526	0.729	0.498	0.525	0.687	-0.362	-0.333	-0.094	0.453	0.021	0.553

Appendix 5. Model fit and quality output from WarpPLS 7.0.

Average path coefficient (APC)=0.174, P<0.001
Average R-squared (ARS)=0.173, P<0.001
Average adjusted R-squared (AARS)=0.168, P<0.001
Average block VIF (AVIF)=2.671, acceptable if <= 5, ideally <= 3.3
Average full collinearity VIF (AFVIF)=2.718, acceptable if <= 5, ideally <= 3.3
Tenenhaus GoF (GoF)=0.380, small >= 0.1, medium >= 0.25, large >= 0.36
Sympson's paradox ratio (SPR)=0.813, acceptable if >= 0.7, ideally = 1
R-squared contribution ratio (RSCR)=0.856, acceptable if >= 0.9, ideally = 1
Statistical suppression ratio (SSR)=1.000, acceptable if >= 0.7
Nonlinear bivariate causality direction ratio (NLBCDR)=0.688, acceptable if >= 0.7