DOCTORAL THESIS

FinTech Business Models and Their Linkages with Customers and Founders

Ekaterina Koroleva

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology, has not been previously submitted for doctoral or equivalent academic degree.

Ekaterina Koroleva

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FinTech ettevõtete ärimudelid ja nende seosed klientide ja asutajatega

EKATERINA KOROLEVA

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List of Publications

The list of author's publications, on the basis of which the thesis has been prepared:

I Laidroo, L., **Koroleva E.**, Kliber A., Rupeika-Apoga R., & Grigaliuniene Z. (2021). Business models of FinTechs – Difference in similarity? *Electronic Commerce Research and Application*s, *46*, 101034. (ETIS 1.1)

II **Koroleva E.** (2022). Attitude towards using FinTech services: Digital immigrants vs. digital natives. *IJITM International Journal of Innovation and Technology Management*, 2250029. (ETIS 1.1)

III **Koroleva E.**, Laidroo, L., & Avarmaa, M. (2021). Performance of FinTechs: Are founder characteristics important? *JEEMS Journal of East European Management Studies*, *26*(2), 306-338. (ETIS 1.1)

Author's Contribution to the Publications

Contribution to the papers in this thesis are:

I The author of the thesis is the second author of the article. The first author developed the conceptualisation and research methodology based on discussions with the co-authors. The article covers five countries. Each of the authors was responsible for carrying out a country-specific survey and collecting and analysing additional data from the assigned country. The author of the thesis performed this for Russia and also collected necessary data for the analysis of attributes of the FinTech environment in all the investigated countries and made modifications to the dataset of all countries for proceeding with the cluster analysis. The author of the thesis also reviewed and edited the final version of the article following discussions with co-authors.

II The author of the thesis is the sole author of the article and was responsible for developing the theoretical framework of the study, designing the questionnaire, collecting and analysing the data and presenting the results, conclusions and contributions.

III The author of the thesis is the first author of the article and was responsible for developing the conceptualisation and theoretical framework of research based on discussions with the co-authors. The article is based on the case of Russia. The author of the thesis prepared the dataset and presented the results, participated in the development and execution of the empirical analysis and wrote the conclusions and contributions.

Other Articles related to the topic of the thesis:

I Avarmaa, M., Torkkeli, L., Laidroo, L., Koroleva, E. (2022). The interplay of entrepreneurial ecosystem actors and conditions in FinTech ecosystems: An empirical analysis. *Journal of Entrepreneurship, Management and Innovation*, 18 (4), forthcoming. (ETIS 1.1).

II Bataev, A. V., & **Plotnikova (Koroleva), E. V.** (2019). Assessment of digital banks' performance. *Espacios*, *40*(20), 24. (ETIS 1.1)

III Efimov, E., **Koroleva E.**, & Sukhinina, A. (2021). Competitiveness in FinTech sector: Case of Russia. *IJTech International Journal of Technology*, *12*(7), pp. 1488–1497 (ETIS 1.1)

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V **Koroleva E.**, & Solgan L. (2019). Развитие финансовых технологий в банковском секторе России [Development of financial technologies in the banking sector of Russia]. *Российский экономический интернет-журнал*, *4*, 79. (ETIS 6.6)

VI **Koroleva E.**, & Solgan L. (2021). Экосистема в экосистеме: развитие финансовых технологий в России [Ecosystem in an ecosystem: development of financial technologies in Russia]. *Финансы и кредит*, *27* (5), 1116–1131. (ETIS 6.6)

Abbreviations

Explanations of abbreviations used in the thesis are in the table.

B2B	Business to business
B2C	Business to consumer
BMI	Business model innovation
C-TAM-TPB	Model combining technology acceptance model and theory of planned behaviour
MM	Motivational model
MPCU	Model of Personal Computer Utilisation
PAM	Partition around medoids
PEU	Perceived ease of use
PU	Perceived usefulness
RBV	Resource-based view of entrepreneurship
SCT	Social cognitive theory
SEM	Structural equation model
TAM	Technology acceptance model
TPB	Theory of planned behaviour
TRA	Theory of reasoned action
UTAUT	Unified theory of acceptance and use of technology

Introduction

The global financial crisis of 2008 exposed the failure of the traditional banking system (Saksonova & Kuzmina-Merlino, 2017). Many consumers lost confidence in the existing financial services and began to look for possible alternatives (Das et al., 2017). Their expectations of financial services also increased. Consumers were interested in obtaining permanent access to their savings, the possibility of instant transfers without physically visiting the offices of traditional financial institutions, etc. At the same time, the development of innovative technologies made it possible to create a more advanced approach to the provision of financial services (Romānova & Kudinska, 2016). Changing consumer attitudes and application of innovative solutions in the financial sector led to emergence of FinTech companies (FinTechs). These are high-tech companies that apply innovative solutions for the provision of financial services and may be either start-ups or existing companies.

FinTechs have experienced a rapid development, which is confirmed by the following facts. In 2021, total investment in FinTechs amounted to $91.5 billion, which is almost twice as much as in 2020 (Contreras, 2021). The number of FinTechs has constantly increased (Laidroo & Avarmaa, 2019); according to CB Insights (2021), 43 FinTechs had become unicorns (start-ups valued at over $1 billion) by the third quarter of 2021, representing a third of the total unicorns' births in the world. Moreover, the share of FinTech adopters nearly doubled from 2017 to 2019 (Ernst and Young, 2019). In 2020 COVID-19 restrictions also led to the mass adoption of FinTech services (White, 2021; Naz et al., 2022). Thus, FinTechs are expected to play a considerable role in shaping the global financial industry in the coming years and have been chosen as the focus of this thesis.

In light of the above-mentioned developments, the number of academic publications on FinTech has increased from year to year (Wang et al., 2022), tackling issues related to regulation, collaborations, and interaction within FinTech ecosystems, as well as the financial ethics, security, and infrastructure for the provision of FinTech services (Milian et al., 2019; Suryono et al., 2020; Tepe et al., 2022; Chelbi, et al., 2022). Still, a recent literature review by Iman (2020) shows that the extant research remains fragmented lacking multidisciplinary analysis of FinTech activities, especially considering the country-specific environment. As FinTechs are either in fierce competition with incumbents or support their key processes, their survival depends on their ability to provide a greater speed of service delivery, flexibility, and focus on the quality of customer service. Competitive advantages and performance are often achieved through the transformation of existing or the creation of new business models (Chatterjee, 2013; Chesbrough, 2010).

According to the recent studies (Cartwright & Allayannis, 2016; Haddad & Hornuf, 2019), FinTechs have innovative business models, allowing to achieve a competitive advantage over incumbents. As innovative business modes carry high risks, they can have either positive or negative consequences for the firm performance. Although many companies will be able to benefit from their business models and improve their performance (Karimi & Walter, 2016), others can perform extremely poorly and not meeting owners' expectations (Halecker et al., 2014; Garfield, 2011). Failure to meet the performance expectations can be explained for instance by ignoring the weaknesses in internal business processes or the specifics of the environment around the company (MacBryde & D'Ippolito, 2015). Nevertheless, empirical grounding for those claims seems to be lacking and the scientific literature about FinTech business models remains scarce (Kavuri & Milne, 2019). Thus, in terms of **the research gap**, a research-based, detailed study of the FinTech business models is required.

To date there exists no common understanding of the attributes of FinTech business models in the previous literature (Eickhoff et al., 2017; Lee & Shin, 2018; Liu et al., 2020). Some authors limit the FinTech business model to the types of services or products provided by hinTech companies (Lee & Shin, 2018; Liu et al., 2020). Others (Lee & Teo, 2015; Eickhoff et al., 2017) see the FinTech business model as a set of different attributes. The definition of these attributes remains important in understanding FinTech business models. FinTechs do not exist in a vacuum and their business models are based on external conditions like country-specific entrepreneurship environment (Tanda & Schena, 2019), changing technologies or customer preferences (Amit & Zott, 2015). Therefore, it is important to investigate FinTech business models in specific settings. In this thesis, **my aim** is to investigate the attributes of FinTech business models and their linkages with customers and founders in a specific country setting.

Changing customer preferences are identified as a driver of the development of FinTech business models (Teece, 2010). Understanding consumer attitudes towards FinTech services enables FinTechs to develop suitable business models and ensure profitability (Khatri et al., 2020). FinTechs provide their services to the following customer segments. First, FinTechs that offer their services to other financial companies are considered as being in the business-to-business (B2B) segment. Second, FinTechs that are orientated to selling their services to consumers (end-users) or non-financial companies belong to the business-to-consumer (B2C) segment. Third, companies servicing both B2B and B2C segments. The factors determining customer attitude towards using FinTech services depend on the segment the consumer occupies. Considering that the B2C FinTech segment is currently more developed than the B2B segment (Codrin, 2021) and the innovation services acceptance of the BC2 segment is required (McKinsey and company 2018), I focus on consumer attitudes towards using FinTech services (B2C segment).

Key resources are recognized as one of the most common business model attributes (Wirtz et. al, 2016). According to the recent literature review (Baima et al., 2020), human capital, as a key resource, is identified as a driver of organizational performance and value capture and it is also considered relevant for high-tech companies (Laužikas & Miliūtė 2020). According to the definition, FinTechs are high-tech companies. Therefore, greater attention in this thesis will be paid to human capital as a key resource. As FinTechs often refer to start-ups that have few employees in the beginning, the success of FinTechs mainly depends on founders. Therefore, in the thesis, I analyse the association of founder characteristics, as a business model attribute, with the performance of FinTechs.

In the thesis, I focus on Russia due to following reasons. In 2021, Russia emerged as a Top 20 country in the Global FinTech Index, having risen 13 positions from the previous year (Findexable, 2021). It has also been ranked in the Top 3 countries for applying innovative solutions in the financial sector (Kunn, 2021) and taken the third position globally in terms of FinTech services penetration (Ernst and Young, 2019). Previous empirical studies also have not covered Russian FinTech (Tepe et al., 2022). The above demonstrates that Russia is an interesting case for the investigation of FinTech business models. As it is possible to identify country-specific aspects of FinTech business models only by comparing these with business models prevalent in other countries, in addition to Russia, I also focus on the analysis of FinTech business models in the neighbouring countries – Estonia, Latvia, Lithuania, and Poland. The choice of the countries is explained by the following reasons. Firstly, they are in the lead in the Central and Eastern Europe in terms of count of FinTechs (Laidroo & Avarmaa, 2020). Secondly, in the Findexable rating (Findexable, 2021) the selected countries take positions from 4 (Lithuania) to 49 (Latvia), while Lithuania and Estonia are ahead of many of the highly developed Western European countries (e.g., Germany, France, Denmark). It allows recognizing them as rapidly emerging FinTech hotspots in Central and Eastern Europe. Also, these five countries provide a suitable background for a comparative analysis of FinTech business models and country-specific entrepreneurial environment due to some similarities as well as differences in the entrepreneurial environment.

Within the above-mentioned context, the answers to the following **research questions** are searched for:

RQ1: What are the main attributes of FinTech business models?

RQ2: What are the features of FinTechs' business models in Russia in comparison to those of the neighbouring countries?

RQ3: Which key factors can influence the positive attitude towards using FinTech services among different categories of consumers?

RQ4: Which key characteristics of a founder are associated with the superior FinTech performance?

The thesis consists of three articles. Article I provides answers to RQ 1 and RQ 2, Article II to RQ 3 and Article III to RQ 4.

Article I provides an investigation of the attributes of FinTech business models. Based on the literature review, it allowed highlighting the main attributes of FinTech business models. It was designed as a comparative analysis of FinTech business models in five countries including Russia, Estonia, Latvia, Lithuania, and Poland. The FinTech business model attributes were defined based on Osterwalder and Pigneur (2010) and Lee and Teo (2015). The analysis was based mainly on data gathered through an online survey of 199 FinTechs registered in the selected countries. The surveys were conducted between February 2019 and January 2020.

Article II relates to consumer attitudes towards FinTech services in Russia. From the perspective of the technology acceptance model (TAM; Davis, 1986), perceived usefulness, personal habits, perceived ease of use, level of digital and financial literacy were considered as key factors for identifying consumer attitudes. The analysis was based on a dataset of 3203 responses from ordinary consumers of financial services. The responses were collected between June and November 2019 through an online survey in Russia.

Article III investigates whether the key characteristics of the founder are associated with the superior performance of FinTechs. Such characteristics refer to the following: age, education and experience. The study was conducted from the perspective of a resource-based view of entrepreneurship (RBV; Barney, 1991). The association between the founder characteristics and the performance of FinTechs was investigated using data from 88 Russian FinTechs. The data was gathered through SPARK, a Russian database, and partly hand-collected from the social media platforms. In this article, the financial data and founder characteristics of FinTechs for 2016 and 2017 are used.

The thesis makes the following **theoretical contributions**.

First, it identifies the key attributes of FinTech business models by adopting the Osterwalder and Pigneur’s (2010) business model canvas to the FinTech taxonomies created in studies by Eickhoff et al. (2017) and Iman (2020) (Article I).

Second, it adopts TAM in the context of using FinTech services by adding new factors, namely personal habits and level of digital and financial literacy, to the model (Article II).

Third, it expands the application of consumers’ classifications proposed by Prensky (2001) and supports the differing attitudes of digital natives and digital immigrants in relation to FinTech services (Article II).

Fourth, it expands RBV by recognising the founder’s education and experience as difficult-to-imitate resources for FinTechs (Article III).

The thesis makes the following **empirical and practical contributions**.

First, it adds new empirical evidence concerning the emerging FinTech market of Russia (Articles I, II and III).

Second, it adds comparative evidence for FinTech business model attributes in Russia in comparison to those of Estonia, Latvia, Lithuania and Poland (Article I).

Third, it highlights the key factors preventing the acceptance of FinTech services by digital natives and digital immigrants (Article II).

Fourth, it demonstrates the relevance of the founder’s specialised knowledge and a properly selected team of experts for establishing a successful FinTech (Article III).

The thesis consists of a cover paper and three articles that are part of the thesis. The cover paper consists of four sections. Section 1 provides an overview of the theoretical and empirical framework of the study. Section 2 focuses on the research methodology; in this chapter, methodological choices, data collection principles and the research process are discussed. The main results and discussions of the research are presented in Section 3. The final section analyses theoretical and practical contributions, the limitations of the results and further possible directions for research.

1 Theoretical and Empirical Framework

1.1 The Definition of FinTech

Although the term FinTech is actively used in the academic and professional world, there is no agreement on its definition. Moreover, the spelling of the term can differ between ‘fintech’, ‘Fin-Tech’, ‘FinTech’ and ‘Fin-tech’ (Milian et al., 2019). FinTech is derived from the words finance and technology. In this dissertation, both terms are considered to be of equal relevance, which is reflected by the choice of spelling being ‘FinTech’. Moreover, such spelling appears the most popular and is used by most researchers (Wójcik, 2020). The analysis of the definitions of FinTech is based on a literature review. The author of the thesis collected frequently cited articles (cited more 50 times) from the Scopus database from 2015 to 2020 and reports of global organisations using the following keywords: ‘definition of FinTech’ or ‘FinTech is’. As a result, an overview of the FinTech definitions is provided in Table 1.

Table 1. Overview of FinTech Definitions.

№	Author	Definition
1	Arner et al. (2015, p. 22)	‘The use of technology to deliver financial solutions.’
2	Deloitte (2016, p. 6)	‘IT solutions dedicated to the financial sector, covering software technologies provided by any established or emerging entity.’
3	Vasiljeva and Lukanova (2016, p. 26)	‘An industry oriented toward arranging financial services for private individuals and industries with the aim of providing customer-oriented solutions in the most efficient way and at the lowest cost possible, ensuring this via innovation and technology.’
4	Dorfleitner et al. (2017, p. 5)	‘Companies or representatives of companies that combine financial services with modern, innovative technologies (…) offer[ing] Internet-based and application-oriented products.’
5	Nicoletti (2017, p. 12)	‘Initiatives, with an innovative and disruptive business model, which leverage on ICT in the area of financial services.’
6	Schueffel (2017, p. 45)	‘New financial industry that applies technology to improve financial activities.’
7	Varga (2017, p. 23)	‘Non- or not fully regulated ventures whose goal is to develop novel, technology-enabled financial services with a value-added design that will transform current financial practice.’
8	Azarenkova et al. (2018, p. 229)	‘Technological innovations in the field of financial services.’
9	Gimpel and Rau (2018, p. 247)	‘The usage of digital technologies such as the Internet, mobile computing, and data analytics to enable, innovate, or disrupt financial services.’
10	Leong and Sung (2018, p. 75)	‘A cross-disciplinary subject that combines Finance, Technology Management and Innovation Management.’

№	Author	Definition
11	World Bank Group (2018, p.7)	‘The advances in technology that have the potential to transform the provision of financial services spurring the development of new business models, applications, processes, and products.’
12	Van Loo (2018, p.238)	‘Innovative technology that aims to operate traditional financial services using computer programs and information technology.’
13	Bank of Russia (2018)	‘the actors, from specialised small companies to large financial institutions, that can provide financial services using innovative technologies.’
14	Chen et al. (2019, p. 2066)	‘Digital computing technologies that have been applied—or that will likely be applied in the future—to financial services.’
15	Das (2019, p. 981)	‘Any technology that eliminates or reduces the costs of financial intermediation.’
16	Ernst and Young (2019, p. 5)	‘Organizations that combine innovative business models and technology to enable, enhance and disrupt financial services.’
17	Milian et al. (2019, p. 2)	‘Companies that are using technology to operate outside traditional business models for financial services, seeking to change the way these services are offered…, using communication, the internet and the automated processing of in- formation.’
18	Thakor (2020, p. 1)	‘The use of technology to provide new and improved financial services.’
19	Wójcik (2020, p. 3)	‘A set of innovations and an economic sector that focus on the application of recently developed digital technologies to financial services.’
20	Financial Stability Board (28.06.2021)	‘Technologically enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services.’

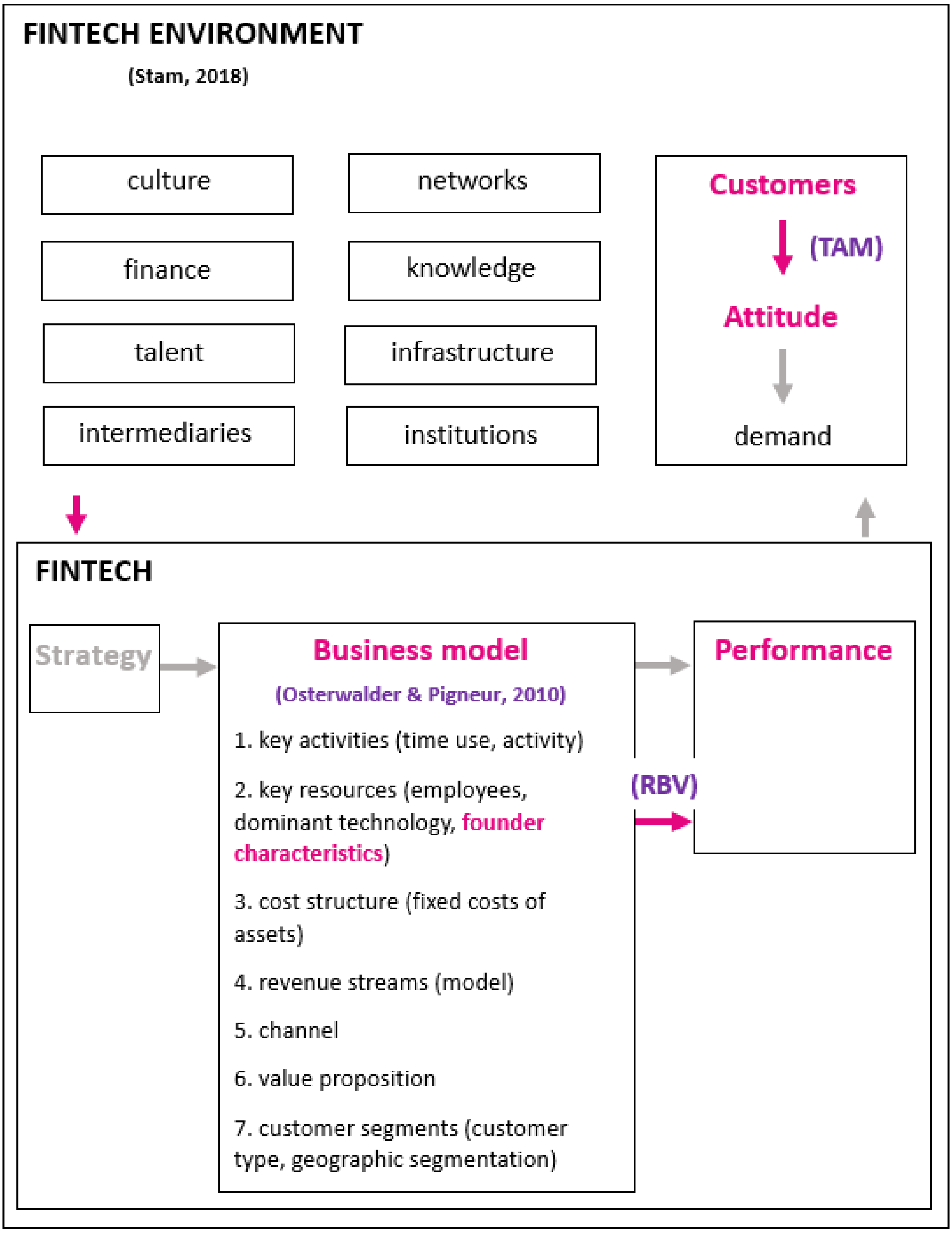
Source: Compiled by the author.

Based on the definitions of FinTech presented above, it is possible to conclude that there has been no significant change in the perception of the term over the last six years. The authors provided definitions of FinTech mainly from three positions: (a) innovative technology solutions (1, 2, 5, 8–12, 14, 17, 19, 20); (b) a set of companies (4, 7, 13, 15, 16) and (c) the whole industry (3, 6, 18).

In the framework of the thesis, FinTechs are recognised as the ‘companies that combine modern technologies (e.g. cloud computing, mobile Internet) to provide financial services (e.g. payments, lending)’ (Article III, Koroleva et al., 2021, p. 303). It can be ‘either start-ups or established companies with varying capabilities for either disrupting or contributing to the provision of traditional financial services’ (Article I, Laidroo et al., 2021, p. 1).

1.2 Theoretical Framework of the Study

In this sub-section, I construct a theoretical framework of the research concept based on the linkages of FinTech business models with other elements of the system in a specific country setting (see figure 1).



Source: Compiled by the author.

Figure 1. The Theoretical Basis of the Research Concept.

The elements on Figure 1 which are in pink color refer to those that are the focus of this thesis. Text in violet presents the theoretical frameworks or perspectives used to investigate respective aspects.

There is no common approach for identifying the attributes of FinTech business models in the previous literature (Eickhoff et al., 2017; Lee & Shin, 2018; Liu et al., 2020; Torriero et al., 2022). The business model of the company is often perceived as the art of doing the business (Zott et al., 2011). It should reflect the relevant activities of a company, how it creates and evolves value-added (Wirtz et al., 2016). That is why the business model framework is more complex than just the main activity of the companies. Therefore, I consider the attributes of FinTech business models from the perspectives of the most comprehensive framework - Osterwalder and Pigneur (2010) model canvas.

According to Casadesus-Masanell & Ricart (2010), companies exist in a certain environment and achieve their competitive advantage through their business models. As a significant portion of FinTech is entrepreneurial (Alaassar, Mention, & Aas, 2021), I consider FinTech environment from position of entrepreneurial ecosystem. It is based on Stam (2018) model because it provides the most comprehensive view of an environment, including institutional arrangements and resource endowment elements. This model consists of 10 attributes: formal institutions, entrepreneurship culture, networks, physical infrastructure, finance, leadership, talent, new knowledge, demand and intermediate services. FinTechs identify their innovative business models based on the specific country environment. Thus, I concentrate on studying the FinTech business models mainly in the context of Russia.

Russia is located in a relatively large territory that is divided into regions and has the population 24 times higher than the aggregate population of Estonia, Latvia, and Lithuania and 4 times higher than in Poland. The GDP in Russia is three times higher than in Poland (Laidroo et al., 2021). The vast territories and uneven distribution of the population create difficulties in managing the regions and ensuring their balanced development. It is reflected in the rather low government efficiency (Fedosov & Paientko, 2018). According to Teorell et al. (2020), the level of corruption is also relatively high and law enforcement is quite weak in the country. It is also reflected in non-progressive regulation in the case of FinTech (Ponomareva et al., 2020).

The level of the infrastructure development, including the IT industry, is comparable with the mean-European level. On a scale of 1 (worst) to 7 (best), Russia scores 5 points compared to the European mean of 5.45 (Laidroo et al., 2021). In the case of entrepreneurial activity, a relatively low value of the indicator, reflecting the number of business registration per 1000 people (3.3 versus 5.68 mean in the EU) can be observed (Barinova et al., 2018).

To ensure the consideration of the specific country environment of FinTech business models, I compare the FinTech business models in Russia with neighbouring countries – Estonia, Latvia, Lithuania, and Poland. The selected countries appeared suitable for performing the analysis due to the FinTech environment characteristics. On one side, these countries are located in the post-Soviet space, have common boundaries and have developed cross-country trade relations. On the other side, they have differences in size, entrepreneurial activity, financial development and infrastructure. This could potentially influence the business models of FinTechs located in the respective countries. In the framework of the thesis, I focus on the Osterwalder and Pigneur (2010) and Lee and Teo (2015) frameworks in analysing the specific country environment of FinTech business models.

The appearance of FinTechs was mostly explained by the application of innovative technologies (Brandl & Hornuf, 2020). These two reasons led to ambiguous consequences. From one side, the expectations of customers increased. They wanted to get financial services at lower commissions, faster transaction speeds and greater availability (Arner et al., 2018; Mohan, 2020; Papadimitri et al., 2021). On the other hand, some customers were unprepared that such financial services require certain skills and experience (Saksonova & Kuzmina-Merlino, 2017). FinTechs use innovative technological solutions to provide financial services. It eliminates middlemen and requires customers to have financial and digital literacy to perform the operations (Tsai, 2019). Thus, the customers' expectations and background identify their attitudes and, accordingly, demand for using FinTech services (Ryu, 2018). In turn, demand as an attribute of FinTech environment has a significant impact on the development of FinTechs' innovative business models (Nakashima, 2018). In the framework of the thesis, I mostly focus on the first part of associations and analyse the determinants, influencing attitudes towards using FinTech services. It allows revealing the background of certain categories of customers and the influence of these background characteristics on their attitudes. As explained in the introduction, I consider the B2C FinTech segment.

The perceptions and attitudes of consumers from different generations are influenced by the different events that they have experienced during their lifetime (Zeithaml et al., 2002). The current generation gap has been widening (Elena-Bucea et al., 2021) since the end of the 20th century. It can be explained by the appearance of new communication channels (Deal, 2007) and changing ways of socialising (Helsper and Eynon, 2010). Depending on attitudes towards using the new information technology, two categories of people, digital natives and digital immigrants, have been distinguished (Prensky, 2001). Digital natives are people born after the digital revolution. For them, receiving information through information systems is the usual means of communication. Digital immigrants are people for whom information systems are not an obligatory part of their life (Kirk et al., 2015). The differences in the attitudes of the two groups have been observed in the context of digital advertisements, tablet use, online medicine and social reliance (Haluza et al., 2017; Kirk et al., 2015; Ransdell et al., 2011; Reith et al., 2020; Vaportzis et al., 2017). Considering the above, one may assume that the differences in attitudes between digital immigrants and digital natives towards using FinTech services could similarly emerge. The differences in attitudes between identified categories of consumers is analysed from the perspectives of the technology acceptance model (TAM), which has been applied in previous empirical studies, focusing on the consumers' willingness (Jiwasiddi et al., 2019; Stewart & Jürjens, 2018).

Most studies on business models also aim to relate the concept to the firm strategy or performance (da Cruz Caria, 2017). Nevertheless, there is also no common understanding of the association between a firm strategy, business model, and performance (Zott, Amit, & Massa, 2011). According to Zott & Amit (2008), companies having the same customer type and similar product-market strategies can employ different business models. They perceive the business models and strategies as complements. On the contrary, Richardson (2005) highlights that business models explain how the company executes its strategy. The statement is also supported by a number of empirical studies (Casadesus-Masanell & Ricart, 2010; Heider et al., 2021; Shafer et al., 2005), where business models are recognised as the reflection of the companies' strategies. Also, the business model of the company may play a significant role in explaining the company's performance. Therefore, a business model can be the source of competitive advantage

(Markides & Charitou, 2004). Moreover, according to Morris et al. (2005), the innovations in business models lead to a firm's superior performance.

Understanding the complexity of the business model framework, its relations with strategies and performance, I mainly focus on assessing the impact of founder characteristics, as key resources, on FinTech performance from positions of resource-based view of entrepreneurship (RBV). Companies have different types of resources: physical, organisational, human, etc. According to Peteraf (1993), human capital is a relevant source, ensuring superior company performance. The role of human capital differs across different industries and types of companies. While RBV was developed for established companies, it has also been applied in the context of new ventures (Kellermans et al., 2016; Marullo et al., 2018). High-tech companies are characterised by a more complex business environment that requires specific knowledge and skills from humans. Often most FinTechs can be considered new ventures which require high-quality human capital. As human capital covers both owners and employees (Kellermans et al., 2016), this thesis focuses on the influence of founders' characteristics on the performance of FinTechs.

Detailed description of the selected theoretical approaches is provided in the following sub-sections.

1.2.1 Business Model Attributes

The influence of FinTechs on the financial sector's development depends heavily on their business models. The literature review by Wirtz et al. (2016) revealed nine main business model attributes found in the business model literature: strategy, resources, network, customers, market offering, revenues, service provision, procurement and finances.

The framework by Hedman and Kalling (2002) covers six of the nine attributes of business models and focuses more specifically on how information and communication technologies create economic value in a business. Nevertheless, the model ignores revenue and cost aspects and does not consider generated and incurred cash flow. Innovative solutions in the financial sector require significant investment that should not only pay off but also make a profit for the company in the long term. As the activities of FinTechs are connected with high risks and sufficiently high amounts of investment (IMF, 2019); it is important to analyse their revenue and costs within the framework of the business model. Due to these shortcomings, the model proposed by Hedman and Kalling (2002) is not well suited for FinTechs.

The business model framework proposed by Wirtz (2001) demonstrates the value chain of insurance companies from the position of applying modern information and communication technologies. Nevertheless, the model ignores networks. Shafer et al. (2005), when analysing the possible problems associated with the creation and use of business models, emphasised that changes in the value network lead to inappropriate business models. Due to high competition in the FinTech sector (Contri & Galaski, 2017), partnerships and other networks may not be constant. This highlights the importance of networks as an attribute of the business models and makes the business model framework proposed by Wirtz (2001) unsuitable for FinTechs.

In comparison to other business model frameworks, that of Osterwalder and Pigneur (2010) is recognised to be among the most comprehensive. It includes seven potential business model attributes of the nine identified by Wirtz et al. (2016). Although the Osterwalder and Pigneur (2010) model ignores strategy and procurement, which are rarely used in business model frameworks[1], it is commonly used in empirical research (Foà, 2019; Jocevski et al., 2020; Specht & Madlener, 2019). In this study, Osterwalder and Pigneur (2010) model is complemented with attributes that have been highlighted as important attributes in the context of FinTech by Eickhoff et al. (2017) and Iman (2020).

Eickhoff et al. (2017) identified six attributes of FinTech business models: customers, delivery channel, dominant technology, product/service offering, revenue streams and value proposition, and. These attributes are similar to those in Osterwalder and Pigneur's (2010) framework except for the dominant technology. Iman (2020) highlighted seven attributes of FinTech business models: customer, key actors, service offered, subsector, underlying technologies, contexts and industries. Iman (2020) also highlighted technologies as an attribute of FinTech business models. The literature remains rather contradictory regarding the attribution of dominant technology either to the inner or external factors of business models. For example, Clauss (2017) relates technology to an external factor that affects business model innovations. In the context of FinTech, the dominant technology is identified through the provision of the FinTech service, which is why I add it as a key resource to Osterwalder and Pigneur (2010) framework.

After modifications, the FinTech business models are represented by the following attributes: key activities, key partnerships, key resources (including dominant technology), value proposition, channels, customer segments, cost structure and revenue streams. Customer relations, which were not covered by Iman (2020) and Eickhoff et al. (2017), are included as additional attributes of the FinTech business models. In the thesis, it is considered also the alternative view of FinTech business models proposed by Lee and Teo (2015).

A country-specific environment identifies the business model's development and features (Clauss, 2017). That is why, I propose the following hypothesis (H1): the features of FinTechs' business models depend on the entrepreneurial environment.

1.2.2. Technology Acceptance Model

According to a number of theories and frameworks (Alexandre et al., 2018), users' attitude affects their subsequent acceptance of a service (or product). User acceptance and confidence are crucial for the further development of any company, including its business model (Ahn et al., 2007; Taherdoost, 2018; Tsang et al., 2004). Therefore, companies are interested in understanding factors that drive users' attitudes towards a service (or product).

To explain consumer acceptance, a number of frameworks have been developed. Most consumer acceptance theories include attitudes towards using services (or products) and suppose that this factor is significant (Li, 2010). In the course of the literature review, I analysed the existing consumer acceptance frameworks and included those that suggested the importance of attitudes towards using services (or products). The results are presented in Table 3.

[1] Examples of inclusion of strategy and procurement in business models are proposed by Hedman and Kalling (2002), Wirtz (2001) and Yip (2004).

Table 2. Consumer Acceptance Theories, Including Attitudes Towards Using Services (or Products) As Key Determinant.

№	Theory	Authors	Key determinants
1	Theory of reasoned action (TRA)	Fishbein and Ajzen (1977)	- Attitude of consumer - Subjective norms of society
2	Theory of planned behaviour (TPB)	Ajzen (1991)	- Attitude of consumer - Subjective norms of society - Perceived behavioural control
3	Social cognitive theory (SCT)	Bandura (1986)	- Personal factors (including attitude) - Behaviour - External environment
4	Technology acceptance model (TAM)	Davis (1986)	- Perceived usefulness; Perceived ease of use → Attitude of consumer
5	Model combining technology acceptance model and theory of planned behaviour (C-TAM-TPB)	Taylor and Todd (1995)	- Perceived usefulness; Perceived ease of use → Attitude of consumer - Subjective norms of the society - Perceived behavioural control
6	Technology acceptance model -2 (TAM2)	Venkatesh and Davis (2000)	- Voluntariness; Experience; Subjective Norm; Image; Job relevance; Output quality; Result demonstrability → Perceived usefulness → Attitude of consumer - Perceived ease of use → Attitude of consumer - Social norms → Attitude of consumer
7	Unified theory of acceptance and use of technology (UTAUT)	Venkatesh et al. (2003)	- Performance expectancy (attitude) - Effort expectancy - Social influence - Facilitating conditions
8	Model of Personal Computer Utilisation (MPCU)	Thompson et al. (1991)	- Job fit - Complexity - Social factors - Long-term consequences - Affect towards use (attitude) - Facilitating conditions
9	Motivational model (MM)	Davis et al. (1992)	- Computer playfulness; Enjoyment → Intrinsic motivation (attitude) - Perceived usefulness; Perceived ease of use; Subjective norm → Extrinsic motivation (attitude)

Source: Compiled by the author, based on Venkatesh et al. (2003), Kim and Crowston (2011) and Taherdoost (2018).

As can be seen from the Table 2, TRA assumes that consumers' acceptance is identified by their attitude towards using a service or product and the subjective norms of society. TBP is a modified theory of TRA that considers perceived behavioural control as an additional factor that influences consumer acceptance of a service or product. According to Davis et al. (1992), TRA and TBP are general theories that require specifications. Moreover, these belong to rational choice theories and assume that humans behave 'in good faith'. SCT, on the other hand, is based on the dynamic interplay between personal factors, behaviour and environment. In a critical review, Sana'a (2016) showed that the degree of influence of personal factors, behaviour and the environment on an individual's behaviour is unclear. Also, the SCT theory is more commonly used in education and motivation (Carillo, 2010). Receiving FinTech services by consumers involves the use of information systems (Gomber et al., Nanggala, 2020). Therefore, using TRA, TBP and SCT, which ignore the features of information systems acceptance, would be impractical.

The continuous development of information leads to the appearance of new, more advanced models. TAM is one of the first theories accounting for the acceptance of information systems. It identifies two main factors perceived usefulness (PU) and perceived ease of use (PEU) that influence attitudes towards using technologies (in this case, FinTech services) and accordingly its acceptance by consumers. PU reflects consumers' assessment of service expediency (Li & Huang, 2009). PEU reflects the efforts made by consumers to get service; if the using service requires less effort, it leads to a positive consumer attitude towards using that service (Krishanan et al., 2015). C-TAM-TBP, TAM2 and UTAUT are different modifications of TAM that enter additional factors into the primary model.

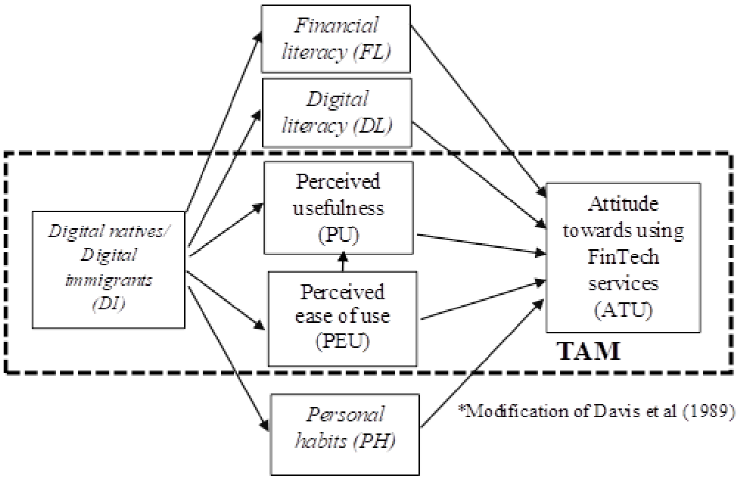
MPCU is based on Triandis's (1979) theory of interpersonal behaviour. The main restriction of the model is the voluntary use of services. In reality, this assumption is not always fulfilled (Alkhwaldi & Kamala, 2017). Moreover, the model has low explanatory power (Thompson et al., 1991).

MM explains the acceptance of information systems from the position of the extrinsic and intrinsic motivation of consumers. The model was recognised as useful for understanding information technology acceptance (Davis et al., 1992). Nevertheless, the model is based on the psychological aspects of consumers and ignores the technology factors for the successful implementation of information systems (Alomary & Woollard, 2015). FinTech services have a number of advantages in comparison with traditional banking services that may play a key role in consumers' attitudes and acceptance of services and should be accounted for in the model.

Based on the results of the literature review, the author of the thesis considered TAM to be the most suitable framework due to the following reasons. First, it enables the consideration of both the technological and psychological aspects of using FinTech services (Robles-Gómez et al., 2021). Second, TAM model is also expected to provide high explanatory power (Arvidsson, 2014; Chi, 2018; Surendran, 2012). Third, TAM has proven its good applicability in the financial sector (Ahmad, 2018; Riza & Hafizi, 2020; Sumerta & Wardana, 2018).

According to the primary technology acceptance model, two factors (PU and PEU) influence attitudes towards using FinTech services and acceptance by consumers.

Nevertheless, the development of the FinTech services market requires consumers to be more advanced and to have a financial and digital background (Abubotain & Chamakiotis, 2021; Yoshino et al., 2020). Also the FinTech services market requires consumers to change their habits to be more digitally-oriented (Liu, 2019). Considering the specific features of FinTech services, I have modified the primary model by adding digital-oriented personal habits, digital and financial literacy (see Figure 2).



Source: Article III.

Figure 2. Modified Technology Acceptance Model.

The differences in attitudes towards using FinTech services are analysed from positions of digital immigrants and digital natives. According to Vaportzis et al. (2017), digital immigrant are afraid to use the new information services and are slower in adopting them. Moreover, they are also skeptical about entering personal data into information systems (Kirk et al., 2015). Therefore, I formulate the hypothesis (H2): Digital natives rate the perceived ease of use of FinTech services more highly than digital immigrants.

Digital natives are technically savvy generation, interested in information services meeting their expectations and requirements (Chung et al., 2010). Digital immigrants on the contrary perceive information technologies as complex systems, that are difficult to understand (Meiring, 2013). Therefore, the following hypothesis (H3) is formulated: Digital natives rate the perceived usefulness of FinTech services more highly than digital immigrants.

Digital natives are perceived as early adopters of innovation technologies (Lei, 2009). Digital immigrants prefer to get information about digital natives' experience and only then decide to use the service (Blackburn, 2011). Based on the above, I propose the following hypothesis (H4): Digital natives have stronger habits orientated towards information systems than digital immigrants.

The digital and financial literacy of consumers can affect their attitude towards using FinTech services (Udo, Bagchi, & Kirs, 2010). On one side, digital natives were growing up with frequent use of digital technologies (Filho et al., 2021). On the other side, digital natives lack basic financial knowledge (Lusardi & Mitchell, 2017). That is why, I propose the hypotheses: Digital natives rate their level of digital literacy as higher than that of digital immigrants (H5a). Digital immigrants rate their level of financial literacy as higher than that of digital natives (H5b).

1.2.3. Resource-Based View of Entrepreneurship

I analyse the association between characteristics of founder and FinTech performance from the perspective of RBV. The choice of this theory is based on a literature review conducted by the author of the thesis. The literature review covering Scopus database articles from 2018 to 2020 was based on the following keywords: 'human capital' and 'firm performance'; 'human capital' and 'company performance'; 'founder characteristic' and 'firm performance'; and 'founder characteristic' and 'company performance'. The author of the thesis manually compared the publications for alignment with the research topic and excluded inappropriate ones. As a result, 117 publications were identified. The results of the analysis of the publications' theoretical background are presented in Table 3.

Table 3. Overview of the Organisational and Management Theories in Human Capital Studies in the Scopus Database Over the Period 2018–2020.

№	Theoretical background	Number of articles, based on the theoretical background		
		2018	2019	2020
1	Human capital theory	10	12	18
2	Resource-based view	10	11	17
3	Knowledge-based view	3	1	4
4	Dynamic capabilities view	0	1	2
5	Resource dependency theory	2	1	1

Source: Compiled by author.

The human capital theory was originally developed by Becker (1962) and Rosen (1976) to estimate the distribution of employees' income in accordance with their investments in human capital. According to Becker (1964), human capital is individuals' knowledge and a set of skills that are gained through investments in schooling, on-the-job training and other types of experience. Many articles (Lajili et al., 2020; Nafukho et al., 2004; Unger et al., 2011) have supported human capital theory and tested the influence of its elements (education, experience, etc.) on entrepreneurial success. The theory focuses mainly on individuals and their investments in human capital.

The RBV emerged as a new paradigm of strategic management during the 1980s and 1990s (Barney, 1991; Prahalad & Hamel, 1997; Wernerfelt, 1984). RBV suggests that a company's resources are the main determinants of its performance. A company can achieve a sustainable competitive advantage if it is able to utilise rare, costly to imitate and non-substitutable resources and capabilities (Barney, 1991). RBV has two main assumptions: heterogeneous distribution of resources or capabilities and their immobility. Heterogeneous distribution means that companies have different sets of resources, skills and capabilities and accordingly react differently to changes in the external environment. As a result, companies formulate different strategies to compete with one another. In this regard, companies endowed with superior resources or capabilities tend to have a competitive advantage (Darwish et al., 2016). Immobility of resources refers to the inability of resources or capabilities to move freely from company to company at least over the short term (Sharma & Erramilli, 2004).

The knowledge-based view is an extension of the RBV. It suggests that knowledge is special strategic resource of a company and the main determinant of its performance (Curado & Bontis, 2006). The theory perceives the knowledge-based resources as difficult-to-imitate ones that allow to achieve the sustainable competitive advantage to company (Grant, 2003). Nevertheless, the knowledge-based view ignores other characteristics of individuals.

The dynamic capabilities view was developed by Teece et al. (1997) to overcome the disadvantages of RBV. It studies the company's ability to respond to the rapidly changing environment. While the static RBV emphasises the value of resources, the dynamic capabilities view explains the changes in valuable resources (Arend & Bromiley, 2009). That is why, the theory is mainly based on the processes of the company, which help it to operate in dynamic markets and manipulate resources into new value-creating strategies (Cavusgil et al., 2007).

The resource dependency theory is suggested by Pfeffer and Salancik (1978). It analyses the relationship between a company's behaviour and the external environment. The theory argues that the behaviour of company depends on the resources within their environment to survive and compete (Yeager et al., 2014).

According to the table 3, two theories – human capital theory and RBV – are the most commonly used in publications over the three years. Knowledge-based view and Dynamic capabilities are the extensions of the RBV, based on certain resources and processes. Resource dependency theory explains the companies' behaviour from positions of external resources. In the context of this thesis, RBV provides a more suitable background due to the following aspects: founder characteristics are direct internal resources of the company; founder characteristics cover not only individuals but also companies, which have initially a different set of resources.

FinTechs deal with the implementation of innovation and information systems. To ensure the competitiveness of the company in the market, the founder should be flexible, open to new technologies and ready to analyse a large amount of information. There are contradictory views on how age impacts on acceptance of technologies. From one side, older founders may face problems in perceiving new technologies and decisions (Cai & Stoyanov, 2016; Hambrick & Mason, 1984; Salthouse, 2009). They may need additional skills and knowledge to adopt them (Kenny & Rossiter, 2018). On the other side, there is a perception that the older generation is more experienced in doing business (Pitkänen et al., 2014; Singh & DeNoble, 2003) and are able to have a more successful business than young people. Considering, that FinTechs requires strong IT skills, I suppose the following hypothesis (H6): FinTechs with younger founders perform better than FinTechs with older founders.

According to Herrmann and Datta (2002), educated entrepreneurs have the necessary base of knowledge and skills, that allow making appropriative decisions and mastering new information. Škudienė et al. (2010) identify that education in business management provides a better start point for entrepreneurs. As the technological component of FinTech is a competitive advantage in comparison with incumbents, I propose the hypothesis (H7): FinTechs with founders possessing IT education perform better than other FinTechs.

Experience gives the founder the necessary background to establish a successful business. The experience allows actors understanding the specifics of industry, analysing the market and determining its needs (Cooper et al., 1994). Also, the experience may be linked to many business contacts, which help to develop the new venture (Granovetter, 2002). FinTechs are associated with the financial sector. Thus, the hypothesis (H8) is the following: FinTechs run by founders with experience in banking perform better than other FinTechs.

2 Methodology

2.1 Research Design

The methodological choices are grounded in the general idea of positivism. It assumes that there is only one objective reality, which is the same for each person (Ryan, 2018). Positivism recognises the method of hypothesis testing as a general approach for generating and validating knowledge of reality (Coolen, 2012). Positivism focuses mostly on the identification of relationships between factors. To accept the result requires conducting a study on a large sample size that better reflects the nature of the phenomena (Picho et al., 2016).

The aim of the thesis is to investigate the attributes of FinTech business models and their linkages with customers and founders in a specific country setting. FinTechs have innovative business models, that may have a positive or negative impact on their performance. Also, country-specific entrepreneurship environment and customer preferences may influence FinTechs' innovative business models. Before analysing how and why these linkages exist, it is necessary to determine the presence of these links based on a large number of observations. The quantitative research methods answer the question what? (Onwuegbuzie & Leech, 2006) and allow identifying the links between different indicators. Also during the last seven decades, quantitative research methods have been dominant in finance (Dewasiri & Yatiwella, 2016). Thus, quantitative research methods ensure the objectivity of research, contribute to the main idea of positivism and the aim of the thesis. One may alternatively consider the use of qualitative methods to provide further insight but as the proposed research questions are better suited for quantitative analysis, the qualitative methods are not employed in this thesis.[2]

The objective reality can be explored by formulating hypotheses and empirical studies (Krauss, 2005). Hypotheses to be tested in this thesis were presented in section 1. The empirical study in the thesis is based on rather large samples, collected using different questionnaires and existing databases. The choice of the data collections is restricted by the short history of FinTech and shortage of ready-made databases. For this reason, questionnaires are used in addition to existing databases. To avoid the bias of the sample, I test its representativeness by using the chi-square test statistic. Still, the short timeframe covered in the dataset containing financial indicators on FinTechs in Russia, limits the possibilities to generalise the results.

The empirical study was designed as a three-stage process. The first stage concentrated on investigating the similarities and differences in business model attributes in Russia and neighbouring countries by applying non-hierarchical cluster analysis (RQ2). The second stage investigated consumer attitudes towards the use of FinTech services by structural equation modelling (SEM; RQ3). The final stage concentrated on univariate tests and regression analysis to examine the association between founder characteristics and FinTech performance (RQ4).

The analysis of the linkages of FinTech business models with customers and founders leads to multilevel research. Multilevel research is more complex and reflects reality (Diez-Roux, 2000; Molina-Azorín et al., 2020). Moreover, the results on one level add

[2] It is important to note that the author has employed qualitative methods in the context of FinTech research in Avarmaa et al. (2022) that is not part of the thesis.

information and explain the other levels (Aboud, 2003). The use of multilevel research, focusing on the level of country and firms, enables the achievement of the aim of the thesis.

2.2 Data Collection and Analysis

In the thesis, I focus mainly on four research questions. RQ1 is theoretically oriented and the answer to it has already been presented in section 1.2.2. of the current thesis. The other RQs require empirical testing. Therefore, the overview of research aims, data collection, and analysis for RQs 2,3, and 4 is presented in Table 4.

Table 4. Overview of Research Aims, Data Collection and Analysis.

	RQ2	RQ3	RQ4
Research aim	To determine the similarities and differences in business model attributes of FinTechs in five rapidly emerging FinTech hotspots in Central and Eastern Europe	To investigate the attitude towards using FinTech services from the position of digital natives and digital immigrants	To examine the association between founder characteristics and FinTech performance
Data collection methods	Online survey (from February 2019 to January 2020); information from official websites	Online survey containing 19 questions (from June to November 2019)	Data on the financials and founders of FinTechs from databases (RusBase, SPARK)
Sample	199 responses (38% in Estonia, 36% in Russia, 32% in Latvia and Lithuania and 19% in Poland)	3203 complete responses collected from ordinary consumers of financial services	88 FinTechs
Data analysis methods	Pearson's Chi^2 test; Non-hierarchical cluster analysis	Pearson's Chi^2 test; Structural equation modelling	Descriptive statistics; Univariate tests (using either Kruskal–Wallis or the Mann–Whitney U test); Regression analysis

Source: Compiled by the author.

RQ2 included a detailed analysis of five FinTech hotspots in Central and Eastern Europe: Estonia, Latvia, Lithuania, Poland and Russia. Most of the data came from an online survey built around 13 questions that covered the business model attributes that were highlighted in the theoretical background of the thesis (see Section 1.2). The average survey period was three months, although its duration depended on the country. The final dataset included 199 responses. To exclude the possible bias of sample, I tested its representativeness by Pearson's Chi^2 test.

The results of the survey were also analysed with non-hierarchical cluster analysis, chosen based on previous studies (Eickhoff et al., 2017; Gimpel & Rau, 2018; Gozman et al., 2018) that had employed cluster analysis while studying taxonomies of business models. The preference for non-hierarchical over hierarchical methods is explained by the non-hierarchical remaining superior in management-based research (Ketchen & Shook, 1996). In the framework of the research, the 'around medoids' algorithm (so-called PAM algorithm) was used as a method for non-hierarchical clustering. The main problem of non-hierarchical methods is finding the optimal number of clusters. In the thesis, two approaches are applied to identify the optimal number of clusters. The first one is focused on minimising the within-cluster sum of squares, the second – on maximising the average silhouette. To check the reliability of the results, the results of non-hierarchical clustering were compared with the results of hierarchical clustering through the silhouette value.

RQ3 aimed to explore attitudes of digital natives and digital immigrants towards using FinTech services. The division into selected categories depends on the level of technology development in a country. In the framework of the study, I assumed the year 1984 to be the boundary dividing the population of digital natives from digital immigrants in the Russian context. The reason is that computers became widely available to the population in 1984 in Russia (Trushkin, 2021). The data originated from an online survey carried out by a business analytics company. The survey was based on the river sample approach where respondents are not taken from database and are attracted in real-time among Internet users to survey. The preference for an online survey was explained by the need to obtain a large sample size so that the researcher would have lower impact on the data. The online survey was conducted between June and November 2019 and the final dataset included 3203 complete responses. The representativeness of the sample was tested using Pearson's Chi^2 test by two indicators: age and gender. The choice of indicators is explained by the availability of official statistics, and these showed no support for sampling bias. SEM was used for investigating the determinants influencing attitudes towards using FinTech services. It is a common model in a number of research (Patel & Patel, 2018; Tan & Teo, 2000) due to its flexibility and ability to analyse different types of variables at the same time (Nachtigall et al., 2003). In the framework of the study, the choice of the methodology was justified by the need to reveal the statistical significance of determinants of attitudes towards using FinTech services and the features of the dataset (latent and observable variables).

To examine the relation between founder characteristics and FinTech performance (RQ4), the data was obtained from Russian databases and the Facebook and LinkedIn social media platforms. To be included in the dataset of the study, companies had to meet the requirements of the definition of FinTech presented in the theoretical framework of the thesis (see Section 1.1) and registered in Russia prior to 2016. This enabled the focus to be only on FinTechs and data for 2016 and 2017 to be used. The study's final dataset covered data on a total of 88 companies. In this case, I was not dealing with a sample, but with the general population.

The following detailed analysis was based on univariate tests and regression analysis for the following reasons. First, the use of regression models is common among most similar previous studies (Arumona et al., 2019; Kaur & Singh, 2019; Prosvirkina & Wolfs, 2019). Second, it would enable the investigation of the impact of multiple explanatory variables on performance at the same time. Thus, I used founder-specific variables, FinTech size and other FinTech characteristics to investigate their influence on FinTech performance. FinTech performance was measured by two growth indicators – revenue growth and asset growth – as well as profitability indicator return on assets. Use of growth indicators as measures of performance is common amongst high-tech companies. The small sample size did not enable to add many explanatory variables to the regression model simultaneously. We tried to tackle this limitation by running different models, initially building them with more variables and then reducing the number of explanatory variables in the models to those that explained the variance in FinTech performance to a greater extent. In all estimations, heteroscedasticity was controlled for, and robust standard errors were reported for each coefficient estimate.

The choice of methodology, data collection and analysis ensured research based, detailed FinTech business models research in the Russian context and increased the validity and reliability of results, corresponding to the aim of the thesis.

3 Results and Discussion

This section provides an overview of the empirical results and discussion from RQ 2-4.

3.1 The Business Model Attributes of FinTechs in Russia in Comparison with Neighbouring Countries

The exploration of the business model attributes in a specific country setting contributes to RQ2. The following features of FinTech business models in Russia were revealed as a result of the study.

The distribution of the FinTech landscape by *key activity* type in Russia was rather balanced and similar to that of Poland. The most popular activities, which accounted for nearly a half of FinTechs, were payment and deposit and lending. The balanced FinTech landscape in Russia and Poland could be explained by the size of the market. In comparison with other analysed countries, Russia and Poland had a greater number of FinTechs. Moreover, Russia was in a more rapid growth phase of the market. According to respondents, 43% of Russian FinTechs participating in the survey were still under construction. Due to that FinTechs in Russia spent the most time on programming and business development. In comparison with FinTechs in the other analysed countries, those in Russia spent less time on marketing. This could be also explained by the bigger domestic market that reduced the necessity to expand to foreign markets.

From the position of *key resources*, more than 71% of FinTechs in Russia had less than 50 employees. This result was close to that in Poland and Estonia and can be explained by the developing nature of the FinTech market. Moreover, there were no unicorns or gazelles in Russia (Stas, 2021). Russian FinTechs had around 19% employees located abroad. This was an average value compared to the same values in Estonia reaching 31% and being only 5% in Poland. Of the FinTechs participating in the survey, 55% were planning to expand their activity in Russia; a trend that corresponded to the trends in the other analysed countries. In relation to the dominant technologies of FinTechs, the most frequently used technology across Russian Fintechs was marketplaces and the least frequent was blockchain. In this way, Russian FinTech appeared similar to Latvia, where marketplace technologies were the most common. In terms of *value propositions*, there were no significant differences between the analysed countries. The most common type of value proposition was the usability of services.

Russian FinTechs exhibited the most even distribution of *customer types*, compared to the other analysed countries. The B2B segment was mostly concentrated in payments and banking infrastructure, while B2C was more prevalent in deposit and lending. The *geographic segmentation* aspect showed similarities between Russia and Poland with the focus of FinTechs from these countries being mostly on local customers. In Russia, all the FinTechs that participated in the survey used digital communication as their main *channel* for the delivery of their services. Also, 51% of the respondents, additionally, used personal communication. In terms of the delivery channel, the most common categories were web applications, application programming interfaces and web applications together with mobile applications. The same tendency was presented in Russia, Poland, Estonia and Lithuania. The most common *revenue model* in Russia was commission fee, and the least popular were the license fee and trading income. The most frequently mentioned source of revenue in Russia was also the same for other analysed countries.

Based on the FinTech business model attributes, proposed by Lee and Teo (2015), the results of Russian FinTechs appeared more competitive than in other analysed countries. This could be explained by greater optimism of Russian respondents, or possibly greater underestimation of the success of the other countries, among Russian respondents.

The analysis of FinTech environment highlighted the differences in local conditions in analysed countries. It explained the significant differences between attributes of FinTech business models.

The results of cluster analysis based on Osterwalder and Pigneur (2010) business model attributes revealed the distribution of FinTechs into four clusters: lending community, payment service, payment community and mixed services. Only Russia and Estonia were represented in each cluster. This points to the greater diversification of business models in these countries compared to the remaining three. The revealed clusters are rather close to the archetypes proposed by Eickhoff et al. (2017). Therefore, the study supports the applicability of the proposed archetypes in practice and also indicates rather standard FinTech business model characteristics in the five selected countries.

The results of cluster analysis based on Lee and Teo (2015) business model attributes revealed two clusters and the extremely uneven distribution of Russian FinTechs between them. 93% of Russian FinTechs fell into the first cluster, while the proportion of Russian FinTechs in it across all analysed countries was 66%. The first cluster differed by FinTechs' high value on innovation, ability to scale and ease of compliance with regulations. As this analysis was entirely based on respondents' evaluations of their competitiveness, it may reflect their inflated or overly optimistic opinions.

3.2 The Consumer Attitude Towards Using FinTech Services

The examination of the differences in attitude of digital natives and digital immigrants towards using FinTech services contributed to RQ3. For analysing the attitudes towards using FinTech services, it was necessary to demonstrate the statistical significance of the determinants of attitudes towards using FinTech services. Using SEM, I identified the relevance of personal habits, perceived ease of use, financial and digital literacy. The determinant *perceived usefulness* was recognised as statistically insignificant.

In line with expectations (H2), digital natives perceived the ease of using FinTech services higher than digital immigrants. By having less experience and knowledge, digital immigrants may make greater efforts to accept FinTech services. The results highlight the relevance of developing user-friendly solutions for FinTechs' services, particularly for digital immigrants. Otherwise, their negative experience is reflected by a negative attitude toward using technology-advanced services, including for FinTechs.

Contrary to (H3), digital immigrants perceived the usefulness of FinTech services higher than digital natives. It can be explained by failure of digital natives, born after digital revolution, in estimating the true effectiveness of FinTech services due to the lack of experience with alternative services. Nevertheless, the statistical insignificance of the perceived usefulness to attitude towards using FinTech services does not allow recognising the perceived usefulness of consumers as determinant, identifying the attitudes towards using FinTech services.

The results showed that digital natives had stronger digital-orientated habits than digital immigrants (H4). Moreover, around 70% of digital immigrants were not aware of the meaning of the term FinTech. The popularisation of the term FinTech through communication channels familiar to digital immigrants may contribute to changing their personal habits and forming positive attitudes towards using FinTech services.

In line with expectations (H5a), compared to digital immigrants, digital natives rated their level of digital literacy higher. As digital immigrants perceived the usefulness of FinTech services higher than digital natives, there is a great potential for helping them to overcome the barriers related to low digital literacy. In accordance with (H5b), digital immigrants perceived their financial literacy to be higher than digital natives. To ensure a positive attitude towards using FinTech services, it would be necessary to find ways to increase the digital literacy of digital immigrants and the financial literacy of digital natives.

3.3 The Role of Founder Characteristics in FinTech Performance

The exploration of the role of the founder in FinTech performance, contributed to RQ 4. The results confirmed the significance of founder characteristics on the performance of FinTechs. This indicates that founder characteristics were difficult-to-imitate resources that created a competitive advantage for FinTechs from a position of RBV.

I attained inconclusive results in relation to founder age (H6). In univariate tests, the mean and median performance indicators for founders below and above 40 years of age were similar, and in regression models, age appeared as statistically significant only for models using return on assets. I observed that FinTechs with younger founders had higher return on assets than other FinTechs. The inconclusive results in relation to founder age can be explained by the responsiveness, adaptability and entrepreneurial skills required of a founder. Some of the mentioned skills are more typical to younger founders, and others – to older founders. Therefore, age may not matter as much as one may expect. Similar results were obtained by Kautonen (2008), who revealed the insignificance of the entrepreneurs' age in the relation to the performance of small- and medium-sized companies in Finland.

I also failed to observe superior FinTech performance if the founder had IT education (H7). I observed that if the founders who were educated in areas other than IT and economics achieved slightly higher revenue growth than those founded by individuals with an IT or economics education. However, I found that the founder's previous banking experience was associated with better FinTech performance (H8). FinTechs established by individuals with previous banking experience had 28% greater revenue growth and 36% greater asset growth than other FinTechs.

When combining founders' previous experience with their education, education started to become more relevant determinant of FinTech performance. FinTechs established by founders with IT education and previous banking experience had 15% greater revenue growth and 20% greater asset growth than those established by founders with economics education and previous banking experience. Moreover, FinTechs with founders with IT education and banking experience achieved 37% greater revenue growth and 45% greater asset growth in comparison with FinTechs founded by individuals with IT education and no previous banking experience. These results show that the importance of the founder's education as a determinant of FinTech performance should not be ignored and founder education and experience need to be viewed in combination.

The research concluded the relevance of founder characteristics towards FinTech performance, the potential implications are discussed in the section below.

3.4 Summary of Results and Discussion

The thesis provides a research-based, detailed understanding of the attributes of FinTech business models and their linkages with customers and founders in a specific country setting. The main findings are summarised in Table 5.

Table 5. Research Questions and Main Findings.

	Research question	Main findings
1	What are the main attributes of FinTech business models?	Key activities (time use, activity); Key resources (employees, dominant technology, founder characteristics); cost structure (fixed costs of assets); Revenue streams (model); Channel; Value proposition; Customer segments (customer type, geographic segmentation)
2	What are the features of development of FinTechs' business models in Russia in comparison to those of the neighbouring countries?	Type of key activity: rather balanced (similar to Poland); most FinTechs under construction Key resources: small number of employees (similar to Poland and Estonia); dominant technology based on marketplaces (similar to Latvia) Value propositions: usability of service (the same as in other countries) Customer types: balanced between B2b and B2C; focus on local customers (similar to Poland) Delivery channel: mostly digital communication through web, mobile applications and application programming interface (similar to Poland, Estonia, Lithuania) Revenue model: commission fee (the same as in other countries)
3	Which key factors influence the positive attitude towards using FinTech services among different categories of consumers?	Digital immigrants: perceived ease of use, digital literacy, personal habits Digital natives: financial literacy
4	Which key characteristics of a founder are associated with the superior FinTech performance?	Previous banking experience, education

Source: compiled by the author.

In the case of the RQ1, I identify the set of attributes of FinTech business models, linking the FinTech taxonomies (Eickhoff et al., 2017; Iman, 2020) with traditional business model canvas (Osterwalder & Pigneur, 2010). Based on this, I reveal the following attributes: key activities, key resources (including the dominant technology), revenue streams, cost structure, channel, value proposition and customer segments. The results of research supports the idea that FinTech business models are not equivalent to types of activity as previously mentioned in a number of studies (Lee & Shin, 2018; Liu et al., 2020).

In the case of the RQ2, the results support the hypothesis (H1). The country-specific entrepreneurial environment influences the business model's development and its features. I found significant differences in a number of attributes of FinTech business models across the selected countries. The main activities of FinTechs vary significantly. In Latvia, Lithuania, and Estonia, there is a predominance of a certain type of FinTech activities. Contrary, the Russian FinTech market is balanced across different types of FinTech activities. The activities of FinTech depend on the maturity of the FinTech market. The Russian FinTech market is the least mature of the investigated countries. It supports the view that Moscow and St. Petersburg are emerging FinTech hubs (CCAF, 2018). Also, the current resource needs vary across the countries. Latvia has 30% of FinTechs with more than 250 employees. In Russia, there is a big concentration of FinTechs having less than 50 employees. In the case of types of customers, Estonia focuses on the B2B segment, and Latvia - on the B2C segment. Russian FinTechs exhibit the even distribution of types of customers. Countries with small territories are more oriented towards international consumers. Contrary, due to its size, Russia is more oriented toward the local market. In the framework of the thesis I also revealed the similarities in value propositions and revenue models of FinTechs in the analysed countries. Similarities in business models (usability of service and commission fee as revenue model) are explained by main advantages of FinTechs over incumbents (He et al., 2017; Hussain et al., 2021) or features of the financial sector (Ozili & Outa, 2019). Overall, the results confirm that FinTech business models depend not on only international conditions but also on country-specific environment (Laidroo & Avarmaa, 2020). This implies that policy-makers should take into account the local FinTech landscape and should try to influence it in case boosting FinTech development is considered desirable. For FinTech entrepreneurs it implies the need to consider local conditions when developing the FinTech business model and selecting the location for its operation. The study also complements the results of previous research for other industries in linking the country specific environment and features of organising business (Fleury & Fleury, 2014; Hryckiewicz & Kozłowski, 2017; Sgriccia et al., 2007). To the knowledge of the author, it is the first paper, which provides comprehensive analysis of the FinTech business models located in several countries.

In the case of the RQ3, I identify key factors influencing the positive attitude towards using FinTech services. The results of research expand the previous studies (Prensky, 2001; Birnholtz, 2010; Tilvawala et al., 2013), investigating the differences in the perception of information systems between digital immigrants and digital natives. Digital natives rate their perceived ease of use higher than digital immigrants (H2). They also rate their digital-orientated personal habits higher than digital immigrants (H4). In the context of personal habits the results complement the research by Gu et al. (2013), Wu & Yen (2014) and highlight that personal habit is important antecedent influencing the use of information services. Finally, digital natives rate their digital literacy higher than digital immigrants (H5a). The results support the research by Alford & Biswas (2002), Kleijnen et al. (2004), who revealed the importance of computer skills in the adoption of information technologies services.

Digital immigrants rate their financial literacy more highly than digital natives (H5b). To the knowledge of the author, no other research has focused on analysing the relationship between financial literacy and attitude towards using FinTech services in the case of digital immigrants and digital natives. I also got inconclusive results in the relation of perceived usefulness of FinTech services (H3). It was recognised as the statistical insignificant factor in relation to attitudes towards using FinTech services. Similar results are presented by Metallo & Agrifoglio (2015).

In the case of the RQ4, I investigate the relationship between founder characteristics and FinTech performance and complement the RBV of entrepreneurship (Barney, 1991; Jardon & Molodchik, 2017; Madhani, 2010; Prahalad & Hamel, 1997) in part of revealing the difficult-to-imitate resources for companies. In the framework of research, I attained inconclusive results in relation to founder age (H6) and found support for the relevance of their education (H7) and previous experience (H8). Thus, the results expand previous studies on non-FinTechs in the context of relevance the education (Arumona et al., 2019; Wai & Rindermann, 2015) and experience (Chen & Chang, 2013; Protogerou et al., 2017). Considering the specifics of the financial sector, previous exposure to it helps in business model development and commercialisation of a business idea. The results also show the importance of a founder's IT education only in combination with his or her previous banking experience. It means that to implement the advantages of their IT education in the FinTech sector, founders should also understand the specifics of the sector. It can be explained by the features of the FinTech sector – it lies at the intersection of finance and technology. Also, to have the education in economics and banking experience may be not sufficient to establish a successful FinTech. In order to boost FinTech development, it may be worth to add IT courses in business and economics programs. Finally, the research suggests that if founders do not have adequate knowledge or experience, they will need a group of experts who fill this gap. Nevertheless, the limited resources of individuals may prevent the formation of such a group.

Conclusions

The thesis aimed to investigate the attributes of FinTech business models and their linkages with customers and founder in a specific country setting. In the framework of the study, four research questions were developed. Answering these questions, I identified the set of attributes of FinTech business models. Also, I revealed the significance of specific country environments in the relation to FinTechs' business model development. Then I identified key factors influencing the positive attitude towards using FinTech services among digital natives and digital immigrants. Finally, I investigated the key characteristics of the founder, that are associated with the superior performance of FinTechs.

Based on the above, I make four main theoretical contributions.

First, in Article I, I adopt the Osterwalder and Pigneur's (2010) business model canvas for the investigation of FinTech business models by supplementing it with dominant technology in the part of key resources (Iman, 2020). Also, customer relations have been excluded from the original model according to Eickhoff et al. (2017).

Second, in Article II, I adopt TAM for revealing the significant factors that influence attitude towards using FinTech services among consumers. TAM has been supplemented with digital-oriented personal habits, financial and digital literacy in the case of FinTech. The factor of perceived usefulness was shown to be insignificant.

Third, in Article II, I expand the application of consumers' classifications proposed by Prensky (2001) and support the differing attitudes of digital immigrants and digital natives towards using information services, including FinTech.

Fourth, in Article III, I expand the RBV of entrepreneurship by highlighting resources that can be recognised as difficult for imitating and creating superior performance in the context of FinTechs. These are founder characteristics such as a combination of IT education and previous banking experience.

The thesis also makes four empirical and practical contributions.

First, the research adds new empirical evidence about the emerging FinTech market in Russia (Article I, II and III) and neighbouring countries (Article I).

Second, it is also one of the first comparative studies on FinTech on a global scale, entrepreneurs can gain an understanding of FinTech business models (Article I).

Third, the thesis reveals the determinants of digital immigrants and digital natives to having a positive attitude towards using FinTech services. The understanding of determinants of certain categories of consumer will promote FinTech services and increase confidence in them (Article II).

Fourth, as it is the first study investigating the association between founder characteristics and FinTech performance (Article III), the thesis demonstrates the relevance of characteristics of the founder to FinTech performance. It helps entrepreneurs to select a team of experts with the necessary background to create a successful FinTech.

There are several general limitations and possible implications for further research.

First, the theoretical basis of the research concept, presented in section 1.2, reflects the comprehensive view of the possible linkages between FinTechs and their environment. In the framework of the thesis, I cover only separate parts of the overall research concept. For example, in Article III I focus only on the founder characteristics as an attribute of FinTech business models and their influence on FinTech performance. The FinTech business model framework is significantly broader and includes the other six attributes. To make a conclusion about the linkage between attributes of FinTech business models and performance, it is not enough to focus only on the founder's characteristics. It is necessary to analyse the linkages between other FinTech business model attributes and performance. In this aspect, future studies can complement the results of the thesis and investigate the linkages between FinTech business model attributes and performance. Also, the theoretical basis of the research concept demonstrates the possible associations between types of consumers, their expectations, demand for using FinTech services, and accordingly on FinTechs' innovative business models. In Article II I mostly focus on the first part of associations and analyse the determinants, influencing attitudes towards using FinTech services among digital natives and digital immigrants. Future studies, focused on the other types of customers and other parts of associations between types of consumers and FinTechs' innovative business models, will allow deepening the results presented in the thesis. In Article I I focus on the general influence of the country's environment on the FinTech business models. However, the study does not analyse how specifically one or another element of the environment affects one or another attribute of FinTech business models. Future studies could fulfil the revealed research gap and expand the results of the thesis.

Second, the research methodology of the thesis is restricted by mainly the quantitative research methods (cluster analysis, regression analysis, SEM). It can be explained by the rather short history of FinTech. Before analysing how and why these linkages exist, it is necessary to determine the presence of these links based on a large number of observations. That is why in the thesis I focus on the quantitative research methods. The application of such methods allows me to reveal the linkages between the attributes of FinTech business models, customers, and founder in a specific country setting. Future studies could focus not only on the existence of the revealed linkages but also analyse them from the positions of how and why they appear (in other words – the causes of existence such linkages).

Third, the short history of FinTech and shortage of ready-made databases influence data collection and analysis. Article I focuses on the period between February 2019 and January 2020. Article II is based on responses from June to November 2019. Article III is restricted to 2016 and 2017. Similar future studies based on a longer timeframe can reveal the dynamics and features of the sector's development.

The collection of the datasets in the thesis is organised based on different questionnaires and existing databases. Therefore, the used dataset could be criticized as being possibly biased. For example, in the Article I the main respondents were founders or CEOs of FinTechs, who can rate the set of indicators as overly optimistic or pessimistic. The same problem is relevant in the case of the consumers of FinTech services, who were the main respondents in Article II. In Article III, hand-gathered information on the company founder was included in the dataset. Nevertheless, in the framework of research, I tested the samples on representativeness.

Fourth, the results may be impacted by the historical, institutional, and cultural background of Russia and its neighbouring countries, which is why the results cannot be generalised to other countries. Nevertheless, I think that the results of the research will be interesting to potential founders of FinTechs in other countries. For example, the thesis reveals the relevance of the country-specific setting in attitude to FinTech business models. Therefore, in the process of founding the FinTech entrepreneur should consider the country's environment. The entrepreneur should also understand the features of consumers and take them into account in the process of the development of FinTech services. Nevertheless, similar future studies in other countries can support or expand the results of the thesis.

Fifth, since there is no official list of FinTechs in Russia and its neighbouring countries, some FinTechs may have remained outside of the scope of the paper.

Sixth, the study was carried out before the COVID-19 pandemic, which could significantly affect the current situation in the FinTech sector. Therefore, the future studies can assess the impact of the COVID-19 pandemic on the dynamics of the sector's development.

Despite the above-mentioned limitations, the thesis provides unique evidence on FinTech development in Russia with an emphasis on business models, founder characteristics and consumer perceptions.

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Abstract

FinTech Business Models and Their Linkages with Customers and Founders

The global financial crisis of 2008 exposed the failure of the traditional banking system (Saksonova & Kuzmina-Merlino, 2017). Changing consumer attitudes and application of innovative solutions in the financial sector led to emergence of FinTech companies (FinTechs). These are high-tech companies that apply innovative solutions for the provision of financial services and may be either start-ups or existing companies.

The number of academic publications on FinTech has increased from year to year, tackling issues related to regulation, collaborations, and interaction within FinTech ecosystems, as well as the financial ethics, security, and infrastructure for the provision of FinTech services (Gai et al., 2018; Milian et al., 2019; Suryono et al., 2020; Tepe et al., 2022). Still, a recent literature review by Iman (2020) shows that the extant research remains fragmented lacking multidisciplinary analysis of FinTech activities, especially considering the country-specific environment. As FinTechs are either in fierce competition with incumbents or support their key processes, their survival depends on their ability to provide a greater speed of service delivery, flexibility, and focus on the quality of customer service. Competitive advantages and performance are often achieved through the transformation of existing or the creation of new business models (Chatterjee, 2013; Chesbrough, 2010; Johnson et al., 2008).

FinTechs have innovative business models, allowing to achieve a competitive advantage over incumbents (Cartwright & Allayannis, 2016; Haddad & Hornuf, 2019). As innovative business modes carry high risks, they can have either positive or negative consequences for the firm performance. Failure to meet the performance expectations can be explained for instance by ignoring the weaknesses in internal business processes or the specifics of the environment around the company (MacBryde & D'Ippolito, 2015). Nevertheless, empirical grounding for those claims seems to be lacking and the scientific literature about FinTech business models remains scarce (Kavuri & Milne, 2019). Thus, in terms of **the research gap**, a research-based, detailed study of the FinTech business models is required.

To date there exists no common understanding of the attributes of FinTech business models in the previous literature (Eickhoff et al., 2017; Lee & Shin, 2018; Liu et al., 2020). The definition of these attributes remains important in understanding FinTech business models. FinTechs do not exist in a vacuum and identify their business models based on external conditions like its country-specific entrepreneurship environment (Tanda & Schena, 2019), changing technologies or customer preferences (Amit & Zott, 2015). Therefore, it is important to investigate FinTech business models in specific settings. In this thesis, **my aim** is to investigate the attributes of FinTech business models and their linkages with customers and founders in a specific country setting.

Within this context, the following **research questions** have been developed:

RQ1: What are the main attributes of FinTech business models?

RQ2: What are the features of FinTechs' business models in Russia in comparison to those of the neighbouring countries?

RQ3: Which key factors can influence the positive attitude towards using FinTech services among different categories of consumers?

RQ4: Which key characteristics of a founder are associated with the superior FinTech performance?

The thesis consists of three articles. Article I provides answers to RQ 1 and RQ 2, Article II to RQ 3 and Article III to RQ 4.

Article I provides an investigation of the attributes of FinTech business models. Based on the literature review, it allowed highlighting the main attributes of FinTech business models. It was designed as a comparative analysis of FinTech business models in five countries including Russia, Estonia, Latvia, Lithuania, and Poland. The FinTech business model attributes were defined based on Osterwalder and Pigneur (2010) and Lee and Teo (2015). The analysis was based mainly on data gathered through an online survey of 199 FinTechs registered in the selected countries.

Article II relates to consumer attitudes towards FinTech services in Russia. From the perspective of the technology acceptance model (TAM; Davis, 1986), perceived usefulness, personal habits, perceived ease of use, level of digital and financial literacy were considered as key factors for identifying consumer attitudes. The analysis was based on a dataset of 3203 responses from ordinary consumers of financial services.

Article III investigates whether the key characteristics of the founder (age, education and experience) are associated with the superior performance of FinTechs. The study was conducted from the perspective of a resource-based view of entrepreneurship (RBV; Barney, 1991). The association between the founder characteristics and the performance of FinTechs was investigated using data from 88 Russian FinTechs. The data was gathered through SPARK, a Russian database, and partly hand-collected from the social media platforms.

The thesis makes the following **theoretical contributions**.

First, it identifies the key attributes of FinTech business models by adopting the Osterwalder and Pigneur's (2010) business model canvas to the FinTech taxonomies created in studies by Eickhoff et al. (2017) and Iman (2020) (Article I).

Second, it expands RBV by recognising the founder's education and experience as difficult-to-imitate resources for FinTechs (Article II).

Third, it adopts TAM in the context of using FinTech services by adding new factors, namely personal habits and level of digital and financial literacy, to the model (Article III).

Fourth, it expands the application of consumers' classifications proposed by Prensky (2001) and supports the differing attitudes of digital natives and digital immigrants in relation to FinTech services (Article III).

The thesis makes the following **empirical and practical contributions**.

First, it adds new empirical evidence concerning the emerging FinTech market of Russia (Articles I, II and III).

Second, it adds comparative evidence for FinTech business model attributes in Russia in comparison to those of Estonia, Latvia, Lithuania and Poland (Article I).

Third, it demonstrates the relevance of the founder's specialised knowledge and a properly selected team of experts for establishing a successful FinTech (Article II).

Fourth, it highlights the key factors preventing the acceptance of FinTech services by digital natives and digital immigrants (Article III).

Lühikokkuvõte

FinTechi ärimudelid ja nende seosed klientide ja asutajatega

2008. aasta ülemaailmne finantskriis paljastas traditsioonilise pangandussüsteemi ebaõnnestumise (Saksonova & Kuzmina-Merlino, 2017). Tarbijate hoiakute muutumine ja uuenduslike lahenduste rakendamine finantssektoris tõi kaasa FinTech ettevõtete (FinTechs) tekkimise. Tegemist on kõrgtehnoloogiliste ettevõtetega, kes rakendavad uudseid lahendusi finantsteenuste osutamisel ning võivad olla nii idufirmad kui ka juba tegutsevad ettevõtted.

FinTechi käsitlevate akadeemiliste publikatsioonide arv on aasta-aastalt kasvanud, käsitledes küsimusi, mis on seotud reguleerimise, koostöö ja FinTechi ökosüsteemidesiseste interaktsioonidega, samuti finantseetika, turvalisuse ja FinTechi teenuste osutamise infrastruktuuriga (Gai et al., 2018; Milian et al., 2019; Suryono et al., 2020; Tepe et al., 2022). Siiski näitab Iman (2020) hiljutine kirjanduse ülevaade, et olemasolevad uuringud on endiselt killustatud, kuna puudub FinTechi tegevuste multidistsiplinaarne analüüs, eriti arvestades riigipõhist keskkonda. Kuna FinTechid konkureerivad ägedalt turgu valitsevate operaatoritega või toetavad nende põhiprotsesse, sõltub nende ellujäämine nende võimest pakkuda kiiremat teenust, paindlikkust ja keskenduda klienditeeninduse kvaliteedile. Konkurentsieelised ja -tulemused saavutatakse sageli olemasolevate ärimudelite ümberkujundamise või uute ärimudelite loomise kaudu (Chatterjee, 2013; Chesbrough, 2010; Johnson et al., 2008).

FinTechidel on uuenduslikud ärimudelid, mis võimaldavad saavutada konkurentsieelise turgu valitsevate operaatorite ees (Cartwright & Allayannis, 2016; Haddad & Hornuf, 2019). Kuna uuenduslikud äriviisid on seotud suurte riskidega, võivad need ettevõtte tegevusele avaldada positiivseid või negatiivseid tagajärgi. Tulemuslikkuse ootustele mittevastamist võib seletada näiteks sisemiste äriprotsesside nõrkade külgede või ettevõtet ümbritseva keskkonna eripärade ignoreerimisega (MacBryde & D'Ippolito, 2015). Sellegipoolest näib nende väidete empiiriline põhjendus puuduvat ja teaduskirjandus FinTechi ärimudelite kohta on endiselt napp (Kavuri & Milne, 2019). Seega on uuringulünka silmas pidades vaja FinTechi ärimudelite uurimispõhist üksikasjalikku uurimist.

Seni puudub varasemas kirjanduses ühtne arusaam FinTechi ärimudelite omadustest (Eickhoff et al., 2017; Lee & Shin, 2018; Liu et al., 2020). Nende atribuutide määratlemine on FinTechi ärimudelite mõistmisel endiselt oluline. FinTechid ei eksisteeri vaakumis ja identifitseerivad oma ärimudeleid välistingimuste, näiteks riigipõhise ettevõtluskeskkonna (Tanda & Schena, 2019), muutuvate tehnoloogiate või klientide eelistuste põhjal (Amit & Zott, 2015). Seetõttu on oluline uurida FinTechi ärimudeleid konkreetsetes seadetes. Käesolevas lõputöös on minu eesmärk uurida FinTechi ärimudelite atribuute ja nende seoseid klientide ja asutajatega konkreetses riigis.

Sellega seoses on välja töötatud järgmised uurimisküsimused:

RQ1: Millised on FinTechi ärimudelite peamised atribuudid?

RQ2: Millised on FinTechsi ärimudelite omadused Venemaal võrreldes naaberriikide omadega?

RQ3: Millised võtmetegurid võivad mõjutada erinevate tarbijakategooriate positiivset suhtumist FinTechi teenustesse?

RQ4: Millised asutaja põhiomadused on seotud parima FinTechi jõudlusega?

Lõputöö koosneb kolmest artiklist. Artiklis I antakse vastused küsimustele RQ 1 ja RQ 2, artiklile II kuni RQ 3 ja artiklile III kuni RQ 4-le.

Artiklis I käsitletakse FinTechi ärimudelite atribuute. Kirjanduse ülevaate põhjal võimaldas see välja tuua FinTechi ärimudelite peamised atribuudid. See koostati FinTechi ärimudelite võrdleva analüüsina viies riigis, sealhulgas Venemaal, Eestis, Lätis, Leedus ja Poolas. FinTechi ärimudeli atribuudid määratleti Osterwalderi & Pigneuri (2010) ning Lee & Teo (2015) põhjal. Analüüs põhines peamiselt andmetel, mis koguti valitud riikides registreeritud 199 FinTechi online-küsitluse kaudu.

Artiklis II käsitleb tarbijate suhtumist FinTechi teenustesse Venemaal. Tehnoloogia aktsepteerimise mudeli (TAM; Davis, 1986) vaatenurgast peeti tarbijahoiakute tuvastamisel võtmeteguriteks tajutud kasulikkust, isiklikke harjumusi, tajutavat kasutuslihtsust, digitaalse ja finantskirjaoskuse taset. Analüüs põhines tavaliste finantsteenuste tarbijate 3203 vastuse andmestikul.

Artiklis III uuritakse, kas asutaja põhiomadused (vanus, haridus ja kogemus) on seotud finantstehnoloogiate paremate tulemustega. Uuring viidi läbi ettevõtluse ressursipõhise vaate vaatenurgast (RBV; Barney, 1991). Asutajate omaduste ja FinTechi jõudluse vahelist seost uuriti 88 Venemaa FinTechi andmete põhjal. Andmed koguti Venemaa andmebaasi SPARK kaudu ja osaliselt koguti käsitsi sotsiaalmeedia platvormidelt.

Lõputöö annab järgmised teoreetilised panused.

Esiteks tuvastab see FinTechi ärimudelite peamised atribuudid, võttes kasutusele Osterwalderi & Pigneuri (2010) ärimudeli lõuendi FinTechi taksonoomiatele, mis on loodud Eickhoffi jt uuringutes. (2017) ja Iman (2020) (artikkel I).

Teiseks laiendab see RBV-d, tunnustades asutaja haridust ja kogemusi finantstehnoloogiate jaoks raskesti jäljendatavate ressurssidena (artikkel II).

Kolmandaks võtab see FinTechi teenuste kasutamise kontekstis kasutusele TAM-i, lisades mudelisse uued tegurid, nimelt isiklikud harjumused ning digitaalse ja finantskirjaoskuse tase (artikkel III).

Neljandaks laiendab see Prensky (2001) pakutud tarbijate klassifikatsioonide rakendamist ning toetab digitaalsete põliselanike ja digitaalsete immigrantide erinevaid hoiakuid seoses FinTechi teenustega (artikkel III).

Lõputöö annab järgmised empiirilised ja praktilised panused.

Esiteks lisab see uusi empiirilisi tõendeid Venemaa areneva finantstehnoloogia turu kohta (artiklid I, II ja III).

Teiseks lisab see võrdlevaid tõendeid FinTechi ärimudeli tunnuste kohta Venemaal võrreldes Eesti, Läti, Leedu ja Poola omadega (artikkel I).

Kolmandaks näitab see asutaja eriteadmiste ja õigesti valitud ekspertide meeskonna olulisust eduka FinTechi loomisel (artikkel II).

Neljandaks tuuakse välja peamised tegurid, mis takistavad digitaalsete põliselanike ja digitaalsete sisserändajate poolt FinTechi teenuste vastuvõtmist (artikkel III).

Appendix

Laidroo, L., **Koroleva E.**, Kliber A., Rupeika-Apoga R., & Grigaliuniene Z. (2021). Business models of FinTechs – Difference in similarity? *Electronic Commerce Research and Application*s, *46*, 101034. (ETIS 1.1)

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Business models of FinTechs – Difference in similarity?

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ABSTRACT

The FinTech industry is gradually maturing and offers a wide range of financial services on the global stage. Still, the understanding of FinTech business models remains at its infancy with a shortage of cross-country comparisons. This paper aims to determine the differences in business model attributes of FinTechs in five rapidly emerging FinTech hotspots in Central and Eastern Europe (CEE). Survey results from Estonia, Latvia, Lithuania, Poland, and Russia, accompanied by cluster analysis, enable us to provide unique in-depth evidence on FinTech business models. Across the selected countries, we observe significant differences in the attributes of FinTech business models: key activities, key resources, value propositions, customer segments, delivery channels, cost structure, and revenue stream. We identify four clusters of FinTechs: “lending community”, “mixed services”, “payment service”, and “payment community”. Although these clusters share similarities with FinTech archetypes proposed in previous research, they remain rather unevenly distributed across countries.

1. Introduction

The application of innovative digital solutions for the provision of financial services has led to the rapid emergence of FinTech companies (hereafter FinTechs). These can be either start-ups or established companies with varying capabilities for either disrupting or contributing to the provision of traditional financial services. The overall influence of FinTech on the functioning of the financial sector relies heavily on the number of FinTechs as well as on the setup of their business models. Existing empirical studies indicate that there exists a significant variation in the count of FinTechs across countries (Haddad and Hornuf, 2019; Laidroo and Avarmaa, 2020). However, the determination of precise counts, including counts by types of activity, remains problematic, as there exists no universal definition and no universal classification system for FinTech (Iman, 2020). In terms of the FinTech business models, the literature remains highly scattered with no common understanding of their attributes. Some authors consider FinTech business model almost equivalent to the type of product/service provided by the company (e.g., Lee and Shin, 2018; Liu et al., 2020), while others acknowledge that it is based on a more diverse set of attributes (e.g., Lee and Teo, 2015; Eickhoff et al., 2017). In line with these arguments, a recent literature review by Iman (2020) emphasizes a need for further research into the characteristics and attributes of FinTech in different settings, and Kavuri and Milne (2019) highlight the lack of comparative evidence on the types of activities (products and services) of FinTechs.

The objective of this paper is to determine the differences in business model attributes of FinTechs in five rapidly emerging FinTech hotspots in Central and Eastern Europe (CEE). The focus is on Estonia, Latvia, Lithuania, Poland, and Russia because they are in the lead in the CEE region in terms of count of FinTechs[1] (Haddad and Hornuf, 2019; Laidroo and Avarmaa, 2020; Raiffeisen Bank International AG, 2018). The increasing global significance of the selected countries is also reflected in the FinTech city rankings with Vilnius, Warsaw, Moscow, and St. Petersburg being mentioned amongst the nine emerging European

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[1] The same indicators in the Czech Republic and Ukraine also exhibit a rather comparable level of FinTech activity (their position compared to the selected countries varies depending on the information source). However, all other CEE countries remain far behind. Estonia, Latvia, and Lithuania also lead the way in CEE based on counts adjusted for the size of the labour force (Laidroo and Avarmaa, 2020).

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FinTech hubs (CCAF, 2018).[2] In a more recent global FinTech country ranking by Findexable (2020), the selected five countries occupy positions from 4 (Lithuania) to 49 (Latvia)[3], while Lithuania and Estonia are ahead of many of the highly developed Western European countries (e.g., Germany 11th, France 16th, Denmark 20th, Luxembourg 23rd). Although FinTech activity in these countries has rapidly increased, to the knowledge of the authors, no previous study has thoroughly investigated the characteristics of FinTechs in any of the five countries. Even in broader European or global contexts, there exist no in-depth investigations of business models of FinTechs in multiple countries simultaneously.[4]

The five countries provide a suitable setting for doing a comparative analysis because of the characteristics of their FinTech environment. They have, in addition to similar post-Soviet past, also common borders with intensive trade, cross-border capital, and labour markets. However, there exist quite significant differences in their size, entrepreneurial activity, information infrastructure, and financial development (as discussed in Section 2.2). This could potentially have a diverse impact on the business models that FinTechs located in respective countries are utilising. Therefore, we aim to answer the following questions. First, what kind of differences and similarities exist in business model attributes of FinTechs, which have emerged in the five countries? Secondly, how similar or different are the business models of individual FinTechs in the selected countries?

This paper is based mainly on data gathered from 199 FinTechs, which are registered in the five countries and responded to an online survey carried out during February 2019 and January 2020. The survey questions were designed based on Osterwalder and Pigneur (2010) business model canvas and FinTech business model attributes of Lee and Teo (2015) to gather information about their key activities, key resources, value proposition, customer segments, delivery channel, and financial viability. The results were analysed using descriptive statistics and cluster analysis for detecting differences and similarities in business models.

The results show that the main activities of FinTechs in the selected countries vary significantly and are strongly influenced by the maturity of the FinTech market. This leads to differences in resource needs, with a high concentration of small FinTechs (less than 10 employees) in Estonia and Poland, and large FinTechs (more than 250 employees) in Latvia. Also, customer orientation is different, from business-to-business (B2B) services in Estonia and Poland, towards business-to-consumer (B2C) services in Latvia. FinTechs from smaller countries (Estonia, Lithuania, Latvia) are more focused on international customers than in bigger countries (Poland and Russia). In terms of service delivery channels, FinTechs from different countries are rather similar, except Latvia, where physical delivery is as popular as digital delivery. Cluster analysis based on Osterwalder and Pigneur (2010) framework revealed that the FinTechs in the five countries can be divided into four clusters: “lending community”, “mixed services”, “payment service”, and “payment community”. Some of these clusters exhibited characteristics very similar to archetypes reported by Eickhoff et al. (2017). Still, we did observe greater diversity of FinTech business models in Russia and Estonia, the least diverse in Poland. This confirms the cross-country differences in FinTech business models observed also while looking at business model attributes of specific FinTechs. Some of these differences can be linked with differences in local conditions. Therefore, improved understanding of these conditions and FinTech business models would benefit both policy-makers and entrepreneurs.

We contribute to the FinTech literature in several respects. First, we extend the literature of FinTech business models by linking the FinTech taxonomies created in the previous studies by Eickhoff et al. (2017) and Iman (2020) with traditional Osterwalder and Pigneur (2010) business model canvas dimensions. Second, to the knowledge of the authors, it is the first paper, which provides in-depth comparative evidence on the FinTech business models of companies located in several countries. Third, it is the first study investigating FinTech activity in the broader set of CEE countries, which are at the forefront of the European FinTech market.

The paper is divided as follows. The theoretical and empirical background is provided in Section 2. Section 3 focuses on the data and methodology. Section 4 concentrates on the results and discussion and, finally, Section 5 concludes.

2. Business model framework and regional context

2.1. Activities and business models of FinTechs

The main challenge in classifying FinTechs arises from the diverse nature of their activities and the rapid development of the field. Although no universal classification system exists (Iman, 2020), different policymakers have attempted to create their classification systems for dealing with the growing FinTech market (Rupeika-Apoga and Thalassinos, 2020). As can be seen from Table 1, the classifications of policymakers exhibit greater similarity with traditional financial services like payments, insurance, deposits and lending, investment management. Greater variability can be observed in the context of different support services related to analytics, cloud computing, digital identity, cybersecurity, and applications of blockchain or distributed ledger technology.

In line with previous categorisations, we distinguish seven activities of FinTechs: payments, deposit and lending, insurance, investment management, analytics, distributed ledger technology, and banking infrastructure. Payments refer to technology-facilitated payment services like online and mobile payments, integrated billing. Deposit and lending include platform-based financing services cover crowdfunding, peer-to-peer lending, consumer financing, leasing, factoring, and microlending. Insurance refers to technology-enabled insurance services (brokerage and underwriting) often termed as InsurTech. Investment management covers robo-advice, automated advice, social trading, technology-enabled brokerage, and clearing. In defining the last three categories we rely on the definitions employed in Ankenbrand et al. (2019) with analytics covering big data, machine learning, artificial intelligence; banking infrastructure covering user interface, processing enhancement (compliance, identity, and security) and infrastructure technology (open banking); and distributed ledger technology focussing on blockchain-enabled financial services (including digital currency).

Difficulties in classifying FinTechs relate to the emergence of new business models for the provision of financial services. The literature review by Wirtz et al. (2016) concludes that the business model should capture the relevant activities of a company, how it creates value-added, and how this value creation evolves. This indicates that the business model is a wider and more complex phenomenon than just the main activity of the company.[5] Osterwalder and Pigneur (2010) business model canvas is built around nine blocks: key activities, key partnerships, key resources, value propositions, customer relationships,

[2] The remaining emerging hubs are Frankfurt, Barcelona, Milan, Geneva, Brussels, and Istanbul.

[3] Estonia is on the 10th, Poland on the 29th and Russia on the 32nd position.

[4] There do exist numerous country-specific reports that tend to focus on some selected business model aspects.

[5] There exist some papers on FinTech which treat the activity of the FinTech equivalent to their business model. For example, Lee and Shin (2018) identify six business models for FinTech start-ups including payment, wealth management, crowdfunding, lending, capital market, and insurance services. Liu et al. (2020) distinguish nine FinTech business models: online lending, crowdfunding/crowdinvesting, transaction and payment terminals, personal finance management, digital currency, mobile point of sale, robo-advisors, e-banking, and InsurTech.

Table 1
Overview of FinTech classifications.

Financial Stability Board (2017)	World Economic Forum (2015)	International Organisation of Securities Commissions (2017)	Ehrentraud et al. (2020)	In this paper
Payments, clearing and settlement	Payments	Payments	Payments, clearing, settlement	Payments
Deposits, lending and capital raising	Deposits and lending/ Capital raising	Lending/crowdfunding	Deposit and lending/ Capital-raising	Deposit and Lending
Insurance	Insurance	Insurance	Insurance	Insurance
Investment management	Investment management	Trading and investments/Planning (personal finance)	Asset management	Investment Management
Market support (cloud computing applications)	Market provisioning (machine learning, big data)	Data and analytics	–	Analytics
–	–	Security (digital identity, cybersecurity)	–	Banking infrastructure
–	–	Blockchain	Cryptoassets	Distributed ledger technology

Source: Synthesis by the authors based on Financial Stability Board (2017), World Economic Forum (2015), International Organisation of Securities Commissions (2017), Ehrentraud et al. (2020).

channels, customer segments, cost structure, and revenue streams. These blocks can be grouped onto a business model canvas under four main areas of business: infrastructure, offer, customers, and financial viability. According to Wirtz et al. (2016), the business model framework by Osterwalder and Pigneur (2010) is one of the most comprehensive ones covering seven of the potential nine business model components found in the business model literature, falling short only in the aspect of strategy and procurement. For this reason, the business model canvas has gained significant popularity in practice and empirical research (e.g., Sinkovics et al., 2014; Foà, 2019; Specht and Madlener, 2019; Jocevski et al., 2020).

The application of Osterwalder and Pigneur (2010) business model canvas for FinTech business models may require some adjustments (see Table 2). Eickhoff et al. (2017) use a method proposed by Nickerson et al. (2013) and reach a FinTech taxonomy based on six dimensions: dominant technology, value proposition, delivery channel, customers, revenue streams, and product/service offering. All of these components, except for dominant technology, are very similar to the original Osterwalder and Pigneur (2010) dimensions. The review by Clauss (2017) indicates that technology is often viewed as an external factor that affects business model innovations but is not part of the business model. Still, for example, Johnson et al. (2008) consider technology as part of the key resources of the firm. We believe that the dominant technology captures the technological resources needed for the provision of FinTech service, therefore, we link this dimension with the key resources in Osterwalder and Pigneur (2010) framework.

Table 2
Overview of FinTech business model components.

Business model component	Osterwalder and Pigneur (2010)	Eickhoff et al. (2017)	Iman (2020)	Variable used in this paper for analysis
Infrastructure	Key activities	Product/ service offering	Subsector	*activity* (as classified in Table 1) *time use*
	Key partnerships	–	Key actors (suppliers, competitors, complementors)	–
	Key resources	Dominant technology component	Underlying technologies	*employees local employees employment trend dominant technology*
Offer	Value propositions	Value proposition	–	*value proposition*
Customers	Customer relationships	–	–	–
	Channels	Delivery channel	–	*channel*
	Customer segments	Customers	Relationship with the customer; Key actors (customers)	*customer type geographic segmentation*
Financial viability	Cost structure	–	–	*fixed costs to assets*
	Revenue streams	Revenue stream	–	*revenue model*
Other	–	–	Contexts	–
	–	–	Industries	–

Source: Synthesis by the authors based on Osterwalder and Pigneur (2010), Eickhoff et al. (2017), and Iman (2020).

A literature review by Iman (2020) uncovers seven taxonomies of FinTech including the relationship with the customer, key actors, service offered, subsector, underlying technologies, contexts, and industries. As can be seen from Table 2, these dimensions can be linked to many of the dimensions in Osterwalder and Pigneur (2010). Similar to Eickhoff et al. (2017), Iman (2020) adds the technology dimension, which could proxy for some of the key resources of the firm, as explained above. However, there are some exceptions. First, the category "key actors" contains a mixture of aspects from "key partnerships" and "customer segments" in Osterwalder and Pigneur (2010). Second, contexts and industries diverge significantly from the Osterwalder and Pigneur (2010) business model canvas elements, covering developed countries, developing countries, and least developed countries, and industries referring to the financial services industry, IT industry, start-up.

The variables that we will use in our analysis of FinTech business models are presented in the last column of Table 2. With these, we capture most of the original dimensions of Osterwalder and Pigneur (2010) except for customer relationships, which was not covered also by Eickhoff et al (2017).[6] We acknowledge that, in addition to FinTech taxonomies discussed above, alternative approaches have been proposed for example in Gozman et al. (2018) and Gimpel et al. (2018). However, the former remains too simplified in comparison to Osterwalder and Pigneur (2010) setup and the latter too broad to be empirically implementable on a larger dataset. Also, both approaches have been designed based on start-ups only, which may limit their applicability to datasets containing established firms. We also acknowledge that some authors consider technology and service relationship (in our context customers) separately from the business model in e-commerce (Yoo and Jang, 2019).

To provide an alternative perspective to FinTech business models, we

[6] We did initially consider the "key partnership" dimension, however, as less than 50% of respondents provided input and this dimension is difficult to quantify, we left that dimension aside.

do consider in this paper, in addition to the business model framework of Osterwalder and Pigneur (2010), also the five FinTech business model attributes proposed by Lee and Teo (2015). These include low profit margin, asset-light, scalable, innovative, and easy compliance. More details about our operationalisation of FinTech business model attributes are provided in Section 3.

2.2. Attributes of the FinTech environment in the selected countries

Different external country- and activity-specific factors influence the development of business models (Clauss, 2017). To provide an overview of the FinTech environment in the selected countries, in comparison to the European average, we summarize some relevant quantifiable attributes in Table 3.As can be seen from Table 3, there exist very significant differences in the size of the selected countries. The population of Russia is 24 times larger than the total population of Estonia, Latvia, and Lithuania added together and 4 times larger than the population of Poland. When considering the GDP, the differences decrease, however, the ordering of countries remains the same as in the case of population. Yet, once GDP is corrected for the size of the population, the ordering of countries reverses with Estonia and Lithuania being in the lead, followed by Latvia, Poland, and Russia.

Different indicators can be used for capturing the quality of the business environment. One of the more complex indicators is the global competitiveness index developed by the World Economic Forum. Based on that indicator Estonia is in the lead, followed by Russia, Poland, Lithuania, and Latvia. In all of the countries (except for Estonia) the overall competitiveness level remains below the EU average.

As quite a significant portion of FinTech activity is entrepreneurial, one could also consider some kind of combined indicator capturing the quality of the entrepreneurial environment. Stam (2018) proposes an indicator for entrepreneurial ecosystems composed of 10 elements: formal institutions, entrepreneurship culture, physical infrastructure, demand, networks, leadership, talent, finance, new knowledge, and intermediate services. As Stam (2018) applied it to compare the ecosystems of provinces in the Netherlands, we modified the initial proxies, according to data available on the country level, and calculated the entrepreneurial ecosystem index using data on all European countries.[7] As can be seen from Table 3, Estonia has the best additive entrepreneurial ecosystem score of 12.49, followed by Latvia, Russia, Lithuania, and Poland. Estonia's overwhelming superiority arises mainly from the entrepreneurship culture – Estonia has nearly three times greater new business formation than in all other countries. This is further supported by more developed formal institutions. As Poland appears rather far from the remaining four countries and also below the EU average, it does raise the question why Warsaw is viewed as an emerging FinTechs hub (e.g., CCAF, 2018). One potential explanation is that the FinTech ecosystem is a bit different from the traditional entrepreneurial ecosystem.

Considering the peculiarities of the activities of FinTechs, we decided to modify the ecosystem index by Stam (2018). As FinTech relies on the availability and use of information technology and not on the transportation infrastructure, we replaced the infrastructure variables. We also added the overall level of financial development and financial sector regulations as additional FinTech ecosystem elements. Our modified FinTech ecosystem index shows rather interesting developments with Estonia remaining in the lead (score 14.73), followed by Poland, Lithuania, Latvia, and Russia. It is also noteworthy that, except for Russia, the remaining four countries score higher than the EU average. This could explain why the FinTech activity in these countries has been reportedly more active than in many of the more developed European countries.

The discussion above indicates that there exist some differences in the entrepreneurial environment for FinTech companies in the selected countries depending on the types of attributes considered. This refers to the possibility that the business models adopted by FinTechs could also differ across the selected countries. We investigate this aspect in the following sub-sections.

[7] In the process, we did omit leadership due to lack of country-based proxies.

3. Data and methodology

As we needed data on FinTechs, we began with the identification of the FinTech population in each country. We defined FinTechs as companies that contribute to the provision of financial services and have a clear, and generally innovative, information technology component in their business model.[8] To find companies falling under this definition, we started with companies listed as FinTechs in Crunchbase and rechecked whether these companies fell under our definition. Then we added FinTechs found from other data sources that varied across countries, including for example Funderbeam, local FinTech associations (e.g. FinanceEstonia), local central banks, expert knowledge of our commercial partners[9] and checked some existing public lists of FinTechs[10]. We included only those companies that were registered in the analysed countries. The final population of FinTechs contained 670 companies: 232 from Poland, 199 from Russia, 90 from Lithuania, 65 from Latvia, and 84 from Estonia. Based on the company descriptions available on their webpage, we then categorised all FinTechs according to the main field of activity (as classified in Table 1).

3.1. The survey

Most of the data on FinTech business models was collected through an online survey. The survey questionnaire was built around 13 questions similar to the ones previously employed in Ankenbrand et al. (2019). The questions covered the Osterwalder and Pigneur (2010) business model canvas components to identify the variables listed in the last column of Table 2. Key activities were identified by two variables. First, as variable *activity* following the classification in Table 1. Second, managers were also asked to determine on which activities they spend most of their time (*time use*), including programming, marketing, or running daily business. For both of these questions, several options could be selected.

Key resources were proxied with three variables. First, by asking the respondents to present the number of their employees (variable *employees*). Second, by indicating the proportion of local employees in their company (variable *local employees*). Third, the respondents were asked to present their view on the coming year's *employment trend* by selecting one option from the following: large growth, moderate growth, no growth, moderate decline, large decline.

Questions concerning customers concentrated on three variables. These included the variable *customer type* selected as either B2B, B2C, or both B2B and B2C. Variable customer *geographic segmentation* as one of the three: local, international, or both. The variable *channel* was based on the selection of service delivery channels being either digital, personal, or both.

Revenue streams were determined through a single variable *revenue model*. Multiple options could be selected amongst the following: interest income, commission income, license fee, centralized hosting of

[8] This definition is very similar to the one used by Milian et al. (2019).

[9] In the case of Poland, the survey was run by commercial company Quantify in cooperation with QuantFin foundation.

[10] We considered lists provided by Key Capital for Estonia (https://www.keycapital.eu/fintechcompaniesinestonia), Lithuania (https://www.keycapital.eu/fintechcompaniesinlithuania), and Latvia (https://www.keycapital.eu/fintechcompaniesinlatvia); RusBase for Russia (https://rb.ru/fintech/), LAFPA (https://www.lafpa.lv/en/about-us/members/) and LIAA (http://www.liaa.gov.lv/en/invest-latvia/start-up-ecosystem) for Latvia.

Table 3
Attributes of FinTech environment.

Stam (2018) element	Indicator	Data source	Estonia	Latvia	Lithuania	Poland	Russia	Median (5 countries)	Mean EU
–	Population (million)	World Bank	1.32	1.93	2.80	37.97	144.48	2.80	20.71
–	GDP (billion USD)	World Bank	30.73	34.41	53.43	585.66	1657.55	53.43	555.28
–	GDP per capita, PPP (th USD)	World Bank	23.27	17.86	19.15	15.42	11.29	17.86	28.75
–	Global competitiveness index (1 to 7 best)	GCI	4.85	4.40	4.58	4.59	4.64	4.59	4.70
Formal institutions	Corruption perceptions index (0 to 100 best)	Teorell et al. (2020)	70.00	59.00	57.00	62.00	29.00	59.00	57.51
	Rule of law (0 to 16 best)	Freedom House	14.00	12.00	12.00	11.00	2.00	12.00	11.24
	Government effectiveness (0 to 5 best)	Teorell et al. (2020)	3.59	3.57	3.51	3.21	2.30	3.51	3.28
	Voice and accountability (0 to 5 best)	Teorell et al. (2020)	3.71	3.50	3.34	3.34	1.37	3.34	3.18
Entrepreneurship culture	New business registrations per 1000 people ages 15–64	World Bank	23.59	8.01	3.33	1.44	3.26	3.33	5.68
Physical infrastructure	Road connectivity index (1 to 100 best)	GCI	78.00	81.60	84.60	78.70	78.00	78.70	73.50
	Efficiency of seaport services (1 to 7 best)	GCI	5.60	4.80	4.60	4.40	4.60	4.60	4.45
	Efficiency of train services (1 to 7 best)	GCI	4.70	4.50	4.50	4.00	4.90	4.50	4.05
	Efficiency of air transport services (1 to 7 best)	GCI	4.60	5.50	4.60	4.80	4.90	4.80	5.00
Demand	Market size (1 to 100 best)	GCI	42.30	44.00	50.10	73.40	84.00	50.10	58.52
Networks	Multi-stakeholder collaboration (1 to 7 best)	GCI	4.00	3.50	4.10	3.10	4.00	4.00	4.01
Talent	Tertiary education enrollment gross %	World Bank	69.55	67.04	68.53	68.11	80.39	68.53	66.89
Finance	Financing of SMEs (1 to 7 best)	GCI	4.40	3.40	3.70	3.90	3.30	3.70	3.95
New knowledge	R&D expenditures as % GDP	GCI	1.50	0.60	1.00	1.00	1.10	1.00	1.38
Intermediate services	Competition in services (1 to 7 best)	GCI	5.70	5.40	5.40	4.90	5.40	5.40	5.20
	Additive entrepreneurial ecosystem index	Calculation, authors	**12.49**	**8.54**	**8.29**	**7.98**	**8.40**	**8.40**	**9.00**
IT infrastructure	IT infrastructure indicator (1 to 7 best)	GITR	6.50	5.00	4.50	5.30	4.70	5.00	5.45
Additional demand indicator	Used a mobile phone or the internet to access an account (% age 15 +)	World Bank	74.82	60.75	55.89	64.60	39.57	60.75	48.99
Financial regulations	Presence of FinTech regulations (1 to 5 best)	Authors	2.00	2.00	3.00	3.00	1.00	2.00	1.88
Financial development	Financial development index (0 to 1 best)	IMF	0.33	0.28	0.26	0.48	0.48	0.33	0.48
	Additive FinTech ecosystem index	Calculation, authors	**14.73**	**10.25**	**10.34**	**10.57**	**9.42**	**10.07**	**9.51**

Source: compiled by authors, GCI refers to the Global Competitiveness Report, GITR to Global Information Technology Report by the World Economic Forum.

business applications, trading income, data, advertising income, or other.

To get a deeper insight into the business model components, we also added six questions to cover the business model aspects of Lee and Teo (2015). Respondents were asked to evaluate their company against competitors based on profit margin, fixed costs to assets, ability to scale, innovativeness, ease of compliance, and costs to customers. The evaluation scale ranged from 1 (very low) to 7 (very high).

Additional questions (outside of the business model focus) covered the operations of the companies including revenue and funding indicators, and maturity of the company (either already running, under construction, or developing). We also asked the respondents to evaluate their sentiment towards competition, finding customers, access to finance, costs of labour, staff, regulation, and expansion to international markets (measured on the scale from 1 – not pressing to 10 extremely pressing). As the purpose of the survey was also to provide input for local stakeholders, FinTechs were asked to indicate their outlook on the prospects of the sector and factors inhibiting its development.

The survey was carried out in Estonia, Latvia, Lithuania, Poland, and Russia from February 2019 to January 2020. The average survey period was three months and it varied across countries. GoogleDocs was used as the main survey platform. In Poland, it was eventually replaced with a professional survey platform provided by the commercial partner Quantify, who ran the survey because the initial attempts led to only 6 responses. Links to the online questionnaire were sent by e-mail to all companies identified as FinTechs (while in Poland a large part of the survey was performed also by telephone interview). Suitable e-mails were determined based on data presented in local business registries, companies' web-pages, or found through personal contacts. If possible, the e-mail was targeted directly to the company's owners, board members, or executives (e.g., CEO, CFO). In remaining cases, it was sent to the company's general e-mail. The first e-mail was followed by two to three reminders. In some cases, also follow-up phone calls and instant messaging through social media were used to increase the response rate. Local institutions helped also by spreading the word about the survey and news sites were used for the same purpose. Despite different measures taken, we got in a total of 199 responses. The response rate remained on average 27%: 38% in Estonia, 36% in Russia, 32% in Latvia and Lithuania, and 19% in Poland. Representativeness of the sample was tested using Pearson's Chi2 test on the proportions of activities in the surveyed FinTechs in comparison to the population. These statistics with their associated p-values are presented in Panel C in Table 4 for all countries together and also for each country separately. The responses are representative for the whole region, less so for Estonia and Latvia individually. As we are focused more on the whole region, the potential bias remains low.

3.2. Modifications to the dataset and cluster analysis

Before the analysis, we made some modifications to the dataset. First, the respondents provided their view of their main activity. As they could select multiple activity types, we needed to narrow it down to the single main activity. Therefore, we used the input from respondents to check the appropriateness of our initial FinTech activity classifications. At least two persons checked the consistency of categorizations and differences in opinion were discussed. Still, it is important to note, that the definition of the main field of activity remains arbitrary.

Second, the survey did not properly cover some business model

Table 4
Distribution of population and final sample by type of FinTech activity.

Panel A. Population (670 companies)	Estonia	Latvia	Lithuania	Poland	Russia	Total
Analytics	4%	5%	0%	9%	12%	8%
Banking infrastructure	17%	15%	27%	19%	20%	20%
Deposit & lending	29%	48%	10%	24%	27%	26%
Distributed ledger technology	32%	9%	9%	5%	4%	9%
Insurance	4%	0%	1%	4%	0%	2%
Investment management	0%	9%	3%	10%	10%	8%
Payment	15%	14%	50%	30%	27%	28%
Total	100%	100%	100%	100%	100%	100%
Total number of FinTechs	84	65	90	232	199	670
Panel B. Final sample (199 companies)	Estonia	Latvia	Lithuania	Poland	Russia	Total
Analytics	9%	10%	0%	11%	11%	9%
Banking infrastructure	16%	0%	34%	20%	24%	21%
Deposit & lending	22%	62%	14%	22%	33%	29%
Distributed ledger technology	22%	0%	7%	2%	1%	6%
Insurance	6%	0%	0%	2%	0%	2%
Investment management	0%	10%	3%	7%	11%	7%
Payment	25%	19%	41%	36%	19%	27%
Total	100%	100%	100%	100%	100%	100%
Total number of FinTechs	32	21	29	45	72	199
Panel C. Tests of representativeness	Estonia	Latvia	Lithuania	Poland	Russia	Total
Pearson Chi2	11.48	11.18	2.90	2.94	6.41	6.46
Pearson Chi2 p-value	0.04	0.05	0.72	0.82	0.27	0.37

Source: compiled by authors.

components like the value proposition[11] and dominant technology. Also, the delivery channel classification was very simple. Therefore, we decided to generate three additional variables for these business model components following the taxonomy presented in Eickhoff et al. (2017). The *value proposition* variable covers automation, collaboration, customisation, insight, intermediation, monetary, financial risk, transparency, consolidation, security, and usability. *Dominant technology* covers blockchain, digital platform, decision support system, marketplace, database system, and transaction processing system. An alternative classification for *delivery channel* covers application programming interface (API), mobile application, physical connection, web application, web application together with the mobile application, and instant message. The missing data for the respondents was backfilled by two persons using public information sources (mainly company web-page and data provided by respondents in a more descriptive format in the survey). One person generated the classifications for all FinTechs in the sample and then the classifications were checked by another person. At least one of these persons had very good local knowledge.

As the dataset contains a lot of information, we try to reduce the number of tables presented in the main body of the paper. The dataset is available from Mendeley Data (Laidroo et al., 2020).[12] To provide a reader with a possibility to look deeper into the numbers, which are mentioned in the descriptive analysis in Section 4.1, we have created Online Appendices which are part of the data repository file. In this paper, we will not refer to the figures contained in the Online Appendix to maintain better readability. However, the online appendices contain references to relevant sections of the paper.

The survey and backfilling of data provide a dataset containing all business model characteristics previously listed in the last column of Table 2 for each respondent. This data was analysed first using descriptive statistics. Previous studies developing FinTech taxonomies (e.g., Eickhoff et al., 2017; Gimpel et al., 2018; Gozman et al., 2018) have employed cluster analysis similarly to studies focusing on taxonomies of business models (e.g., Täuscher and Laudien, 2018; Camisón and Villar-López, 2010; Urban et al., 2018). Therefore, we also decided to use partition-based clustering for determining the groups of more similar FinTechs based on their business models using the following R packages: cluster (Maechler et al., 2019) and skmeans (Hornik et al., 2012). We preferred partition-based clustering over hierarchical clustering because non-hierarchical methods have been considered superior over hierarchical ones in management-based research (for discussion see Ketchen and Shook, 1996). Therefore, our baseline results reported in Section 4 will rely on partition-based clustering.

The standard method for non-hierarchical clustering is the k-means algorithm in which the objects are partitioned in such a way that the Euclidean distance between the cluster centre (centroid) and the members of the cluster are minimized. In other words, each observation belongs to the cluster with the nearest mean. The method has been further modified and extended. One possible modification is to use the median instead of the mean. In this case, we talk about the partitioning of the data into k clusters "around medoids" (so-called PAM algorithm), which is a more robust version of k-means algorithm. In the first step of the PAM method, the algorithm searches for the k representative objects (or medoids). Next, each observation is assigned to the nearest medoid and the k clusters are constructed. The goal of the algorithm is to find k representative objects, which would minimize the sum of the dissimilarities of the observations to their closest representative object (see Reynolds et al, 1992; Struyf et al., 1997 or Schubert and Rousseeuw, 2019 for details).

The main problem in the partition-based clustering algorithms is to find the optimal number of clusters. We applied two approaches. The first is based on minimizing the within-cluster sum of squares – hereafter WSS (so-called *elbow method*). The idea of the elbow method is to minimize the total intra-cluster variation, measured by the WSS. It treats the total WSS as a function of the number of clusters. The number of clusters should be chosen in such a way that adding another cluster does not improve the total WSS much. The curve of WSS against the number of clusters is plotted and the location of a bend (knee) is considered as an appropriate number of clusters.

[11] The value proposition was covered in the survey in four countries of the five. However, the response was provided as a description and these descriptions remained hard to classify.

[12] Interested readers can find more about the FinTech environment and FinTechs in selected countries in reports prepared for Poland (Kliber et al., 2020), Latvia (Rupeika-Apoga et al., 2020) and Estonia (Tirmaste et al., 2019). In the Polish report, a slightly modified definition of FinTech is used compared to the one used in this paper.

An alternative approach is based on maximizing the average silhouette (Kaufman and Rousseeuw, 1990). It computes the average silhouette of observations for different values of *k*. The optimal number of clusters is the one that maximizes the average silhouette over a range of possible values of *k*. The silhouette analysis itself measures how well an observation is clustered and it estimates the average distance between clusters. The silhouette plot displays a measure of how close each point in one cluster is to points in the neighbouring clusters.

The silhouette value $s(i)$of the object *i* can take any value from the interval $<-1;1>$ and:

- if $s(i)$ is close to 1, the object *i* is well classified (in cluster A),
- if $s(i)$ is close to 0, the object *i* can either belong to cluster A or B,
- if $s(i)$ is close to -1, the object is badly classified (closer to B than to A).

Struyf et al. (1997) suggest the following interpretation: if $0.71 \leq s(i) \leq 1$, the strong structure has been found, if $0.51 \leq s(i) \leq 0.7$ – the classification is called reasonable.

When using PAM algorithm on the Osterwalder and Pigneur (2010) classification, we proxied key activities with *activity*. We disregarded the alternative key activity indicator *time use* as it did not seem to exhibit distinctive variation across clusters in the first round of cluster analysis. Key resources were proxied with three variables: *employees*, *local employees*, and *dominant technology*. Indicator *employment trend* was left aside as the other indicators concerning employees are more objective. Value propositions were represented by the variable *value proposition*. Customers were proxied with three variables: *delivery channel*, *customer type*, and customer *geographical segmentation*. We disregarded the simpler indicator for the delivery channel (*channel*) as it did not seem to exhibit distinctive variation across clusters in the first round of cluster analysis. The cost structure was proxied by *fixed costs to assets*. Revenue stream was represented with the *revenue model*. As the data for all selected variables was not available, the final sample for Osterwalder and Pigneur (2010) classification drops to 192 FinTechs. The silhouette measure for the different number of clusters together with the size of the cluster is presented in Appendix 3. The average silhouette width was maximized for the two clusters containing 42 and 150 FinTechs. With three and four clusters, the average silhouette was almost equal, however, the individual silhouette for cluster 1 in the three cluster case (0.416) remained too small to be acceptable. In the 5-cluster case, the individual silhouette of Cluster 1 and 3 was too small to be acceptable. As in the 4-cluster case the silhouette exceeded 0.5 in each individual case and we considered that it would give us more insight in the data (compared to the best 2-cluster case), we decided to use four clusters.

To check the robustness of the results, we compared the results of partition-based clustering with the results of the hierarchical clustering through the value of the silhouette. The results of hierarchical clustering on Osterwalder and Pigneur (2010) dimensions using single, complete, and centroid linkage are presented in Appendix 4. As can be seen from Appendix 4, the average silhouette obtained with complete and centroid linkage is similar to that obtained with PAM. When we compare the clusters obtained with PAM and hierarchical methods, we observe that the clusters remain similar, especially with the centroid linkage method. This indicates that the classification obtained with PAM is rather robust. We tried also a robustness test with the mixture-model clustering[13], however, this algorithm used to end up in local maxima despite trying the same or different starting points, giving unstable and, hence, rather unreliable results (see the discussion on the pros and cons of using different types of clustering algorithms for instance in Nerurkar et al., 2018 or Jung et al., 2014). As in the case of mixture-model clustering the silhouette values for any number of clusters from 2 to 5 were also much lower (below 0.4) than the ones obtained for the hierarchical and partition-based methods, we will not report these in the paper.

In the case of the Lee and Teo (2015) model, we use the spherical *k*-means partition, in which all vectors are normalized, and distance measure is cosine dissimilarity – for details see Dhillon and Modha (2001). We used the following five types of variables: profit margin, asset-light (the fixed cost to assets), ability to scale, innovativeness and ease of compliance. Each of the variables took value from 1 to 7. As the data for all selected variables was not available, the final sample with Lee and Teo (2015) model drops to 197 FinTechs. The best results in terms of the silhouette measure were obtained for spherical *k*-means algorithm and two clusters. Still, we acknowledge that the average silhouette value (0.51) is on the verge of acceptable value. In addition to spherical k-means algorithm, we tried, as a robustness test, also hierarchical partitions using cosine distance matrix and Euclidean dissimilarity matrix with 2 clusters. As can be seen from Appendix 5, the average silhouette was maximised for single/centroid partition of cosine dissimilarity. However, the size of clusters (2 and 195) was not desirable for our purposes and the other methods were outperformed by the spherical *k*-means. This indicates that *k*-means provides the best classification based on Lee and Teo (2015), however, this classification is significantly harder to replicate compared to the one based on Osterwalder and Pigneur (2010).

4. Results and discussion

4.1. Comparative evidence on the business model attributes of FinTechs

In the following sub-Sections 4.1.1–4.1.5. we will discuss the results concerning the business model dimensions based on Osterwalder and Pigneur (2010). Section 4.1.6. focuses on results based on the business model framework proposed by Lee and Teo (2015).

4.1.1. Key activities

One of the most important characteristics of FinTech is its main activity (variable *activity*). This is the only characteristic for which we have data covering the whole population of 670 FinTechs in Estonia, Latvia, Lithuania, Poland, and Russia.

As can be seen from Panel A in Table 4, over 25% of all FinTechs in the selected countries are involved either in payments (28%) or deposit and lending (26%). As these activities represent the more frequently used financial services, their dominance in the context of FinTech services is not surprising. The least popular activities covering insurance, analytics, and investment management account for less than 12% of FinTechs in all five countries. However, on a country basis, the ordering of the most popular types of activities does vary referring to country-specific drivers' influence on the development of the FinTech market. The most striking difference is related to Estonia, where companies involved in distributed ledger technology applications (32%) dominate the whole FinTech landscape. These types of companies account for less than 10% of the FinTechs in the remaining countries. This result could be partly a reflection of the more developed IT infrastructure and greater demand for digital financial services (see Table 3). On the other hand, the deeper investigation did reveal that many of these companies are foreign-owned, meaning that one of the reasons why they are headquartered in Estonia could also be related to the e-residency, which allows foreigners to set-up companies easily through digital channels. The lower dominance of payments (compared to other countries) could also be explained with very developed digital payment infrastructure within commercial banks, which reduces the need for niche payment services.

[13] We applied a latent class mixture model using fpc package in R (Henning 2020). Since we had in our dataset a mixture of categorical and continuous variables, they were modelled by a mixture of distributions. The categorical variables were modelled within components by independent multinomial distributions, while the continuous one by the Gaussian distribution. The model was fit by maximization of the likelihood function computed with the EM-algorithm. The number of components was chosen using the Bayesian information criterion.

Lithuanian and Latvian FinTech landscape is less balanced than in Poland and Russia with the most popular types of FinTechs (payments and deposit and lending, respectively) accounting for nearly half of the FinTechs. In Latvia, more often than in other Baltic countries, people borrow at times when there is an unforeseen need for additional financial resources, moreover, the majority of such borrowers are young people (Rupeika-Apoga et al., 2020). This tendency explains the popularity of deposit and lending type dominance in Latvia, showing that banks are not interested in providing loans to this group of customers (Rupeika-Apoga and Saksonova, 2018). It is also noteworthy that compared to other countries Lithuania has a stronger presence of banking infrastructure FinTechs (27%). This could reflect the fact that many international banking groups have set up their support activities in Lithuania and this is fuelling the development of services that could potentially decrease the use of workforce. Greater balance of FinTech activities in Poland and Russia could be explained by the significantly greater size of the market which allows easier creation of a critical mass of FinTechs in a given activity area.

As our survey covered only 29.7% of the population, we provide also an overview of the activities of those FinTechs that responded to our survey. The distribution of their activities, presented in Panel B in Table 4, shows that FinTechs involved in payments or deposits and lending dominate also our sample. As the differences in proportions of all FinTech activities of our regional sample in comparison to the population remain between +-3% compared to the population, the representativeness of the whole sample is good. Greater differences in proportions are observed on a country basis, especially for Estonia and Latvia.

The respondents were also asked to classify their business as already running or under construction. 77% of respondents had already passed the construction phase and were already running their businesses. However, there existed rather significant cross-country differences. The most mature FinTechs were in Latvia where all respondents were already running their business. In Russia the share of respondents under construction was almost two times greater than in other countries, reaching 43% of all respondents. This does seem to indicate that the Russian FinTech market is in a more rapid growth phase compared to the other four countries. The distribution of companies in the construction phase across types of activity was very similar to those already running their business. This indicates that the attention of entrepreneurs continues to be rather evenly divided across the types of FinTech activities. The only exception was analytics where 39% of companies were under construction. However, this result was entirely driven by Russian FinTechs.

FinTechs were also asked to indicate which activities they spend most of their time on (variable *time use*). 68% of respondents indicated engagement in programming activities and 61% in running the daily business while only 32% mentioned marketing. Again, a bit more mature companies seemed to dominate the Latvian FinTech market where twice as many respondents (86%) mentioned running daily business compared to those mentioning programming (43%). In all other countries, the programming activity was mentioned more frequently than running daily business. Considering that the proportion of companies under construction is three times lower than the proportion of companies mentioning programming (except for Russia), FinTechs do seem to focus on this activity strongly even when the company becomes more mature. In most types of FinTechs, the effort made for programming and running the daily business were considered equally important. However, in FinTechs focusing on distributed ledger technology, the importance of programming was mentioned by all respondents with other activities being mentioned five times less frequently. This shows that although all FinTech activities require programming efforts, the success of distributed ledger technology FinTechs is more reliant on the application of technology. Rather surprisingly, marketing was mentioned three times less frequently by Russian FinTechs (11% of respondents) compared to FinTechs in the other countries. This could reflect the combined impact of a bigger share of companies under construction and the big domestic market, which could lower the relevance of marketing efforts. When looking at all responses, the popularity of marketing activity was equally relevant for all types of FinTechs with roughly 1/3 of respondents mentioning it.

4.1.2. Key resources

In terms of the number of employees (variable *employees*), 58% of all respondents had 25 or fewer employees and only 13% had more than 100 employees. From the five countries, Poland and Estonia had the greatest proportion of smaller FinTechs with less than 7% of FinTechs having more than 100 employees and over 40% of FinTechs having less than 10 employees. On the other hand, in Latvia, the share of FinTechs with over 250 people is 30% (again leading back to the conclusion of having more mature companies). When looking at the main activity of FinTechs, deposit and lending and investment management FinTechs tended to be bigger with over 20% of FinTechs having over 100 employees and less than 46% of FinTechs having less than 25 employees. These traditional financial services could be dominated by more established companies. However, it is interesting to note that in the context of payments, 68% of FinTechs have less than 25 employees. This seems to indicate that FinTechs involved in payments tend to be smaller companies providing niche products. At the same time, all surveyed FinTechs in distributed ledger technology had less than 50 employees.

It appeared that the Estonian and Latvian FinTechs were the most international with 31% and 24% of their employees being located abroad. In the whole sample, the share of employees abroad was 17% and the lowest share of employees abroad was observed in Poland (5%). The need for foreign labour could be linked to the size of the domestic labour market as well as the international ambition of the company. We will focus more on the internationality aspect when discussing customers and revenues in Section 4.1.4 and Section 4.1.5.

Employment trend was clearly towards increasing employment with 64% of respondents expecting moderate or large growth and only 3% referring to a decline (the remaining 33% expected no changes). The greatest employment growth potential was expected in Lithuania and Estonia where nearly 90% of respondents were expecting to increase their employment. From the types of activity, distributed ledger technology exhibited the most optimistic growth outlook with 89% of respondents referring to employment growth. The latter result seems to reflect the young age of the technology the application of which has great growth potential. As the surveys were conducted before the COVID crisis, it is difficult to estimate how that could affect the future growth potential of FinTechs in the region.

We also determined the *dominant technology* of FinTechs (one or several). The most frequently utilised technologies across all surveyed FinTechs included marketplaces (37%), transaction processing systems (36%), and digital platforms (23%). Marketplace technology dominated in deposit and lending activity, transaction processing systems in payments and digital platforms were used more frequently in banking infrastructure and payment services. Database systems, decision support systems, and blockchain were used in less than 12% of FinTechs and did not play a dominant role in any of the recorded FinTech activities. Still, most of the technologies were detected at least once for five or more FinTech activities (except for blockchain which was observed only in three types of FinTechs). The close connection of the technology with the main activity of the FinTech explains also some striking country-based differences in the popularity of different technologies in Latvia and Estonia compared to other surveyed countries. In Latvia, 62% of surveyed firms used marketplace technologies. In Estonia, marketplace technologies and digital platforms were followed instead by blockchain (recorded for 28% of firms). These results refer to the Latvian market being dominated by deposit and lending FinTechs and the Estonian market exhibiting a stronger presence of FinTechs providing services based on distributed ledger technology.

4.1.3. Value proposition

Instead of narrative descriptions provided by FinTechs in the survey, we determined the value proposition through publicly available data after the survey. The most common type of value proposition was usability which was observed in 56% of surveyed firms and dominated the results in all surveyed countries. The remaining rather equally frequently detected types of value proposition included monetary, intermediation, transparency, automation, and collaboration, being detected in 21 to 26% of surveyed FinTechs. Customisation, security, financial risk, consolidation, and insight were detected in 6 to 15% of cases. No significant differences emerged in the frequencies of the types of value propositions across countries. In terms of the fields of FinTech activity, the value propositions did differ. For example, payments and analytics could be linked to almost all types of value propositions (except for insight) rather equally. The value proposition of deposit and lending FinTechs, on the other hand, was more clearly concentrated around monetary, intermediation, financial risk, and transparency. In banking infrastructure FinTechs, the same value propositions were the least relevant, with more focus being on collaboration, automation, customers, usability, and security.

4.1.4. Customer segments and delivery channel

The respondents were asked to determine their *customer type*. 43% of FinTechs concentrated only on businesses, 26% only on consumers, and the remaining FinTechs on both. Over 53% of FinTechs in Estonia and Poland concentrated only on businesses, while consumers were the main focus of 62% of Latvian respondents and both types by 59% in Lithuania. The most even distribution of customer groups was observed in Russia. Business customers were more common amongst FinTechs focusing on payments and banking infrastructure, while consumers were the dominant customers of deposit and lending FinTechs. Still, even in all of these activity fields, at least some FinTechs reported also other types of main customer groups.

In terms of customer's *geographic segmentation*, 43% of respondents concentrated on international customers and 53% on local customers (the remaining on both). However, the focus of FinTechs located in different countries was very different. 77% of Estonian, 69% of Lithuanian, and 57% of Latvian FinTechs concentrated on international customers. The same indicator in Russia was 26% and in Poland only 22%. As the first three countries are smaller in terms of population and economy, it refers that FinTechs established in smaller countries do seem to have a more ambitious agenda due to the limitations of the domestic market. In Poland and Russia, the vast domestic market provides rather good opportunities to develop their business domestically. However, over the long run, it may hinder the capability of these companies to compete internationally. This conclusion is also supported by the proportion of employees abroad which was greater in smaller countries (see Section 4.1.2) When looking at the main customers of FinTechs involved in different main activities, it appears that the most international focus characterises FinTechs in distributed ledger technology 90% of which concentrate on international customers. 79% of investment management FinTechs focus instead on the domestic market. Both of these results could be partially driven also by country-specific factors as most distributed ledger FinTechs originate from Estonia and most investment management FinTechs from Russia and Poland.

In terms of the delivery channel of their services (variable *channel*), 64% of respondents were using both digital and personal communication, 35% only digital communication, and almost negligent 1% only personal communication. Digital-only communication was a bit less common in Latvia and Poland with shares less than 18%. The greatest proportions of digital-only communications were observed in FinTechs focusing on distributed ledger technology and investment management (60% and 57% respectively). This indicates that digital-only communication is a bit activity-specific. Considering that almost all FinTechs are concentrating on digital communication even if it is mixed with personal communication, the digital literacy of their customers remains a key driver of their success.

We determined the delivery channel also through publicly available data after the survey following a wider set of categories (variable *delivery channel*). The most frequently detected channels for all surveyed FinTechs included web applications (40%), application programming interfaces (28%), and web application together with mobile applications (27%). These delivery channels dominated in all surveyed countries except for Latvia. In Latvia, the physical connection was detected for 90% of FinTechs, at the same time the share of a web application together with the mobile application was also high compared to other countries (48%). This refers that Latvian FinTechs are trying to combine traditional physical delivery with innovative ones and such tendency can be partly explained with the dominance of deposit and lending activity and that all respondents were already running their business. In all other countries, the physical connection was detected in 6 to 18% of FinTechs. Almost negligible relevance was detected for instant messaging which was present only in 2% of FinTechs. In terms of the type of FinTech activity, the most even distribution of delivery channels is observed in payments and analytics across all possible delivery channels (except for instant messaging which remained at modest levels). Deposit and lending activities exhibited a strong reliance on web applications followed closely with a physical connection (as in the case of Latvia) while banking infrastructure FinTechs focused mainly on the delivery through application programming interfaces.

4.1.5. Revenue streams

Revenue of FinTechs may be based on different sources and FinTechs could indicate all models that are relevant for them (variable *revenue model*). The most frequently mentioned sources of revenue of respondents covered commission income (59%), interest income (24%), license fee (21%), and centralised hosting of business applications (21%). Trading income, data, advertising, and other income were mentioned by less than 10% of respondents. While commission income was the most frequently mentioned revenue model in all countries, the relevance of other revenue models varied. For example, interest income was mentioned as the second most frequent model by 62% of respondents from Latvia while in other countries it was mentioned by less than 34% of respondents. Centralized hosting of the business applications was mentioned as the second most frequent in Estonia (by 40% of respondents) and the license fee in Poland (by 47% of respondents). Revenue sources tended to vary depending on the main activity of the FinTech. In our sample, the commission income was the most common amongst payment, deposit and lending, and investment management and distributed ledger technology FinTechs. It very clearly dominated other revenue sources in payments, however, in deposit and lending it was almost as relevant as the interest income. FinTechs involved in analytics relied more on income from data and banking infrastructure FinTechs on income from centralized hosting of business applications. As revenue structure is easier to analyse in the context of the whole business model, we will turn to this issue in Section 4.2.

4.1.6. Evaluation of Lee and Teo (2015) business model dimensions

The mean evaluations of business model components suggested by Lee and Teo (2015) by countries are mapped in Fig. 1. Lee and Teo (2015) suggest that successful FinTechs should have a low profit margin and low fixed costs to assets. The lowest profitability was observed in Poland, while the highest in Latvia. The level of fixed costs to asset ratio puts Estonian FinTechs into a better position and Lithuanian FinTechs in the worst position. The remaining dimensions should score higher for more competitive FinTechs. In all three remaining dimensions, Russian FinTechs stand out with very positive results. Better scalability could be explained by the size of the domestic market. However, the Polish scalability indicator remains half of that of the Russian indicator, indicating that perhaps our Russian respondents have been more optimistic or were comparing themselves to less-developed FinTechs. The latter conclusion is partly supported by the innovativeness dimension where

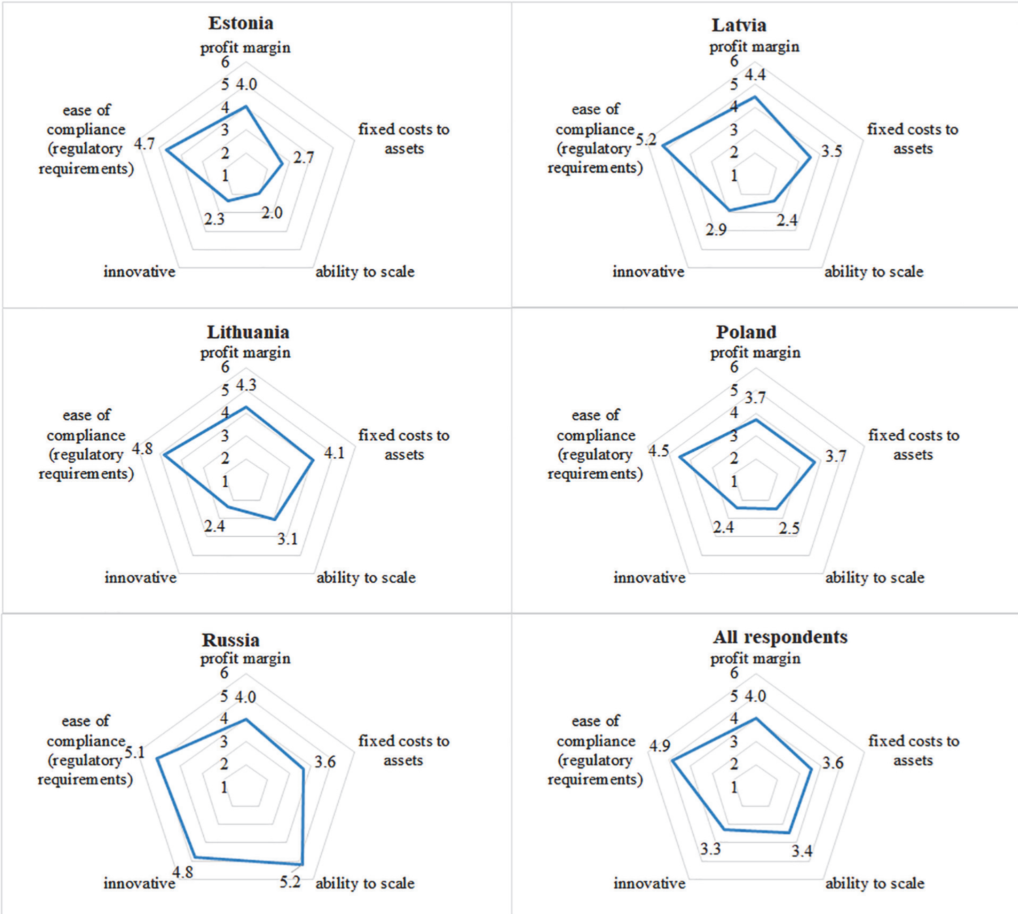

Fig. 1. Mean evaluations of Lee and Teo (2015) business model dimensions by countries Source: compiled by authors.

for example Estonian FinTechs got 2.5 points lower result while there is a very clear dominance of distributed ledger focused FinTechs in that sample.

When trying to rank the FinTechs by countries based on the selected five attributes, we would conclude that the Russian FinTechs are in a significantly more competitive position, followed by Latvia and Poland. Lithuania and Estonia are further behind. Although these rankings are based on a subjective evaluation of a limited number of business model attributes, they do provide an interesting insight into the thinking of managers or FinTechs in the five countries.

We also mapped the five attributes across the main activity of FinTech (instead of the country of registration). As can be seen from Appendix 1, the evaluations vary significantly with distributed ledger technology FinTechs providing rather conservative evaluations to all five attributes. The highest evaluations for profit margins are observed in analytics and lowest in the distributed ledger technology area. This is not too surprising as FinTechs in the latter field are more in the construction phase. The most asset-light companies are also in distributed ledger technologies and the most asset-heavy in deposit and lending. Surprisingly banking infrastructure stands out with the best evaluations for scalability, innovativeness, and ease of compliance. The latter results seem to be partly driven by the very optimistic responses of Russian FinTechs involved in banking infrastructure.

4.2. Similarities and differences in the business models

The cluster analysis based on Osterwalder and Pigneur (2010) business model components led to the distribution of 192 FinTechs into four clusters (see Table 5).[14] Clusters are of very uneven sizes with 132

Table 5
Number of FinTechs by home country within a given cluster.

Country	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Total
Estonia	4	11	10	5	30
Latvia	5	1	14	0	20
Lithuania	0	1	22	5	28
Poland	2	0	41	0	43
Russia	5	11	45	10	71
Total number of FinTechs	**16**	**24**	**132**	**20**	**192**

Source: compiled by authors.

[14] We lost seven observations as some respondents skipped the question providing input on some of the business model components.

(69%) FinTechs belonging to cluster 3 and the remaining FinTechs being more evenly distributed between the remaining three clusters.

It is possible to observe that FinTechs from different countries are rather unevenly distributed between the clusters. Cluster 1 has no Lithuanian, cluster 2 no Polish, and cluster 4 no Latvian or Polish FinTechs. In general, Polish FinTechs are mainly in cluster 3 with a very low presence in cluster 1, while Estonian and Russian FinTechs are present in all clusters. This indicates that the diversity of FinTech business models is greater in these two countries. To interpret these results, we need to understand the dominant business model characteristics of FinTechs within the four clusters. Therefore, we calculated for each cluster the proportions of FinTechs within a given Osterwalder and Pigneur (2010) business model category. The detailed percentages by categories are presented in Appendix 2. In Table 6, we summarize the most dominant results by each business model dimension.

We label cluster 1 as a "lending community" (LC). A typical FinTech belonging to the cluster can be characterised as a well-established crowdfunding platform with strong international ambition servicing exclusively either consumers or businesses. In terms of FinTech *activity*, cluster 1 stands out from other clusters by being more focused on fewer FinTech activities. It is dominated by FinTechs involved in the deposit and lending (56%). This also explains why the greatest portion (59%) of FinTechs have *dominant technology* related to a marketplace and their value proposition is, in addition to usability that is important in all clusters, related to intermediation, monetary, and financial risk. Cluster 1 is also characterised by the greatest average size of companies having the largest portion of FinTechs with over 250 employees and the lowest portion with less than 10 employees. It also has the greatest average percentage of employees abroad (12.3%). This indicates that FinTechs in cluster 1 are larger, more established firms with a large international workforce. It is also the only cluster that has the *delivery channel* being dominated by physical contact and web applications, the main *customer type* being B2C with customer *geographic segment* being dominantly international. It is rather striking that the share of FinTechs focusing simultaneously on B2B and B2C services is very low, indicating that the "typical" FinTech in this cluster concentrates only on one customer segment at a time. The *revenue model* of FinTechs in cluster 1 is uniquely being dominated by interest income. This indicates that many of the dominant characteristics of this cluster coincide with lending community archetype in Eickhoff et al. (2017).

We label cluster 2 as "mixed services" (LC + PS + O) because it shares some common traits with cluster 1 by having the most FinTechs also in deposit and lending, however, the banking infrastructure and payments are also quite strongly represented. This creates a situation where FinTechs of all sizes are present, digital platforms arise next to the marketplace as the second most relevant *dominant technology*. 74% of the employees are local. Customer dimension becomes dominated by application programming interfaces (APIs), and web applications, B2B relationships, and greater relevance of local customers. The main *revenue model* is now commission income. This indicates that a typical FinTech in cluster 2 could be characterised as locally focused business-oriented FinTech providing services through APIs for a commission fee. Based on the archetypes in Eickhoff et al. (2017) cluster 2 is a hybrid of lending community, financial markets intermediary, and payment service archetypes.

Cluster 3 and 4 are more similar to each other. We label cluster 3 as "payment service" (PS). Cluster 3 is tilted more towards "true" payment activities with greater use of transaction processing systems, web applications, servicing more frequently businesses and local customers for a commission fee. The workforce in this cluster is almost exclusively local. Therefore, we could characterise a typical FinTech in cluster 3 as users of transaction processing systems for the delivery of mainly payment services to local businesses through web and/or mobile applications. Many of the dominant characteristics of cluster 3 coincide with the payment service archetype in Eickhoff et al. (2017).

We label cluster 4 as a "payment community" (PS + LC) because it is characterised by FinTechs using marketplaces for the provision of payment or deposit and lending services to a wide range of customers for a commission fee. Compared to cluster 3, it contains more FinTechs which also utilise marketplaces (to a lesser extent also transaction processing systems) and has a diverse mix of customers both in terms of their type and geographic segmentation. Their revenue model is also almost equally dominated by commission fees and interest income. Based on the archetypes in Eickhoff et al. (2017) it is a mixture of payment service archetype and lending community archetype.

We conducted also a cluster analysis of FinTech business model dimensions of Lee and Teo (2015). This led to the identification of two clusters of FinTechs with 100 FinTechs in cluster 1 and 97 FinTechs in cluster 2. The composition of the clusters by countries exhibits some interesting results (see Table 7). As can be seen from Table 7, 66 (93%) of FinTechs from Russia fall into the first cluster leading to a result where Russian FinTechs account for 66% of FinTechs within cluster 1. The proportion of FinTechs from other countries in cluster 1 is 36% or below.

When looking at the number of FinTechs by the main field of activity in the two clusters (see Panel A in Table 8), most investment

Table 6
Dominant characteristics of identified clusters.

Variable	Cluster 1 (LC)	Cluster 2 (LC + PS + O)	Cluster 3 (PS)	Cluster 4 (PS + LC)
Activity	Deposit and lending	Deposit and lending; banking infrastructure; payments	Payment	Payment; deposit and lending
Employees (most popular category)	10–25 employees	1–9 employees	1–9 employees	10–25 employees
Employees (average number of employees)	93.7	58.1	41.7	42.4
Local employees (average % of all employees)	12.3	74.2	99.2	43.5
Dominant technology	Marketplace	Marketplace; digital platforms	Transaction processing system	Marketplace; transaction processing system
Value proposition	Monetary; transparency; financial risk; usability	Intermediation; usability	Usability	Usability
Delivery channel	Physical connection; web application	APIs; web application	Web application; web application + mobile application	Web application; web application + mobile application
Customer type	B2C	Both; B2B	B2B	Both
Geographic segment	International	Local	Local	Both
Fixed costs to assets – average based on a scale 1 to 6 (highest)	2	5	4	4
Revenue model	Interest income	Commission income	Commission income	Commission income; interest income

Source: compiled by authors.
Notes: Average number of employees is calculated as a weighted average based on the midpoint of each size category (category more than 250 employees taken as 250).

Table 7
Number of FinTechs by home country in clusters based on Lee and Teo (2015) business model dimensions.

Country	Cluster 1	Cluster 2	Total
Estonia	6	25	31
Latvia	5	16	21
Lithuania	7	22	29
Poland	16	29	45
Russia	66	5	71
Total number of FinTechs	**100**	**97**	**197**

Source: compiled by authors.

Table 8
Characteristics of clusters based on Lee and Teo (2015) business model dimensions.

Panel A. Distribution of the number of FinTechs by field of activity	Cluster 1	Cluster 2	Total
Analytics	7	10	17
Banking infrastructure	23	18	41
Deposit and lending	34	24	58
Distributed ledger technology	1	9	10
Insurance	1	2	3
Investment management	10	4	14
Payment	24	30	54
Panel B. Mean evaluation by respondents (scale 1 to 6)	Cluster 1	Cluster 2	Difference
Profit margin	3.85	4.19	−0.34
Fixed costs to assets	3.73	3.38	0.34
Ability to scale	5.02	1.84	3.18
Innovative	4.70	1.89	2.81
Ease of compliance (regulatory requirements)	4.66	5.04	−0.38

Source: compiled by authors.

management FinTechs are in cluster 1 and most distributed ledger FinTechs in cluster 2. FinTechs focusing on other activities seem to be more evenly divided between the clusters. The differences in average evaluations across clusters are presented in Panel B in Table 8. The indicators for profit margin and fixed costs to assets are more favourable for FinTechs in cluster 2. However, the remaining three indicators are significantly better in cluster 1 compared to the ones in cluster 2. Considering the dominance of Russian FinTechs in cluster 1, the differences in the scalability and innovativeness dimensions can be directly linked to the optimistic responses of Russian FinTechs (see discussion in sub-Section 4.1.6). As the evaluations were made by the respondents, we would emphasise the superiority of the results obtained from the cluster analysis using Osterwalder and Pigneur (2010) business model attributes.

4.3. Connecting the dots

Based on the differences in the FinTech ecosystems, we expected to observe country-specific differences in FinTech business models in the selected countries. In line with expectations, we observe several significant differences at the end of 2019. First, the main activities of FinTechs vary significantly. FinTechs in Estonia are more active in distributed ledger technology, in Lithuania in payments and in Latvia in deposit and lending. Polish and Russian FinTech market remains more balanced across types of FinTech activities. These differences can be explained with the peculiarities of local country-specific conditions, which play an important role in the development of FinTechs. This result also exemplifies that the development of FinTechs remains dependent not only on international conditions but also on local conditions as also supported in Laidroo and Avarmaa (2020).

Second, the activities of FinTechs are strongly influenced by the maturity of the FinTech market. Latvian market is the most mature with the lowest levels of FinTechs under construction and the greatest proportion of FinTechs spending most of their time running daily business. The Russian market is the least mature (43% of respondents under construction) with FinTechs spending their time more frequently mainly on programming compared to running their business or marketing. This tendency supports the view that Moscow and St. Petersburg can be viewed as emerging FinTech hubs (CCAF, 2018).

Third, the current resource needs of FinTechs vary across countries. Estonia and Poland have the biggest concentration of very small FinTechs with over 40% of FinTechs having less than 10 employees. While in Latvia we observe 30% of FinTechs with more than 250 employees. These differences relate to the different activity profiles and maturity of FinTechs. Still, most FinTechs (irrespective of their location) refer to moderate or large expected growth in their employee count. This reflects the continuing growth potential of the sector.

Fourth, significant differences are observed in the types of customers FinTechs mainly serve. In Estonia and Poland, the greater focus seems to be on the provision of B2B services, in Latvia tilted towards B2C services. Even more striking differences are observed in the context of customers' geographic segmentation. Smaller countries (Estonia, Lithuania, Latvia) focus more strongly on international customers while bigger countries (Poland and Russia) with a big home market focus mainly on the local market. The level of internationality of sales seems also to be reflected in the location of employees, with Estonian and Latvian FinTechs exhibiting greater proportions of employees located outside of the company's home country. The latter result indicates that FinTechs with a home base in a smaller country may be able to develop superior business models, which are competitive globally. Although FinTechs located in big countries have a big home market advantage, it may hinder their international growth potential.

Fifth, when evaluating the success factors of FinTechs by dimensions suggested by Lee and Teo (2015), the outlier seems to be Russia where managers indicate that their FinTechs are significantly more innovative, able to scale, and are in a better position when complying to regulatory requirements. As the gap between Russia and other countries is so large, at least part of this result seems to arise from a possibly too optimistic outlook of Russian FinTech managers. Still, we acknowledge that the big home market provides very good possibilities to scale, and weaker institutions (as shown in Table 3) may expose FinTechs to a lower level of regulatory pressure than in other countries. High evaluation of innovativeness could relate to a bit lower level of sophistication in average financial services provision, which is reflected for example in the use of mobile or Internet for accessing an account.

We also see that the main activity of the FinTech has a strong association with its other business model attributes. More mature FinTech activities are associated with greater resource use. For example, FinTechs in the field of deposit and lending and investment management have significantly more employees and lower employment growth than those in distributed ledger technology. The dominant technology partly defines the FinTech activity. Therefore, it is not surprising that deposit and lending FinTechs rely more on marketplace technologies, payments on transaction processing systems, and distributed ledger technology on blockchain. Although usability appears a key value proposition for all FinTech activities, more distinct value propositions appear in deposit and lending and banking infrastructure. Consumer-orientation remains superior to business-orientation in FinTechs providing payments and banking infrastructure services and the delivery channels vary significantly across types of FinTech activity. Revenue sources correspond to the type of FinTech with payment FinTechs relying on commission income, deposit and lending FinTechs both on commission and interest income, and FinTechs in analytics on income from data.

Cluster analysis based on Osterwalder and Pigneur (2010) framework revealed that the FinTechs in the five countries can be divided into four clusters: "lending community", "mixed services", "payment service", and "payment community". These clusters exhibited characteristics very similar to the three FinTech archetypes reported by Eickhoff et al. (2017). This indicates that their FinTech taxonomy has clear applicability in practice and some business model characteristics of FinTechs in the selected countries remain rather "standard". Still, we did observe that the business models of Russian and Estonian FinTechs were significantly more versatile (being the least versatile in Poland). This confirms the cross-country differences observed while looking at business model attributes of specific FinTechs. It also indicates that although some aspects of FinTech business models share similar traits globally, local conditions seem to play an important role in shaping the business models of individual FinTechs.

5. Concluding remarks and future research directions

The objective of this paper was to determine the differences in business model attributes of FinTechs in Estonia, Latvia, Lithuania, Poland, and Russia. The FinTech ecosystem scores referred to some distinct differences in local conditions. As expected, these seemed to explain some of the observed differences in business models of FinTechs across countries. As we did not take a closer look at the specifics of local conditions, further research is needed into more qualitative aspects of the functioning of local FinTech ecosystems and how that influences the development of FinTech business models over time. Without such deeper understanding policy-makers and entrepreneurs are acting blindfolded. The same reasons also highlight the need for more comparative research in the business models of FinTechs in other countries, as previously highlighted by Iman (2020) and Kavuri and Milne (2019).

Four main FinTech business model clusters identified in this paper exhibit some basic characteristics that are more or less similar to payment service, lending community, and financial markets intermediary archetypes proposed by Eickhoff et al. (2017). Although some common traits with archetypes exist, the attributes of Fintech business models differ in the five countries analyzed. This refers to the relevance of local conditions in shaping the business models of individual FinTechs. Our results support also the notion that the business model of FinTech is not equivalent to its main activity, as considered in some earlier works (e.g., Lee and Shin, 2018; Liu et al., 2020). As significant changes in FinTech business models are expected to continue, further research is needed into the gradually evolving attributes of FinTech business models.

Our results do remain vulnerable to several limitations. First, the results cannot be directly extended to other countries and within the selected countries outside of the selected timeframe. This relates to business models of specific FinTechs being influenced by local conditions and ecosystems, as well as to the possible changes in conditions and business model attributes over time. Second, three of the business model dimensions analysed in the paper were backfilled by the authors unlike other business model attributes, which were gathered through survey responses. Third, although the representativeness of the sample across the whole dataset is good, it remains below desired levels on a country-level for two countries. Therefore, country-specific results need to be interpreted with caution. Fourth, since there is no official list of FinTechs, some FinTechs may have remained outside of the scope of the paper. Eventually, the surveys were run before the COVID pandemic, and the sentiment of the respondents may have changed during 2020.

Despite these limitations, the paper provides unique comparative evidence on the development of FinTech business models in emerging European FinTech hubs. It also demonstrates that the "traditional" Osterwalder and Pigneur (2010) business model canvas can be easily utilised for the investigation of FinTech business models. Especially, if it is simultaneously considered with FinTech specific aspects determined by Eickhoff et al. (2017). Policy-makers and entrepreneurs can benefit from the use of this approach to understanding the local FinTech landscape.

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CRediT authorship contribution statement

Laivi Laidroo: Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing, Project administration. **Ekaterina Koroleva:** Investigation, Writing - original draft, Writing - review & editing. **Agata Kliber:** Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **Ramona Rupeika-Apoga:** Conceptualization, Investigation, Writing - original draft, Writing - review & editing. **Zana Grigaliuniene:** Investigation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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Attitude Towards Using Fintech Services: Digital Immigrants Versus Digital Natives

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As information technologies continue to evolve, the gap between those who were born before (digital immigrants) and after (digital natives) the technology revolution continues to widen. Building on the technology acceptance model, we examine the determinants and influences on attitudes towards using FinTech services and analyze differences in attitudes between the two categories of consumers. The results show the relevance of digital literacy, financial literacy, perceived ease of use and the personal habits of consumers in prompting a positive attitude towards the use of FinTech services. Digital natives have stronger personal habits oriented towards information systems; they rate their own levels of digital literacy higher and also perceive ease of use in FinTech. Digital immigrants rate their levels of financial literacy higher. The research highlights the relevance of improving the financial literacy of digital natives and the digital literacy of digital immigrants. Moreover, it is important to investigate further measures that would increase the perceived ease of use of FinTech by digital immigrants.

Keywords: FinTech service; consumer attitudes; technology acceptance model; digital natives; digital immigrants.

1. Introduction

The perceptions and behavior of people from different generations are influenced by the events and movements that they have experienced during their lifetime [Zeithaml *et al.* (2002)]. The current generation is shaped by digital transformation and the extensive implementation of information systems. A major part of their daily activities, such as communication, meetings and reading, depends on Internet access and information technologies [Kesharwani (2020)]. Observing the behavioral preferences and attitudes of people towards information systems, Prensky [2001] suggest two terms: "digital natives" and "digital immigrants". The first describes the younger tech-savvy generation. It refers to people born after the digital revolution who are accustomed to receiving information through digital channels. Digital immigrants are people born before that period. Information technologies are a necessary part of the lives of digital natives but not of digital immigrants

[Kirk *et al.* (2012)]. Information systems are implemented in different areas of people's daily activities and prompt different attitudes towards them. It is believed that in the educational context, learning patterns of digital natives differ from those of digital immigrants [Bennett *et al.* (2008); Chaves *et al.* (2016); Prensky (2001)]. Differences in the behavior of the two groups have also been observed in the context of digital advertisements [Kirk *et al.* (2015)] and tablet use [Vaportzis *et al.* (2017)], while a number of authors [Haluza *et al.* (2017); Ransdell *et al.* (2011); Reith *et al.* (2020)] have indicated behavioral and attitudinal differences between the generations in relation to information technologies used for online medicine and social reliance.

The use of information systems in the financial sector led to the emergence of the FinTech service: a "technology-driven financial service, which provides a new solution, a new business model or an alternative to what already exists in the financial sector... " [Carmona *et al.* (2018, p. 47)]. Examples of such services include robo-advisors, cryptocurrencies, e-wallets, crowdfunding, open banks and online payment platforms. The FinTech market is recognized as one of the fastest growing in the world. According to the Ernst and Young Global FinTech Adoption Index [2019], the share of FinTech adopters nearly doubled from 2017 to 2019. Consumers of FinTech services mention faster transaction speeds or lower commissions in comparison with traditional banking services [Papadimitri *et al.* (2021)]. FinTech services have higher mobility and the ability to respond more quickly to new needs and the wishes of consumers [Mogaji *et al.* (2021)].

To the knowledge of the author, no previous article has investigated the difference in attitudes towards using FinTech services by digital natives and digital immigrants and their possible reasons. This paper addresses this gap by analyzing and comparing the digital and financial backgrounds, the perceived ease of use, the perceived usefulness and the habits of digital immigrants and digital natives. The relevance of such research is highlighted by Kavuri and Milne [2019], who point to a gap in investigating customers' attitudes and barriers to the adoption of FinTech.

We investigate the determinants, the factors influencing attitudes towards using FinTech services, and the differences in attitude of the digital natives and digital immigrants towards using FinTech services. The study applies the technology acceptance model (TAM), which has been applied in previous empirical studies focusing on consumers' willingness to use FinTech services [Jiwasiddi *et al.* (2019); Stewart and Jürjens (2018)]. According to the technology acceptance model, perceived usefulness and perceived ease of use influence technology adoption [Davis (1986)]. To use FinTech services, the consumer must have the necessary financial literacy to assess the risks and benefits of the financial operations and the digital literacy required to perform them. It is important to note that personal habits also influence consumers' attitudes towards financial information technologies. In the framework of this article, we expand TAM by adding the personal habits and the levels of digital and financial literacy of the consumers as possibly relevant factors in determining differences in attitude towards using FinTech services by digital natives and digital immigrants.

In this study, we use a unique dataset of responses collected from the ordinary consumers of financial services through an online survey in Russia, conducted in the middle of 2019. The analysis of Russian consumers' attitudes towards FinTech services warrants attention for the following reasons: First, one of the undeniable drivers of the emergence of FinTech is the broad development of information systems [Suryono *et al.* (2020)]. In 2020, there were 118.0 million Internet users in Russia (sixth position in the world). Mobile banking development in Russia is also comparable to global trends [PricewaterhouseCooper (2019)]. Second, every second top manager of a financial organization in Russia is convinced that their company's clients have a high level of readiness to use digital financial services [National Agency for Financial Studies (2019)]. This shows that Russia has the necessary technology base for the active use of FinTech services by its consumers. This situation makes Russia an interesting case for investigating the influence of consumers' habits, of perceived usefulness, of perceived ease of use, and of levels of digital and financial literacy on the attitudes to FinTech services held by digital natives and digital immigrants.

Structural equation modelling (SEM) was conducted, based on a dataset of 3203 responses. The results show the relevance of financial literacy, digital literacy, perceived ease of use and the personal habits of consumers in their attitudes towards FinTech services. In comparison with digital immigrants, the digital natives have stronger personal habits oriented towards information systems; they also rate more highly their own levels of digital literacy and the perceived ease of use of FinTech services. This highlights the fact that digital natives are more tech-savvy than the older generations. Digital immigrants rate their own level of financial literacy more highly because of their experience and knowledge. Based on the results of this study, it is necessary to find ways to supplement the knowledge that is missing from various population groups (for example, by developing certain educational tools). Moreover, it is important to investigate further advances that would increase the perceived ease of use of FinTech by digital immigrants.

This paper contributes to the literature on FinTech [Alkhaldi and Kharma (2019); Laidroo and Avarmaa; Martens *et al.*; Stewart and Jürjens [2019; 2017; 2018]] and on digital immigrants and digital natives [Bennett *et al.* (2008); Kirk *et al.* (2015); Prensky (2001); Vaportzis *et al.* (2017)] by being the first to investigate the differences, and the reasons for them, in the attitudes towards FinTech services held by the two identified groups. Moreover, this paper contributes to the literature on TAM [Aboobucker and Bao (2018); Davis (1986); Jiwasiddi *et al.* (2019)] by adding new factors relating to financial information systems — personal habits and levels of digital and financial literacy — to the model. It also complements the FinTech literature in Russia [Evloeva (2019); Koroleva *et al.* (2021); Kurmanova (2019)] by identifying the factors that influence consumer attitudes towards using FinTech services.

This paper is structured as follows. Section 2 summarizes the theoretical and empirical background. Data and methodology are discussed in Sec. 3 and the results in Sect. 4. Finally, Sec. 5 provides a discussion and conclusion.

2. Theoretical and Empirical Background

The generation gap is a serious problem that expresses itself in miscommunication and misunderstanding between younger and older groups of people. The reasons for the gap are the varying life experiences, opinions, skills and perceptions of events of the different generations [Aggarwal *et al.* (2017)]. A generation gap will exist in every society and is determined by changes in a wide set of factors (civil liberties, gender roles, intergroup relations, social welfare, etc.) [Smith (2000)]. For example, the changing role of women or an increase in the literacy rate in a society will define the generation gap experienced in certain countries during the 20th century [Dhiman and Jain (2016)].

The end of the 20th century was marked by the digital revolution and the emergence of new communication channels [Deal (2007)]. This led to the widespread use of information systems and changes in the way young people communicate, socialize, create and learn [Helsper and Eynon (2010)]. The end of the 20th and beginning of the 21st centuries was also defined by a widening of the generation gap [Elena-Bucea *et al.* (2020); Subramanian (2017)]. To emphasize the differences in attitude towards technologies, including the digital, among the generations, [Prensky (2001)] suggest two terms: "digital natives" and "digital immigrants". The main criterion for the distinction between the two generations is age. Age accounts for most of the differences between the digital natives and digital immigrants in their acceptance of technologies. In contrast, Helsper and Eynon [2010] suggest that it is the experience and breadth of use of information systems that are the main criteria of the generation distinction. These authors argue that while age cannot bring digital immigrants closer to the digital natives, it is possible to close this gap through experience and breadth of use. Jung *et al.* [2010] and Czaja *et al.* [2006] indicate that the computer anxiety of digital immigrants predicts their lower use of technology. Alvseike and Brønnick [2012] point out that the cognitive deficits and low self-efficacy associated with older age significantly reduce participants' ability to use technology. Heinz *et al.* [2013] reveal that digital immigrants are ready to adopt new technologies when their usefulness and ease of use surpass their feelings of inadequacy. Thus, age-related (e.g. cognitive decline) and technology-related (e.g. ease of use) problems are the main barriers to digital immigrants accepting any technology.

The attitudes of digital immigrants and digital natives towards using digital services will depend on a number of factors, some of which were mentioned above. This has been explained by several theories (theory of reasoned action, technology acceptance model, theory of planned behavior, etc.) and has been tested empirically Bagozzi and Warshaw; Carbó-Valverde *et al.*; Jonker; Tan and Teo [1990; 2018; 2019; 2000].

One of the first theories to emerge was the theory of reasoned action (TRA), suggested by Fishbein and Ajzen [1975]. This assumes that the attitude of the consumer and the subjective norms of the society together influence consumer behavior. It is important to note that TRA considers human behavior to be "in good faith". However, TRA is repeatedly criticized because it ignores the resources and skills that are necessary to accept a service [Eagly and Chaiken (1993); Pinder

(2014)]. The continuous development of information technologies and the appearance of additional skill requirements intensify this drawback, leading to the emergence of new, more advanced models.

The technology acceptance model was developed by Davis in 1986 [Davis (1986)]. TAM is based on TRA, and it is used to study the technology adoption process of consumers. In the framework of TAM, two main factors — perceived usefulness (PU) and perceived ease of use (PEU) — influence attitudes towards the use of technology (in our case, the FinTech services) and its acceptance by consumers. Review papers by Mathieson [1991], Turner *et al.* [2010] and Surendran [2012] show that TAM predicts the intention to use an information system quite well.

According to recent studies [Abubotain and Chamakiotis (2020); Ramos (2017); Yoshino *et al.* (2020)], the ongoing developments in the FinTech services market require users to be more capable and to have both financial and digital knowledge. Moreover, the development of the FinTech services market requires consumer habits to change towards more digitally oriented services [Liu (2019); Vijai (2019)]. Therefore, we consider TAM to be the most suitable framework for this paper and we expand TAM by adding personal habits, levels of digital and financial literacy and by analyzing their significance in relation to attitudes towards FinTech services. We also add an external variable, characterizing the type of consumer as a digital native or a digital immigrant, to identify differences in their attitudes towards using the FinTech services. The modified TAM model is presented in Fig. 1.

Based on the framework depicted in Fig. 1, hypotheses, which are discussed in the following sub-sections, 2.1. and 2.2, were proposed.

2.1. *Hypotheses based on the classic technology acceptance model*

Perceived ease of use reflects the person's getting the required service when they apply the relevant information technology [Krishanan *et al.* (2015)]. If the use of the technology requires less effort, it leads to the consumer having a positive attitude towards the service. Digital immigrants are generally afraid to use new technologies

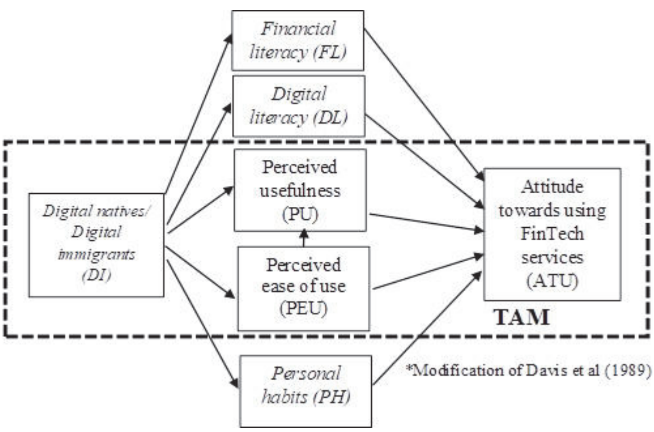

Fig. 1. Modified technology acceptance model.

and are slower at accepting them [Vaportzis *et al.* (2017)]. They are also more skeptical about providing their personal data to the information system [Kirk *et al.* (2015)]. In contrast, digital natives constantly interact with new technologies. Moreover, the adoption of new technologies is a normal situation for them, while for the digital immigrants, the process of learning requires a special effort [Bennett *et al.* (2008); Prensky (2001)]. Therefore, we propose the following hypothesis:

(H1) *Digital natives rate the perceived ease of use of FinTech services more highly than digital immigrants.*

This hypothesis has not been tested previously in the context of FinTech services. However, a number of studies [Birnholtz (2010); Chaouali and Souiden (2019)] highlight that younger generations have an advantage over older generations in accepting mobile technologies with less effort.

Perceived usefulness reflects the person's assessment of the information technology's expediency [Li and Huang (2009)]. As has been found in the case of mobile services, it includes an estimation of the possible risks and the effectiveness of using the service [Pedersen and Nysveen (2003)]. The following risks can be identified as the main risks of using FinTech services: security and privacy issues [Hussain *et al.* (2019)], operational complexities [Prasad (2019)] and legal uncertainty [Alam and Zameni (2019)]. The risks revealed are compared with the benefits of using FinTech services.

Digital natives are technology-oriented and interested in ensuring that the technologies meet their requirements and expectations as far as possible [Chung *et al.* (2010)]. In contrast, digital immigrants have not developed competency in digital language and refer to it as a second language [Meiring (2013)]. Based on the information above, we propose the following hypothesis:

(H2) Digital natives rate the perceived usefulness of FinTech services more highly than digital immigrants.

Little research has been conducted to empirically test the proposed hypothesis in a non-FinTech setting. [Metallo and Agrifoglio (2015)] reveal that digital natives find Twitter less useful than digital immigrants. Similar results are presented in an article by Hoffmann *et al.* [2014], which shows that digital immigrants are more critical in weighing the risks of an online service against its benefits, but they tend to rate the perceived usefulness of such a service more highly. In contrast, Tilvawala *et al.* [2013] show that the usefulness of various information systems is not seen as a major issue by either digital immigrants or digital natives.

2.2. *Hypotheses based on the modified technology acceptance model*

In addition to perceived ease of use and perceived usefulness, the influence of personal habits can be a significant factor in shaping consumers' attitudes towards using a service [Saba *et al.* (2000)]. Personal habits include self-efficacy and personal innovativeness with technology [Lewis *et al.* (2003)]. Self-efficacy refers to the readiness of the consumer to perform a specific action [Lown (2011)]. In the acceptance of FinTech services, it means, for example, to be ready to use cryptocurrency or to resort to crowdfunding. Personal innovativeness shows the willingness of the consumer to use new technologies [Agarwal and Prasad (1998)], for example, to use blockchain technologies or to communicate with robo-advisors.

In the context of digital natives and digital immigrants, digital natives are perceived as innovative consumers of available technology and eager adopters of new technology [Lei (2009)]. Digital immigrants wait to hear the digital natives' experience and only then decide whether to use the technology [Blackburn (2011)]. Thus, the following hypothesis is formulated:

(H3) *Digital natives have stronger habits oriented towards information systems than digital immigrants.*

This hypothesis has not yet been directly tested for FinTech services. Previous empirical studies mostly confirm the relevance of habit in the assessment of consumers' behavior [Mahon *et al.* (2006); Mittal (1988)]. Wu and Yen [2014] support the significance of personal habits in the context of mobile services use. Gu *et al.* [2013] reveal personal habits as being an important factor in the acceptance of information systems in education by both categories: digital immigrants and digital natives.

The digital and financial literacy levels of consumers using FinTech services can affect the outcomes that they receive from the service and, accordingly, their attitudes towards using it [Udo *et al.* (2010)]. Sánchez-Franco and Roldán [2005] show that differences in consumers' backgrounds influence their outcomes when utilizing a service and therefore their e-service satisfaction. FinTech services are based on the use of information systems for accessing financial services. This requires consumers of FinTech services to have the necessary financial literacy to assess the risks and benefits of financial operations and the digital literacy to perform such operations. Guo *et al.* [2008] and Helsper and Eynon [2010] both highlight the gap between digital natives and digital immigrants in their competence in using digital technologies. Digital natives grew up with easy access to and frequent use of digital technologies [Filho *et al.* (2021)]. This category of consumers constantly interacts with the world through information systems, which makes them more digitally literate than the digital immigrants. Digital natives, on the other hand, lack basic financial knowledge [de Bassa Scheresberg (2013); Lusardi and Mitchell (2017)], with many of the younger people not understanding financial terms such as interest rates, inflation and risk diversification [Lusardi *et al.* (2010)]. This means that digital natives often face financial issues because of their lack of experience in managing finances [Tan (2018)].

Therefore, we propose the following hypotheses:

(H4a) Digital natives rate their level of digital literacy as higher than digital immigrants do.

(H4b) Digital immigrants rate their level of financial literacy as higher than digital natives do.

These hypotheses have not been directly tested for FinTech services in a comparison of digital immigrants with digital natives. Previous empirical studies [Alford and Biswas (2002); Kleijnen *et al.*; Yoshino *et al.* (2020)] have proven the significance of digital and financial literacy in the adoption of FinTech services.

3. Data and Methodology

According to the purpose of this study, customers of financial services in Russia were the subjects of the research. To obtain a large sample size with a minimum level of influence by the researcher on the respondents, we preferred to use an online survey. For the data collection, we used an online survey containing 20 questions. The questions and the measurement scale for the study were based on previous research reported in the literature [Cheng *et al.* (2006); Hu *et al.* (2019); Huh *et al.* (2009); Patel and Patel (2018); Schueffel (2016); Teo and Pok (2003); Zandhessami and Geranmayeh (2014)], and they included appropriate expansions and adjustments relating to the characteristics of FinTech services. After designing the draft questionnaire, a pretest was performed on three respondents to determine potentially ambiguous expressions. Based on the respondents' feedback, the questionnaire was adjusted to improve its readability and perception. The final survey questionnaire is presented in appendix. To avoid misunderstandings by respondents, a definition of financial services (the same as in the Introduction) was also presented in the questionnaire. The questionnaire was designed in such a way that higher ratings corresponded, as a rule, to a more digitally-oriented consumer.

An online survey was created in Google Forms and distributed to the respondents using the river sample approach of a business analytics company. This is a technique for conducting online research where respondents are not taken from a database (a panel) but are attracted in real-time from among Internet users, specifically for a given survey [Lehdonvirta *et al.* (2021)]. The river sample approach has two significant advantages: it attracts respondents from across the Internet, not from a pre-selected database, and pre-screening is done during the survey. One of the disadvantages of the approach is the possibility of passing the survey to the same respondent twice. In an effort to reduce this risk, we asked respondents to provide their email addresses in the survey. When responses had the same email address, all but one were deleted. To motivate the respondents to respond to the survey and to include their email addresses, we promised to give free access to one of the paid courses on digital and financial literacy supplied by our university on their online platform. Responses were collected from June to November, 2019. The final sample contained 3203 complete responses. The demographic characteristics of the respondents, such as gender, age and employment status, are shown in Table 1.

Among the 3203 valid responses, 1495 (46.7%) respondents were males and 1708 (53.3%) were females. Regarding age distribution: people aged 56 years and older (38.1%) accounted for the highest proportion. The smallest group involved respondents aged 18–25 years. In terms of employment status, around 61% were employed, and only 4% of the respondents were employers.

Table 1. Sample demographics.

Measure	Item	Frequency	Percentage (%)
Gender	Male	1495	46.7
	Female	1708	53.3
Age		Digital natives	
	18–25	348	10.9
	26–35	479	14.9
		Digital immigrants	
	36–45	504	15.7
	46–55	653	20.4
	> 56	1219	38.1
Employment status	Student	290	9.1
	Employed	1944	60.7
	Employer	138	4.3
	Self-employed	680	21.2
	Other	151	4.7

The division into digital natives and digital immigrants as dependent on age remains somewhat arbitrary. According to Prensky [2001], digital natives are people who were born after 1980. Zur and Zur [2011] identify digital natives as being born into the digital era. VanFossen and Berson [2008] define the demarcation line at the age of 36. In determining the division between the categories analyzed, it is also important to understand the country's context. In Russia (formerly, the Soviet Union), computers became widely available to the population in 1984. That is why 1984 is recognized as the boundary year for distinguishing between digital natives and digital immigrants in the Russian context [Trushkin (2021)]. Based on this, we divided respondents into two groups: digital natives (18–35 years) and digital immigrants (36 and older).

The use of an online survey is possible in Russia due to the high Internet penetration into most age groups. The Internet has become available to almost all groups of the Russian population, regardless of place of residence, size of the settlement, age, education or gender [Mediascope (2021)]. Nevertheless, our survey could not reach people who did not have computers or Internet access via their phones. FinTech services are most relevant to the use of Internet-based digital technologies in the financial services industry, and they, therefore, remain inaccessible to non-users of digital technologies [Dwivedi *et al.* (2021); Tapanainen (2020)]. Thus, the latter group of people was not included within the target group of the survey due to their inability to choose between traditional and digital financial services. As social networks were used to distribute the survey, there is a sampling bias towards people who are more likely to use social media (digital natives). Therefore, the results of the survey might be affected by a sampling bias. To assess the severity of the sampling bias, we tested the representativeness of the sample using the chi-square test statistic and two indicators: age and gender. The choice of indicators was based on the availability of official statistics. Thus, we tested the following hypothesis: the distribution of the population in the sample is the same as the distribution of the population according to the official information [Blinov (2019); Kagan (2019)]. The results are presented in Table 2.

Table 2. Comparison of sample and population distributions.

Gender			
Observed	Expected	Observed - Expected	Pearson
1495	1486	9	0.233
1708	1717	−9	−0.217
$Pearson\ chi^2 test(1) = 0.1017 Pr = 0.750$			
Age			
Observed	Expected	Observed - Expected	Pearson
348	352	−4	−0.213
479	450	29	1.367
504	480	24	1.095
653	672	−19	−0.733
1219	1249	−30	−0.849
$Pearson\ chi^2 test(4) = 4.3721 Pr = 0.358$			

The insignificant chi-square test statistic in both cases implies that the hypothesis should be accepted, that is, the age and gender distribution of the sample is the same as for the population. Thus, this sample represents the Russian population. We do acknowledge that the data may contain some self-selection bias; however, we do not have access to any variables that could be used to adjust for this selection bias.

To empirically test the hypotheses within the framework of the modified technology acceptance model, we created six latent variables (digital literacy, financial literacy, perceived usefulness, perceived ease of use, personal habits and attitude towards using) and one observable variable (digital natives versus digital immigrants) (see Table 3 for details).

Each latent variable was composed of two to four observable variables. To achieve content validity, the observable variables were selected based on a detailed review of the related literature, as shown in Table 3.

Most of the observable variables were measured on a five-point scale except for PH_1 and ATU_3 (three-point scales), while a dummy variable was used to distinguish between digital natives (1) and digital immigrants (0). We assumed that the answers of respondents expressed their opinions. It is important to note that some people tend to rate themselves either lower or higher than others, even though they have the same level of ability [Lussier and Hendon (2017)]. For example, older people tend to have greater confidence in their financial literacy, although they do rather poorly on the test questions [Lusardi and Tufano (2015)]. This indicates that the results may be biased because of the potential overconfidence of some respondents.

To analyze the results, a comparative analysis was conducted, and then a structural equation model (SEM) was implemented. SEM is a combination of factor analysis and path analysis. It is popular among researchers [Patel and Patel (2018); Tan and Teo (2000); Teo and Pok (2003)] due to its flexibility and ability to analyze latent and observable variables at the same time [Nachtigall *et al.* (2003)]. SEM has two main components: the measurement model and the structural model [Anderson and Gerbing (1988)]. The measurement model describes the interrelation between

Table 3. Variables and questions included in the questionnaire.

Latent variable	Observable variable	Question	Scale	Sources
Financial literacy (FL)	FL_1	I know about different financial products and instruments, their advantages and disadvantages.	1 - completely wrong; 2 - wrong; 3 - more yes than no; 4 - true; 5 - absolutely true	Zueva [2018]
	FL_2	I can assess and diversify financial risks.	1 - completely wrong; 2 - wrong; 3 - more yes than no; 4 - true; 5 - absolutely true	
Digital literacy (DL)	DL_1	I am a confident PC (phone) user, I use the Internet and mobile applications.	1 - completely wrong; 2 -wrong; 3 - more yes than no; 4 - true; 5 - absolutely true	Teo and Pok [2003]
	DL_2	I use the mobile (Internet) bank, am able to open a personal account and make transactions.	1 - completely wrong; 2 - wrong; 3 - more yes than no; 4 - true; 5 - absolutely true	
Perceived usefulness (PU)	PU_1	FinTech services can increase efficiency.	1 - completely wrong; 2 - wrong; 3 - more yes than no; 4 - true; 5 - absolutely true	Huh *et al.* [2009]; Hu *et al.* [2019]
	PU_2	You can save a lot of time by using the services of FinTech companies.	1 - completely wrong; 2 - wrong; 3 - more yes than no; 4 - true; 5 - absolutely true	
	PU_3	FinTech companies provide the whole range of services I need.	1 - completely wrong; 2 - wrong; 3 - more yes than no; 4 - true; 5 - absolutely true	

Table 3. (*Continued*)

Latent variable	Observable variable	Question	Scale	Sources
Perceived ease of use (PEU)	PEU_1	For me, the services of a FinTech company are more affordable than the services of traditional banks.	1 - completely wrong; 2 - wrong; 3 - more yes than no; 4 - true; 5 - absolutely true	Zandhessami and Geranmayeh [2014]; Cheng *et al.* [2006]
	PEU_2	I think the FinTech application interface is extremely simple and convenient.	1 - completely wrong; 2 - wrong; 3 - more yes than no; 4 - true; 5 - absolutely true	
	PEU_3	It is easy to use FinTech services.	1 - completely wrong; 2 - wrong; 3 - more yes than no; 4 - true; 5 - absolutely true	
Personal habits (PH)	PH_1	Do you prefer to interact with the bank by mobile or Internet banking?	1 - by mobile, 2 - doesn't matter which 3 - by Internet banking	Teo and Pok [2003]
	PH_2	How often do you use bank cards?	1 - do not use; 2- occasional payments; 3 - monthly; 4 - weekly; 5 - daily	
	PH_3	How often do you use mobile technology payment methods?	1 - do not use; 2 - occasional payments; 3 - monthly; 4 - weekly; 5 - daily	
Attitude towards using (ATU)	ATU_1	If I have used FinTech services, I am willing to continue using them.	1 - completely wrong; 2 - wrong; 3 - more yes than no; 4 - true; 5 - absolutely true	Patel and Patel [2018]
	ATU_2	I would recommend the services of FinTech companies to my friends.	1 - completely wrong; 2 - wrong; 3 - more yes than no; 4 - true; 5 - absolutely true	
	ATU_3	Do you know what the term FinTech means?	1 - no; 2 – I have heard it, but I don't know what it means; 3 - yes	Schueffel [2016]
—	Digital natives/ Digital immigrants (DI)		Digital natives: 18–35 yrs.; Digital immigrants: > 36 yrs.	VanFossen and Berson [2008]

Notes: Author made appropriate expansions and adjustments in development of questions according to the characteristics of FinTech services and goals of the paper.

observable and latent variables, which are inferred from the observable variables (factor analysis). In this study, we estimated measurements of latent variables using three criteria: composite reliability, average variance extracted, and Cronbach's alpha [Fornell and Larcker (1981)]. The structural model analyzes the interrelations among the variables investigated, principally among the latent variables (path analysis). We estimated the overall goodness-of-fit and carried out structural equation analysis to investigate the strength and direction of the interrelations among the variables investigated in the model (Fig. 1).

4. Results

4.1. *Comparative analysis*

The results of the averaged evaluations by digital natives and digital immigrants are presented in Table 4 and permit the differences in the groups to be analyzed.

The T-test shows that there is a significant difference between digital immigrants and digital natives for all observable variables analyzed. In line with expectations (H1), digital natives rate the perceived ease of use of FinTech services higher by 1.5 points than digital immigrants and achieve an average value of 3 (where 5 is the maximum). This means that digital natives are more inclined to choose FinTech due to its more affordable and simpler service relative to the traditional banks. The low average rate for the digital immigrants means that this category of consumers faces difficulties in using the FinTech services. Contrary to H2, digital immigrants rate the perceived usefulness of FinTech services higher, on average, by 0.8 points than digital natives. According to these results, digital immigrants agree with the advantages of FinTech services, such as efficiency and saving time, and they recognize that FinTech provides the whole range of services that they need. In line with (H3), the habits of digital natives are more digitally oriented than is the case with

Table 4. Analysis of differences in average rates of answers between digital natives and digital immigrants.

Latent variable	Observable variable	Digital natives	Digital immigrants	t-test	p-level
Perceived ease of use (PEU)	PEU_1	3.20	1.68	−47.30	0.000
	PEU_2	2.98	1.26	−58.80	0.000
	PEU_3	2.88	1.35	−54.29	0.000
Perceived usefulness (PU)	PU_1	2.20	2.60	6.53	0.000
	PU_2	3.02	3.87	18.97	0.000
	PU_3	2.55	3.90	27.76	0.000
Personal habits (PH)	PH_1	3.12	2.69	−8.44	0.000
	PH_2	3.43	2.13	−20.20	0.000
	PH_3	3.24	2.53	−9.95	0.000
Financial literacy (FL)	FL_1	2.22	3.58	27.30	0.000
	FL_2	2.07	2.54	8.63	0.000
Digital literacy (DL)	DL_1	4.21	2.62	−32.25	0.000
	DL_2	4.03	2.68	−27.40	0.000
Attitude towards using (ATU)	ATU_1	2.25	1.80	−12.61	0.000
	ATU_2	2.57	1.90	−14.67	0.000
	ATU_3	2.78	1.98	−12.91	0.000

the digital immigrants. The results also support (H4a) and (H4b), reflecting the relative financial literacy and digital literacy of the correspondents. Digital immigrants rate their financial literacy higher by 0.9 points in comparison to digital natives. Digital natives rate their digital literacy higher by 1.47 points than digital immigrants. Digital natives achieve high values (4.12 on average) for self-assessed digital literacy. The FinTech services market requires people who have both financial and digital knowledge. According to the results presented in Table 4, there are few people in Russia today who have sufficient financial and IT background and are ready to use the FinTech services. Overall, digital natives are more optimistic about accepting FinTech services than digital immigrants. Nevertheless, low rates, reflecting attitudes towards FinTech services among both categories, also prove the low level of readiness among the general population for digital transformation in the financial sector.

4.2. *SEM: Analysis of the measurement model*

To estimate the measurement model, we used confirmatory tests of internal consistency, reliability and validity. The results are presented in Table 5.

Based on those shown in Table 5, we analyzed the results obtained. The factor loadings range from 0 to 1, with the larger value indicating a better latent construct. The acceptable level is more than 0.7 [Tang and Chiang (2009)]. The lowest loading obtained is 0.58, belonging to perceived usefulness (PU_3). There is another variable (PH_2), reflecting personal habits, which is close to the minimum acceptable level and falls just below the 0.7 standard. To capture the phenomenon more thoroughly, we retained these in the further analysis.

As suggested by Fornell and Larcker [1981], the composite reliability (CR) of the sample should be larger than 0.7. In our case, it exceeds this critical value (see

Table 5. Reliability and validity measures.

Construct/indicator	Item	Factor loading	Composite reliability (CR)	Cronbach's alpha	Average variance extracted (AVE)
Financial literacy (FL)	FL_1	0.85	0.8332	0.8312	0.7141
	FL_2	0.84			
Digital literacy (DL)	DL_1	0.85	0.8905	0.8850	0.8031
	DL_2	0.94			
Perceived usefulness (PU)	PU_1	0.93	0.8842	0.8582	0.7271
	PU_2	0.99			
	PU_3	0.58			
Perceived ease of use (PEU)	PEU_1	0.72	0.8714	0.8613	0.6951
	PEU_2	0.90			
	PEU_3	0.87			
Personal habit (PH)	PH_1	0.70	0.8215	0.8111	0.6135
	PH_2	0.64			
	PH_3	0.97			
Attitude towards using (ATU)	ATU_1	0.79	0.9188	0.9278	0.7917
	ATU_2	0.97			
	ATU_3	0.90			

Table 6. Goodness-of-fit indices for the structural model.

Criteria	RMSEA	GFI	SRMR	CD	CFI	TLI
	< 0.08	> 0.9	<0.08		>0.9	>0.9
Measurement	0.08	0.901	0.079	0.995	0.927	0.911

Table 4), indicating that the model has good internal consistency. This fact is also confirmed by Cronbach's alpha, which is larger than 0.8 for all constructs [Shevlin *et al.* (2000)].

The average variance extracted (AVE) of the sample should be larger than 0.5 [Parolia *et al.* (2007)]. If the AVE is less than 0.5, the validity of the observable variables and construct is questionable. In our case, each construct had acceptable validity.

Overall, the results presented in Table 4 support the reliability and validity of the supposed constructs.

4.3. *SEM: Analysis of the structural model*

After the estimation of the measurement model, the structural model was estimated. Six common model-fit measures were used to estimate the model's overall goodness-of-fit. These are the root mean square error of approximation (RMSEA), goodness-of-fit index (GFI), standardized root mean square residual (SRMR), coefficient of determination (CD), comparative fit index (CFI) and Tucker–Lewis index (TLI). Table 6 presents the results of the estimation of goodness-of-fit.

According to Table 6, the indices are within the commonly acceptable bounds [Hair *et al.* (1998)]. CD shows that the model explains 99.5% of the variation of variables used in the model. This indicates that the obtained results can be used to indicate the key factors influencing consumers' attitudes and adoption of FinTech services. The RMSEA is related to the residual of the model. Its value is 0.08, indicating a well-fitting model. The FI and the TLI are high and moderate, respectively, given their 0.9 acceptance levels. The SRMS is below the acceptance level of 0.08. It can therefore be concluded that the measurement model has a good fit with the data collected and the results obtained are relevant. Based on the previous results, the model is accepted and we proceed with the interpretation of the path coefficients of the model. The test results for the hypotheses are shown in Table 7.

In line with H1, digital natives perceive higher ease of use of the FinTech services than digital immigrants. They estimate the perceived ease of use as 45% higher than the digital immigrants. Interestingly, we see that the digital immigrants estimate the usefulness of the FinTech services to be 29% higher than the natives. This contradicts H2.

The positive relationship between digital natives and personal habits supports H3. Digital natives evaluate their personal habits as oriented on information systems to be 38% higher than digital immigrants evaluate theirs to be. In line with expectations (H4), digital natives rate their level of digital literacy as 159% higher than the digital immigrants; while the digital immigrants rate their level of financial

Table 7. Results of the structural model.

Path	Coefficient	Std. Err.	z	$P > \|z\|$
PEU ← DN	0.45	0.03	13.03	0.00
PU ← DN	−0.29	0.03	−9.29	0.00
PH ← DN	0.38	0.04	9.91	0.00
DL ← DN	1.59	0.05	32.08	0.00
FL ← DN	−0.39	0.05	−8.12	0.00
PU ← PEU	0.90	0.02	36.16	0.00
ATU ← PEU	0.37	0.02	15.75	0.00
ATU ← PU	0.03	0.02	1.59	0.11
ATU ← PH	0.37	0.01	25.69	0.00
ATU ← FL	0.13	0.01	10.11	0.00
ATU ← DL	0.06	0.01	6.27	0.00

literacy as 39% higher than the digital natives. As a result, all hypotheses, except for H2, are accepted.

Consumers who have stronger digitally oriented habits have a 37% more positive attitude towards the FinTech services. This means that personal perceptions of technologies and the possibility of their use prevail over other factors. This fact confirms the advisability of including this factor in the model. The next factor is the perceived ease of use of FinTech services: We observed that consumers who estimated the ease of use as higher also had a 37% more positive attitude towards using the FinTech services. This supports the view that the attitude of consumers and their acceptance of FinTech services depend on the simplicity, transparency and understandability of the information systems used in the FinTech area. Consumers who considered their levels of financial literacy and digital literacy to be high have, respectively, a 13% and a 6% more positive attitude towards FinTech services. Our results show that for an information system to be accepted, it is not necessarily enough to have a sufficient level of digital literacy, but it may also be necessary to have sufficient knowledge of the field to which it is applied. What is more remarkable is that the perceived usefulness of the FinTech services does not affect consumers' attitudes towards using the FinTech services.

5. Discussion and Conclusions

The results show that, in line with expectations (H1), digital natives rate the perceived ease of use of the FinTech services more highly than digital immigrants do. This result confirms and extends the results from other technology-oriented studies [Birnholtz (2010); Metallo and Agrifoglio (2015); Tilvawala *et al.* (2013)]. It supports the view that digital immigrants must make greater effort to accept new technologies due to their lack of knowledge and experience. Taking into account the significant relationship between the perceived ease of use of the FinTech services and attitudes towards using them, it highlights the necessity of developing more intuitive and user-friendly interfaces for solutions in the FinTech area, particularly in relation to digital immigrants. Otherwise, the older generation will face difficulties and complexities in the use of the FinTech services and have negative experiences. Such an experience is likely to involve a negative attitude towards the service itself and a subsequent refusal to accept it. Therefore, service providers need to consider the characteristics of digital immigrants during the process of developing their services.

Contrary to expectations (H2), our results show that digital immigrants rate the perceived usefulness of FinTech services more highly than digital natives. Similar results were reported by Hoffmann *et al.* [2014] and Metallo and Agrifoglio [2015]. This can be explained as follows: digital natives, born after the digital revolution, have difficulties estimating the true effectiveness of information systems due to their lack of experience with the alternatives, and they may, therefore, underestimate their usefulness. The relationship between perceived usefulness and attitude towards using FinTech services has little significance. As a result, it does not seem reasonable to promote the usefulness of FinTech services to digital natives.

The results show that digital natives have stronger digitally-oriented habits than digital immigrants (H3). The results concerning personal habits complement the studies by Mahon *et al.* [2006], Gu *et al.* [2013] and Wu and Yen [2014]. Digital immigrants tend to be skeptical of innovative technologies. As a result, they decide to use them only based on the experience of digital natives. Moreover, according to the answers of respondents, 70% of the digital immigrants did not fully understand the term FinTech. It is difficult to develop a personal attitude towards technologies without understanding their capabilities and advantages. FinTech companies could consider promoting their services in ways that are more familiar to digital immigrants (for example, via television or news publications). Today, in Russia, information about FinTech companies is presented only through specialized portals. This leads to ignorance regarding the FinTech area in a large part of the population. As far as the author knows, no other article has investigated the impact of personal habits on attitude towards using FinTech services from the standpoint of generational differences. The results obtained support the importance of personal habits and their influence on adoption by consumers. We suggest that TAM should be expanded and personal habits added as an obligatory factor in future studies focusing on FinTech adoption.

In line with expectations (H4a), digital natives rate their level of digital literacy more highly than digital immigrants do. Similar results were reported by Alford and Biswas [2002] and Kleijnen *et al.* [2004]. However, since digital immigrants consider the usefulness of FinTech services more highly than digital natives, there is greater potential for helping the immigrants to overcome their barriers relating to digital literacy. In the context of FinTech, consumers also need sufficient financial literacy. The results show that digital immigrants rate their level of financial literacy more highly than digital natives do (H4b). To the knowledge of the author, no other article has investigated the influence of level of financial literacy on the adoption of FinTech services. The results emphasize that to attract consumers to adopt the FinTech services, it is necessary to develop both the digital and financial literacy of the population, as dependent on their category (whether digital immigrant or digital native).

Our results may be impacted by the cultural and institutional background of the country concerned and therefore cannot be generalized to other countries. As this article was the first to consider the differences in attitude towards using FinTech services between digital natives and digital immigrants, further research is needed to verify these results in a broader set of countries. Our dataset could also be challenged due to ambiguity in the definition of latent variables and the chosen method of data collection. Although the representativeness of the sample as based on gender and age was good, the online survey limited the range of respondents and could remain biased in relation to other characteristics.

Despite the above-mentioned limitations and due to the increasing role played by FinTech services, our results highlight the differences in perceptions of technology by digital immigrants and digital natives. FinTech services are well accepted by people who have both financial and digital knowledge. In Russia, digital immigrants have a low level of digital literacy, and digital natives have a low level of financial literacy. To ensure a positive attitude towards using the FinTech services and to increase the level of their acceptance, it is necessary to find ways to increase the knowledge of the population through certain educational measures and in accordance with the category they fall into. In addition, the low rate of perceived ease of use by the digital immigrants means that these consumers face difficulties in using FinTech services. This highlights the importance of investigating further measures that would increase the perceived ease of use of FinTech.

Appendix A. The final survey questionnaire

1. Please provide your email address:
2. Your gender is:
    - Male
    - Female
3. Your age is:
4. Your employment status is:
    - Student
    - Employed
    - Employer
    - Self-employed
    - Other
5. Do you prefer to interact with your bank by mobile or by Internet banking?
    - By mobile
    - Doesn't matter which
    - By Internet
6. How often do you use mobile technology payment methods?
    - Do not use them
    - Occasional payments
    - Monthly

- Weekly
- Daily

7. How often do you use bank cards?

- Do not use them
- Occasional payments
- Monthly
- Weekly
- Daily

8. Do you know what the term FinTech means?

- No
- I have heard it, but I don't know what it means
- Yes

The FinTech service is "technology-driven financial service, which provides a new solution, a new business model or an alternative to what already exists in the financial sector."

9. Please give an assessment of the extent to which you agree with the statements (1 = completely wrong; 2 = wrong; 3 = more yes than no; 4 = true; 5 = absolutely true)

– You can save a lot of time by using the services of FinTech companies.
– FinTech companies provide the whole range of services I need.
– For me, the services of a FinTech company are more affordable than the services of traditional banks.
– It is easy to use FinTech services.
– I think the FinTech application interface is extremely simple and convenient.
– FinTech services can increase efficiency.
– If I have used FinTech services, I am willing to continue using them.
– I would recommend the services of FinTech companies to my friends.
– I know about different financial products and instruments, their advantages and disadvantages.
– I can assess and diversify financial risks.
– I am a confident PC (phone) user, I use the Internet and mobile applications.
– I use the mobile (Internet) bank, am able to open a personal account and make transactions.

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Performance of FinTechs: Are founder characteristics important?*

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Abstract

Building on the resource-based view of entrepreneurship, we examine the association between founder characteristics and performance of FinTechs, high-growth technology-driven companies. We use cross-sectional regression models on a dataset of 132 FinTechs from Russia. The results show that FinTechs established by companies perform better than FinTechs established by individuals. Further, FinTechs founded by persons with banking backgrounds grow more quickly. In contrast to economics or business education, a combination of IT education and banking experience is also associated with greater company growth. Our results provide insights into the resource-based view of entrepreneurship, demonstrating that a FinTech founder's characteristics play an important role in its success. While parent company support creates a stronger competitive advantage for FinTechs in the establishment phase, the combination of IT education and banking experience are a difficult-to-imitate asset for FinTechs founded by individuals.

Keywords FinTechs, performance, founder characteristics, type of founding entity
JEL Codes: L25 M13 L26

1. Introduction

In the last decade, the financial services landscape has changed due to the emergence of FinTechs – companies that combine modern technologies (e.g. cloud computing, mobile Internet) to provide financial services (e.g. payments, lending). Their growing influence is evidence of the increasing flow of investments into FinTechs. According to KPMG (2019), in 2018, the global annual volume of investments in FinTechs amounted to $111.8 billion, over 120 % higher than in 2017. Nearly 82 % of banks and other financial organisations plan to collaborate with FinTechs in the future, and over 88 % have some fear of not being able to compete with FinTechs (PWC 2017). Since FinTechs are expected to play a considerable role in shaping the global financial industry, it is important to understand the various factors impacting their development. The recent litera-

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ture review by Kavuri and Milne (2019) highlights the need to investigate the drivers of FinTech success. We address this gap from the perspective of FinTech founders.

The resource-based view (RBV) of entrepreneurship considers resources to be key drivers of firm performance. Resources that are rare and inimitable make it possible for a company to develop a competitive advantage and to achieve superior performance (Barney/Wright/Ketchen 2001) – the characteristics of founders can be considered such a resource. Review papers by Sorensen and Chang (2006) and Klotz et al. (2014) show that the relationship between a company's performance and its founders' characteristics (e.g. level of education, gender) remains mixed, and the outcomes tend to vary across industries, selected founder characteristics and performance indicators. This indicates that the association should be investigated in more homogeneous firms. To our knowledge, no previous paper has investigated the impact of various founder characteristics on FinTech performance. Compared to many other enterprises, FinTechs, as high-technology companies, are exposed to a more complex business environment, which calls for founders with multidisciplinary knowledge and skills. Therefore, this context would provide an interesting testing ground for RBV of entrepreneurship.

We use a unique dataset of Russian FinTechs at the end of 2017. Despite the peculiarities of history as well as the economic and political situation in Russia, the country deserves attention for the following reasons. First, the FinTech market in Russia demonstrates an investment growth rate similar to global trends (Shustikov 2018), and it is among the top 20 in the world in terms of the number of FinTechs established in the country (Laidroo/Avarmaa 2019). Second, Russian M&A deals in FinTech periodically reach the global top of FinTech deals, like the Yandex deal in 2018 (KPMG 2019). Third, the share of FinTech users in Russia (nearly 42 %) is the same as in the UK and in Europe (Ernst & Young 2017). Fourth, there is a similar distribution of FinTech companies by area of activity in Russia as there is in the world (Soloviev 2018). Considering the size of Russia, this demonstrates that the country is an interesting case for investigating FinTech founder aspects.

We examine the association between founder characteristics and FinTech performance. Specifically, we use cross-sectional regression models on a dataset of 132 Russian FinTechs, 88 of which have been established by individuals and the rest by existing companies. We measure FinTech performance by year-on-year revenue and asset growth during 2016–2017 as well as return on assets (ROA) in 2017. The results show that FinTech performance depends on the type of founder (company or individual) as well as on the previous work experience and education of the founding individual. The FinTechs founded by other companies tend to grow more quickly and be more profitable than similar companies founded by individuals. This suggests that the support of the parent company is a difficult-to-imitate resource, which creates a competitive advantage. If the founder is an individual, the FinTech grows more quickly when the founder has previous banking experience. Interestingly, a founder's education in economics or business provides no clear advantage over other types of education; however, the combination of the founder's previous banking background and IT education is associated with significantly greater growth in FinTech revenue and assets. This demonstrates the relevance of specialised knowledge for FinTech development.

Our paper contributes to the literature on FinTechs by being the first to investigate the relationship between founder characteristics and FinTech performance and thus addresses the gap that Kavuri and Milne (2019) identified. It also complements the FinTech literature in Russia that has thus far been limited to assessments of local FinTech development trends (Nikitina/Nikitin/Galper 2017; Eskindarov/Abramova/Maslennikov/Amosova/Varnavskii/Dubova 2018) and problems associated with digitalisation (Krivosheeva 2018). We also contribute to the RBV of entrepreneurship (Barney 1991; Prahalad/Hamel 1997; Čater/Čater 2009; Madhani 2010; Jardon/Molodchik, 2017) by investigating a combination of founder education and experience as a difficult-to-imitate resource for FinTech companies that is likely to be relevant for other high-growth, technology-driven ventures. Kellermans et al. (2016) argued that the performance implications of the founder as a resource need to be investigated separately from those of other human resources -we address this gap.

The paper is structured as follows. Section 2 provides an overview of the theoretical and empirical background. We discuss our data and methodology in Section 3 and our results in Section 4. Finally, Section 5 contains the discussion and concludes.

2. Literature review

The RBV that emerged in the field of strategic management in the 1980s and 1990s (Wernerfelt 1984; Barney 1991; Prahalad/Hamel 1997) suggests that the resources a company possesses are the primary determinants of its performance and may contribute to its sustainable competitive advantage. A firm that acquires and controls valuable, rare, inimitable, non-substitutable resources and capabilities – and is able to apply them – can achieve a sustainable competitive advantage (Barney 1991). Among the different company resources (physical, human, organisational capital), human capital is a critical source of competitive advantage because it is usually heterogeneous, rare and difficult to imitate (Peteraf 1993). Since its emergence, the RBV has been extensively tested in the empirical literature and has gained a moderate level of support (Newbert 2007). Although the RBV was initially developed for established companies, researchers have increasingly applied its insights to understand new venture performance

(Kellermans et al. 2016; Marullo/Casprini/Di Minin/Piccaluga 2018). Kellermans et al. (2016) call for separating the two types of human capital – owners and employees – and seeking evidence on the performance implications of each type of human capital. We intend to fill this gap by focusing on the association between founder characteristics and venture performance.

As Dixon and Day (2010) highlighted, applying RBV depends heavily on the company's external environment. Therefore, while formulating the hypotheses, we consider the specifics of the FinTech activity as well as the peculiarities of the historical and institutional context of Russia.

2.1 The performance of FinTechs and type of founding entity

It is possible to broadly distinguish between two types of founders: companies and individuals. Based on the RBV, firms established by different types of founders are likely to experience different founding conditions. Founding conditions are interpreted as financial or human resources, which are required to achieve effective company functioning (Cooper/Gimeno-Gascon/Woo 1994). Compared to individuals, companies are likely to have more resources and experience in analysing the market – as a result, they should be able to develop products or services with greater potential. Established companies also tend to have more useful professional contacts to promote their business ideas (Hannanova 2008) and better access to financing due to lower information asymmetry between the company owners and funding providers (Spence 2002). If resources are more easily available to established firms than individuals, FinTechs established by firms are likely to perform better. In the context of Russia, established firms may also be more experienced (compared to individuals) in handling the institutional peculiarities of the regulation-sensitive field of FinTech. Therefore, we propose the following hypothesis:

H1. FinTechs founded by individuals perform worse than FinTechs founded by companies.

2.2 The performance of FinTechs and characteristics of founders

Founders must identify their company's strategy in a rapidly changing technological environment. Their characteristics influence their knowledge creation in establishing a new venture, and their capabilities comprise the firm's resources, based on which the company may create a competitive advantage (Arvanitis/Stucki 2012). Therefore, founder characteristics are likely to be important determinants of start-up performance.

FinTech activities are directly related to innovations and information technology that are changing at an accelerated pace. To keep up with the trends and be competitive in the market, a FinTech company founder needs to be flexible to change and capable of processing new information. Previous literature on founder characteristics has reported a number of reasons why younger people are in a better position for starting and managing a new venture. The age of the founder is assumed to be connected with the capability to analyse and handle a large amount of information. Older founders may face difficulties in perceiving new information and mastering new technologies (Hambrick/Mason 1984). As a result, older people might have a hard time competing with the more progressive younger generation in the field of digitalisation and informatisation (Salthouse 2009; Cai/Stoyanov 2016). With age, people may also become more sensitive to physical and psychological stress (Child 1974) and may need additional skills and professional support to overcome social barriers to start and run a business (Kenny/Rossiter 2018). The context of Russian history and its impact on company performance also needs to be considered. The Soviet-style economy did not value entrepreneurial activity; however, the modern-day FinTech landscape requires entrepreneurial spirit that is more natural for the younger generations of Russians. As they are more used to entrepreneurial activity and profit-seeking, the companies they have founded are likely to perform better.

In contrast, it has also been argued that older entrepreneurs are able to conduct successful businesses because of their accumulated life experience and their human and social capital (Singh/DeNoble 2003; Pitkänen/Parvinen/Töytäri 2014). Still, considering that in Russia, the life experience of the older generation is unlikely to support superior FinTech performance, and taking into account that FinTech activity requires strong IT skills (which are more natural for the younger generations), we propose the following hypothesis:

H2. FinTechs with younger founders perform better than FinTechs with older founders.

Herrmann and Datta (2002) argued that educated entrepreneurs have an appropriate knowledge base that helps them to master new information, make informed decisions and adapt to changing conditions. It has also been shown that education directly related to business management provides more suitable preparation for future entrepreneurs than other types of education (McMullan/Gillin 1998; Škudienė/Auruškevičienė/Pundzienė 2010). FinTechs operate at the junction of financial services and technology – this requires certain skills that may be acquired through either formal education or real-life experience. Although FinTechs are connected to the financial world, education in IT might provide a better starting point, as the technological component generally forms the source of FinTechs' competitive advantage in comparison to traditional financial services companies. Thus, we formulate the following hypothesis:

H3. FinTechs with founders possessing IT education perform better than other FinTechs.

The importance of personal experience for new venture success is supported by several arguments. First, former experience in the particular area allows actors to learn the specifics of the industry, analyse the target market and competitors and determine the features of the products or services provided (Cooper/Gimeno-Gascon/Woo 1994). Second, the experience can be linked to many business contacts, which could help to attract the resources needed to develop the company and organise the sale of services (Granovetter 2002). As FinTechs compete and collaborate with traditional financial intermediaries, having experience in the financial sector is a clear advantage for an entrepreneur. Therefore, we propose the following hypothesis:

H4. FinTechs run by founders with experience in banking perform better than other FinTechs.

3. Data and methodology

We began our selection process with a population of Russian FinTechs included on a Fintech map at the end of 2018 composed by RusBase[1]; it contained a total of 322 companies. To be included in our dataset, the FinTech had to be registered in Russia and had to be founded 2001–2016; this enabled us to use the financial data available for 2016 and 2017. As we were only interested in FinTechs, we only included companies that utilised modern technologies (e.g. cloud computing, mobile Internet) to provide financial services (e.g. payments, lending). We also divided FinTechs into different segments based on their distinctive business models. Dorfleitner et al. (2017) suggested categorising FinTechs into financing, asset management, payments and other FinTechs. Alternative classifications exist that go beyond traditional financial services. For example, the World Economic Forum (2015) distinguishes FinTechs involved in payments, deposits and lending, capital-raising, insurance, investment management and market provisioning (including machine learning and big data). The International Organization of Securities Commissions (2017) maps FinTech activity across eight categories: payments, insurance, planning (personal finance), lending and crowdfunding, blockchain, trading and investments, data and analytics and security. We decided to follow a taxonomy that would correspond to the distinctive business models of Russian FinTech companies and would grasp in detail the technology-driven activities that Dorfleitner et al. (2017) did not specifically cover. Therefore, our taxonomy is more similar to the one the International Organization of Securities Commissions (2017) proposed. It covers traditional financial services (payments, deposits and lending, investment management) and technology-driven business models (distributed lender technology, banking infrastructure and analytics). Our technology-driven business models fall under Dorfleitner et al.'s (2017) 'other FinTechs group'. We also broadened the financ-

1 https://rb.ru/fintech/.

ing category they proposed to include deposits, as proposed in the World Economic Forum (2015).[2] After applying the above-mentioned inclusion and exclusion criteria, the population decreased to 182 FinTechs.

We retrieved data on the financials and founders of FinTechs from SPARK, a Russian database connected to various state databases. We merged these data with hand-collected information on founder education and observations from the social media platforms Facebook and LinkedIn. Due to some missing data and extreme observations[3], the final dataset we used in our estimations contained data on 132 companies, 88 (66 %) of which were established by an individual and 44 of which by a company.

We focus mainly on FinTech performance measured by growth indicators such as revenue growth (*revg*) and asset growth (*assg*). These indicators allow us to capture start-up performance better than profitability indicators because start-ups tend to initially operate at close to zero income (Rompho 2018). We also have to take into account the Russian cultural and institutional context, which may be more tolerant toward misreported profits (Malofeeva 2018). In such an environment, indicators unrelated to profits may provide a more objective picture of reality. Still, to provide some comparison with more traditional performance measures, we use return on assets (*roa*) as a robustness indicator.

We investigate the associations between founder characteristics and FinTech performance in the context of univariate tests (using either Kruskal–Wallis or the Mann–Whitney U test) followed by a regression analysis. Regression models using performance as dependent variables were common in most of the previous studies (e.g. Arumona/Onmonya/Omotayo 2019, Kaur/Singh 2019; Prosvirkina/Wolfs 2019). As regression models allowed us to control for the impact of multiple variables on FinTech performance simultaneously, we use founder-specific variables, FinTech size (measured by the natural log of total assets) and other FinTech characteristics as explanatory variables. In terms of founder-specific indicators (marked with the prefix *f_*), we focus on the type of founder (company or individual) and several individual-specific characteristics of founders.[4] The latter includes the founder's age, education, work experience in banking and education combined with experience in banking. We also control for the founder's gender (see Table 1 for details on the dummies employed). FinTech characteristics (marked with the prefix *c_*) cover the FinTech's location (Moscow or other), age and activity. FinTech business model variables (marked with the prefix *b_*)

2 We consider our investment management category to be equivalent to the asset management in Dorfleitner et al. (2017).

3 We eliminated extreme observations with revenue growth above 500 %, asset growth above 1500 % and ROA above 1500 %.

4 We focus on the person with the largest holding in the FinTech. There are only nine FinTechs with more than one founder.

include the FinTech's market (Russia or other), type of customers (business, private or both), channel of customer contact (personal, information system or both) and source of revenue (see Table 1 for the variables' definitions and descriptive statistics).

As can be seen from Table 1, FinTechs' size and performance are rather heterogeneous. In terms of founder characteristics, 48 % of the individuals who founded a FinTech in Russia are below 40, and in 81 % of cases, they are male. A total of 76 % of the founders have previous education in IT or economics, and 51 % have previous work experience in the banking sector. FinTechs tend to have rather similar characteristics: 75 % of the FinTechs are registered in Moscow, and 64 % are less than five years old. Also, FinTech activity is rather evenly distributed between the identified six activity categories, demonstrating that there is no clear dominant specialisation. In terms of business model characteristics, there is a rather strong focus on the Russian market. Although 42 % of FinTechs concentrate on business-to-business services, many FinTechs are also involved in business-to-customer activities or engage in both types of activities. We also observe that both the information systems and personal contact are rather equally used when providing their services. Russian FinTechs' revenue sources are rather diverse, with commission fees and interest income dominating over other sources of income.

As we have only financial data for 2016 and 2017, we estimate cross-sectional regression models in which we calculate the performance indicators revenue and asset growth over 2016–2017 and ROA from 2017. As no data were available for the control variables in 2016 (with the exception of size), we take all the control variables from 2017.[5]

5 We acknowledge that our inability to use all explanatory variables in 2016 creates potential endogeneity concerns. Still, considering that most of the explanatory variables are not heavily time-variant, using the 2016 indicators would not enable significantly more reliable results.

Table 1: Variable definitions and descriptive statistics

Variable	Description	Obs.	Mean	Std. Dev.	Min	Max	Count of ones
FinTech performance measures							
revg	Growth in revenue 2016–2017 in %	132	22.66	69.87	-95.93	413.68	-
assg	Growth in assets 2016–2017 in %	132	98.44	199.36	-75.31	908.12	-
roa	Return on assets 2017 in %	132	15.53	86.51	-382.03	589.47	-
Founder characteristics							
f_individ	Dummy 1 if founder is an individual, 0 otherwise	132	0.67	0.47	0.00	1.00	88
f_age	Dummy 1 if founder is less than 40 years old, 0 otherwise	88	0.49	0.50	0.00	1.00	43
f_male	Dummy 1 if founder is a male, 0 otherwise	88	0.81	0.40	0.00	1.00	71
f_edu_it	Dummy 1 if founder has IT education, 0 otherwise (used as a base value and omitted in regressions)	88	0.26	0.44	0.00	1.00	23
f_edu_o	Dummy 1 if founder has other education than IT or economics, 0 otherwise	88	0.24	0.43	0.00	1.00	21
f_edu_ec	Dummy 1 if founder has education in economics/business, 0 otherwise	88	0.50	0.50	0.00	1.00	44
f_bank	Dummy 1 if founder has previous work experience in banking	88	0.51	0.50	0.00	1.00	45
f_bank_it	Dummy 1 if founder has previous work experience in banking and IT education, 0 otherwise (used as a base value and omitted in regressions)	88	0.11	0.32	0.00	1.00	10
f_bank_ec	Dummy 1 if founder has previous work experience in banking and education in economics/business, 0 otherwise	88	0.50	0.50	0.00	1.00	44
f_bank_o	Dummy 1 if founder has previous work experience in banking and education in other areas besides IT and economics, 0 otherwise	88	0.24	0.43	0.00	1.00	21

Variable	Description	Obs.	Mean	Std. Dev.	Min	Max	Count of ones
f_nobank_it	Dummy 1 if founder has no previous work experience in banking and has education in IT, 0 otherwise	88	0.15	0.36	0.00	1.00	13
Size							
lnta	Natural log of total assets in 2016	132	17.62	2.67	11.11	27.20	132
FinTech characteristics							
c_Moscow	Dummy 1 if the company is registered in Moscow, 0 otherwise	132	0.75	0.43	0.00	1.00	99
c_age	Dummy 1 if the company is younger than 5 years, 0 otherwise	132	0.64	0.48	0.00	1.00	84
c_act_paym	Dummy 1 if FinTech is involved in payments, 0 otherwise (used as a base value and omitted in regressions)	132	0.22	0.42	0.00	1.00	29
c_act_dlt	Dummy 1 if FinTech is involved in distributed ledger technology, 0 otherwise	132	0.17	0.37	0.00	1.00	22
c_act_binfra	Dummy 1 if FinTech is involved in banking infrastructure, 0 otherwise	132	0.18	0.39	0.00	1.00	24
c_act_anal	Dummy 1 if FinTech is involved in analytics, 0 otherwise	132	0.16	0.37	0.00	1.00	21
c_act_deplend	Dummy 1 if FinTech is involved in deposit and lending, 0 otherwise	132	0.17	0.37	0.00	1.00	22
c_act_invest	Dummy 1 if FinTech is involved in investment management, 0 otherwise	132	0.11	0.31	0.00	1.00	14
Business model characteristics							
b_market	Dummy 1 if company's main market is Russia, 0 otherwise	132	0.75	0.43	0.00	1.00	99
b_b2b	Dummy 1 if company is involved in business-to-business activities, 0 otherwise (used as a base value and omitted in regressions)	132	0.42	0.50	0.00	1.00	56

Variable	Description	Obs.	Mean	Std. Dev.	Min	Max	Count of ones
b_b2bc	Dummy 1 if company is involved in both business-to-business and business-to-customer activities, 0 otherwise	132	0.25	0.43	0.00	1.00	33
b_b2c	Dummy 1 if company is involved in business-to-customer activities, 0 otherwise	132	0.33	0.47	0.00	1.00	43
b_cust_is	Dummy 1 if customer is contacted through information system, 0 otherwise (used as a base value and omitted in regressions)	132	0.48	0.50	0.00	1.00	63
b_cust_p	Dummy 1 if customer is contacted in person, 0 otherwise	132	0.02	0.15	0.00	1.00	3
b_cust_isp	Dummy 1 if customer is contacted through information system and in person, 0 otherwise	132	0.50	0.50	0.00	1.00	66
b_r_app	Dummy 1 if company revenues come from centralised hosting of business applications	132	0.20	0.40	0.00	1.00	27
b_r_commission	Dummy 1 if revenues come from commission fees, 0 otherwise (used as a base value and omitted in regressions)	132	0.33	0.47	0.00	1.00	43
b_r_data	Dummy 1 if revenues come from data, 0 otherwise	132	0.09	0.29	0.00	1.00	12
b_r_interest	Dummy 1 if revenues come from interest income, 0 otherwise	132	0.23	0.42	0.00	1.00	30
b_r_license	Dummy 1 if revenues come from license fee, 0 otherwise	132	0.11	0.32	0.00	1.00	15
b_r_trading	Dummy 1 if revenues come from trading fee, 0 otherwise	132	0.04	0.19	0.00	1.00	5

Notes: All the founder characteristics are recorded as they were at the time of FinTech establishment. All the FinTech characteristics and business model characteristics are recorded as they were at the end of 2017.

While setting up the regression models, we had to consider the small sample size. In order to reduce the number of explanatory variables used simultaneously, we proceed step-by-step considering only the FinTech characteristics initially and then only the business model characteristics thereafter. As a result, we test H1 using two separate models on the entire sample:

$$Perf_i = f\begin{pmatrix} f\_individ; lnta; c\_Moscow; c\_age; c\_act\_dlt; c\_act\_binfra; \\ c\_act\_anal; c\_act\_deplend; c\_act\_invest \end{pmatrix} \quad (1)$$

$$Perf_i = f\begin{pmatrix} f\_individ; lnta; b\_market; b\_b2b;\ b\_b2c; b\_cust\_p; b\_cust\_isp; \\ b\_r\_app; b\_r\_data; b\_r\_interest; b\_r\_license; b\_r\_trading \end{pmatrix} \quad (2)$$

To avoid overfitting the model, we initially test H2–H4 using two separate models with fewer control variables covering only the founder characteristics in a sample of FinTechs founded by an individual. We focus on founder characteristics separately to test H2 and H3:

$$Perf_i = f(f\_age; f\_male; f\_edu\_o; f\_edu\_ec; f\_bank; lnta) \quad (3)$$

$$Perf_i = f(f\_age; f\_male; f\_bank\_ec; f\_bank\_o; f\_nobank\_it; lnta) \quad (4)$$

We consider founder education in combination with previous experience to test H4:

In order to control for other FinTech and business model characteristics, we test H2–H4 by including additional control variables in the models:

$$Perf_i \begin{pmatrix} f\_age; f\_male; f\_edu\_o; f\_edu\_ec; f\_bank; lnta;\ c\_Moscow; c\_age; c\_act\_dlt; \\ c\_act\_binfra; c\_act\_anal; c\_act\_deplend; c\_act\_invest; b\_market; b\_b2b;\ b\_b2c; \\ b\_cust\_p; b\_cust\_is; b\_r\_app; b\_r\_data; b\_r\_interst; b\_r\_license; b\_r\_trading \end{pmatrix} \quad (5)$$

$$\begin{aligned} &Perf_i \\ &= f\begin{pmatrix} f\_age; f\_male; f\_bank\_ec; f\_bank\_o; f\_nobank\_it; lnta; c\_Moscow;\ c\_age; c\_act\_dlt; \\ c\_act\_binfra; c\_act\_anal; c\_act\_deplend; c\_act\_invest; b\_market; b\_b2b; b\_b2c; \\ b\_cust\_p; b\_cust\_is; b\_r\_app; b\_r\_data; b\_r\_interest; b\_r\_license; b\_r\_trading \end{pmatrix} \end{aligned} \quad (6)$$

As we have many explanatory variables and are more interested in the variables that would explain the greatest portion of the variance in FinTech performance, we do a backward elimination. Specifically, in each equation, we eliminate the variable or set of dummies step-by-step with the lowest p-value until all the explanatory variables in the model become statistically significant at $p < 0.1$. In Section 4, the results presented in the columns marked with ‘a’ represent the initial estimates from the equations; those marked with ‘b’ refer to the results of the backward elimination exercise. In all the estimations, we control for heteroscedasticity and report robust standard errors for each coefficient estimate.

4. Results

4.1 Results from the univariate tests

The results of the univariate tests are presented in Table 2.

In line with our expectations (H1), if the founder is an individual, the FinTech has lower growth in revenue and assets and experiences a lower ROA in 2017. The differences in the performance of FinTechs founded by individuals versus companies are also statistically significant. The economic significance of the differences is also rather compelling, as the median revenue growth in FinTechs established by companies in 2017 is over 10 times higher than in FinTechs established by individuals; asset growth in the former is over 30 times higher than the latter. This indicates that FinTechs established by companies tend to perform better than FinTechs founded by individuals.

In terms of the founder's age (H2), the results remain inconclusive. The mean and median performance indicators in 2017 for founders below and above 40 years remain rather similar (especially for revenue and asset growth indicators). The lack of significant differences in the performance of FinTechs by founder age might be due to the responsiveness, adaptability and entrepreneurial skills required of a founder. Some of these skills are more natural for younger founders, and others are more natural for older founders – therefore, age may not matter as much as one may expect.

A founder's education also plays a less significant role than we expected, with inconclusive results regarding H3. Still, the descriptive statistics reveal that, surprisingly, we observe the highest mean and median performance indicators for the FinTechs founded by people with no education in IT or economics.

In line with H4, if the founder has previous experience in banking, the FinTech has higher performance. The differences in the median and mean revenue and asset growth are especially striking. In FinTechs with founders lacking prior banking experience, the growth in 2017 was negative, whereas the same indicator was positive for FinTechs with founders who possess such experience. This indicates that prior exposure to the financial sector may provide significant skills needed for setting up and managing a FinTech.

Table 2: Univariate tests of founder characteristics and FinTech performance

	Revenue growth			*Asset growth*			*Return on assets*		
	Mean	Median	No. of obs.	Mean	Median	No. of obs.	Mean	Median	No. of obs.
Founder individual									
Yes	-7.16	3.86	88	4.99	5.50	88	1.25	4.61	88
No	82.29	41.24	44	285.32	177.01	44	44.10	9.39	44
Difference	p-value	0.000	***	p-value	0.000	***	p-value	0.068	*
Founder age below 40 years									
Yes	-6.18	4.00	49	5.27	5.59	49	2.21	7.08	49
No	-8.39	3.70	39	4.64	5.26	39	0.04	2.85	39
Difference	p-value	0.923		p-value	0.923		p-value	0.174	
Founder previous education									
IT	-13.58	1.79	23	-0.84	3.85	23	-11.75	4.91	23
Economics	-7.44	4.16	44	4.54	5.73	44	2.74	3.55	44
Other	0.47	4.42	21	12.32	6.43	21	12.35	6.04	21
Difference	p-value	0.383		p-value	0.377		p-value	0.726	
Founder with experience in banking									
Yes	7.66	7.39	45	23.56	19.05	45	-2.31	9.29	45
No	-22.66	-6.31	43	-14.44	-7.46	43	4.97	2.81	43
Difference	p-value	0.000	***	p-value	0.000	***	p-value	0.061	*
Founder previous education & experience in banking									

	Revenue growth			*Asset growth*			*Return on assets*		
	Mean	Median	No. of obs.	Mean	Median	No. of obs.	Mean	Median	No. of obs.
Economics & experience in banking	-7.44	4.16	44	4.54	5.73	44	2.74	3.55	44
Other & experience in banking	0.47	4.42	21	12.32	6.43	21	12.35	6.04	21
IT & no previous experience in banking	-30.55	-21.06	13	-21.31	-14.41	13	3.91	4.91	13
IT & experience in banking	8.48	8.84	10	25.79	27.57	10	-32.10	3.98	10
Difference	p-value	0.000	***	p-value	0.000	***	p-value	0.840	
Founder male									
Yes	-7.99	3.70	71	4.41	5.26	71	-4.24	4.08	71
No	-3.66	4.00	17	7.40	5.59	17	24.15	10.10	17
Difference	p-value	0.739		p-value	0.735		p-value	0.120	

Notes: We tested the differences in performance indicators across the categories of founder characteristics using either the Kruskal–Wallis test or the Mann–Whitney U test. Statistical significance: ***$p < 0.01$, **$p < 0.5$, *$p < 0.1$.

However, if we combine experience in banking with prior education, education begins to matter in terms of the asset and revenue growth indicators. The greatest average and median asset and revenue growth pertained FinTechs founded by an individual with prior experience in banking and with IT education. This result can be explained by the fact that individuals with IT education can master the technology more easily than their peers; further, if they simultaneously have prior exposure to banking, they can perform better overall.

We observe no significant differences in the performance of FinTechs established by men or women, especially in the context of growth indicators. In terms of ROA, the differences are very close to being significant (p-value = 0.12), with the median ROA in FinTechs founded by men being two times higher than in FinTechs founded by women. As only 17 of the FinTechs we studied (19 % of the total sample) were founded by women, failure to detect very significant gender differences is not too surprising.

4.2 Results of the multivariate regression analysis

4.2.1 Results for the founding entity

The results of Equations 1 and 2 are presented in Tables 3 and 4, respectively. The models' explanatory power is the highest in the models based on asset growth and the lowest in the models that use ROA.

Table 3 illustrates a robust negative association between the type of founder (*f_individ*) and all the dependent variables. FinTechs founded by individuals have nearly 112 % lower revenue growth, nearly 278 % lower asset growth and up to 41 % lower ROA than FinTechs founded by companies.

Table 3: FinTech performance and FinTech characteristics

Dependent variable,	Revenue growth		Asset growth		Return on assets	
Model	1a	1b	1a	1b	1a	1b
Constant	83.31	105.00 ***	412.20 ***	428.80 ***	-49.54	50.97 ***
	(56.46)	(26.15)	(82.55)	(78.70)	(52.64)	(17.78)
f_individ	-113.20 ***	-112.10 ***	-277.10 ***	-278.50 ***	-37.21 **	-41.28 **
	(25.30)	(26.30)	(36.97)	(37.89)	(16.68)	(17.45)
lnta	2.81		-7.62 **	-8.28 **	3.33	
	(5.61)		(3.81)	(3.69)	(2.52)	
c_Moscow	-45.95		-16.49		19.82	
	(33.74)		(29.65)		(13.81)	
c_age	-4.76		12.60		30.23	
	(18.02)		(24.03)		(19.14)	
c_act_dlt	30.20		2.45		-5.93	-22.43
	(29.32)		(39.81)		(21.47)	(17.54)
c_act_binfra	21.07		60.06		42.10	34.10
	(18.30)		(46.36)		(31.02)	(28.39)
c_act_anal	11.13		9.74		-49.81 **	-46.73 **
	(21.15)		(49.98)		(23.55)	(23.48)
c_act_deplend	3.63		-0.60		-19.06	-20.47
	(13.95)		(25.34)		(17.82)	(17.25)
c_act_invest	-13.75		-40.93		11.70	1.03
	(16.71)		(33.75)		(18.75)	(16.24)
No. of obs.	132	132	132	132	132	132

Dependent variable,	*Revenue growth*				*Asset growth*				*Return on assets*			
Model	1a		1b		1a		1b		1a		1b	
Adj. R2	0.206		0.202		0.431		0.438		0.110		0.098	
F stat.	5.44	***	18.17	***	7.17	***	27.91	***	1.34		1.71	

Notes: Specifications marked with ‘b’ present the results after we ran the backward elimination (see Table 2 for a description of the explanatory variables). Robust standard errors are in parentheses. Statistical significance: ***p < 0.01, **p < 0.5, *p < 0.1.

Table 4: FinTech performance and FinTech business model

Dependent variable,	*Revenue growth*				*Asset growth*				*Return on assets*			
Model	2a		2b		2a		2b		2a		2b	
Constant	-21.43		105.00	***	421.80	***	442.00	***	48.92		95.20	***
	(121.30)		(26.15)		(80.53)		(80.80)		(53.26)		(32.41)	
f_individ	-100.70	***	-112.10	***	-282.10	***	-280.10	***	-46.17	**	-50.17	**
	(17.64)		(26.30)		(38.84)		(38.37)		(18.76)		(19.75)	
lnta	5.67				-8.55	**	-8.58	**	2.11			
	(6.63)				(3.93)		(3.74)		(2.83)			
b_market	16.58				13.97				-35.89	**	-28.36	*
	(20.96)				(35.23)				(17.98)		(17.06)	
b_b2bc	-27.85				1.94				-22.52			
	(26.87)				(29.69)				(18.89)			
b_b2c	-25.40	*			-23.38				9.82			

Dependent variable,	Revenue growth				Asset growth				Return on assets			
Model	2a		2b		2a		2b		2a		2b	
	(15.24)				(27.70)				(18.44)			
b_cust_p	261.30				-92.23	**	-87.21	**	33.25			
	(216.40)				(42.26)		(38.42)		(37.58)			
b_cust_isp	-6.62				-4.43		-8.77		19.98			
	(13.68)				(29.34)		(26.99)		(16.50)			
b_r_app	28.48				16.29				-42.72	**	-49.19	**
	(26.33)				(31.61)				(19.09)		(20.35)	
b_r_data	14.86				-2.20				-28.85		-38.08	*
	(26.59)				(52.36)				(22.39)		(20.97)	
b_r_interest	19.25				40.81				-10.39		-11.04	
	(17.62)				(31.20)				(21.03)		(18.41)	
b_r_license	11.20				-12.82				-65.71	*	-70.68	*
	(19.34)				(40.20)				(37.87)		(40.52)	
b_r_trading	100.30				121.50				-14.11		-30.63	
	(66.07)				(127.30)				(34.17)		(26.59)	
No. of obs.	132		132		132		132		132		132	
Adj. R2	0.333		0.202		0.419		0.435		0.099		0.098	
F stat.	3.24	***	18.17	***	6.65	***	15.23	***	1.24		1.87	***

Notes: Specifications marked with 'b' present the results after we ran the backward elimination (see Table 2 for a description of the explanatory variables). Robust standard errors are in parentheses. Statistical significance: ***$p < 0.01$, **$p < 0.5$, *$p < 0.1$.

A rather similar result appears in Table 4. While the coefficients for *f_individ* in the revenue and asset growth models do not change much, the FinTechs established by individuals experience 46–50 % lower ROA than those established by companies. These are significant differences in economic terms and provide strong support for H1.

In terms of other explanatory variables, Tables 3 and 4 convey a significant negative association between FinTech size and asset growth. This result reflects the fact that it is more difficult for a bigger company to exhibit larger asset growth rates. The coefficient *c_act_anal* is also significant and negative; it shows that FinTechs involved in analytics have a 46–50 % lower ROA than FinTechs focused on payments. In addition, the business model characteristics reveal that if the FinTech's main market is Russia (*b_market*), then it has a 28–36 % lower ROA than a FinTech focusing on a broader market. If the main contact with the customer is personal (*b_cust_p*), then compared to a FinTech that contact customers via an information system, its asset growth is 87–92 % lower. In terms of revenue sources, several significant differences occur in terms of commission fees. The ROAs for FinTechs relying on centralised hosting of business applications (*b_r_app*), data (*b_r_data*) and license fees (*b_r_license*) are lower than for the FinTechs depending on commission fees.

4.2.2 Results for founder characteristics

As founder characteristics are only relevant for FinTechs established by individuals, the following analysis concentrates on 88 FinTechs. Tables 5 and 6 present the results of Regression Models 3 and 4, which include FinTech size and different founder characteristics. The estimations in Table 7 are based on Equations 5 and 6.

Table 5: FinTech performance and founder characteristics

Dependent variable,	*Revenue growth*				*Asset growth*				*Return on assets*			
Model	3a		3b		3a		3b		3a		3b	
Constant	-5.10		-3.59		6.74		10.07		-44.46		24.15	***
	(14.72)		(12.62)		(13.03)		(11.17)		(53.03)		(8.34)	
f_age	3.22				1.70				1.13			
	(4.67)				(4.49)				(14.82)			
f_male	-0.14				1.53				-25.86	**	-28.39	**
	(5.20)				(5.36)				(12.91)		(11.93)	
f_edu_o	11.21	*	10.79	*	9.41	*			19.59			
	(6.34)		(6.21)		(5.57)				(17.61)			
f_edu_ec	3.73		3.60		2.29				13.95			
	(6.47)		(6.40)		(5.65)				(18.79)			
f_bank	27.92	***	27.97	***	35.61	***	36.25	***	-6.02			
	(4.70)		(4.67)		(4.33)		(4.38)		(12.93)			
lnta	-1.29	**	-1.27	**	-1.46	**	-1.35	**	3.27			
	(0.62)		(0.62)		(0.57)		(0.58)		(2.73)			
No. of obs.	88		88		88		88		88		88	
Adj. R2	0.328		0.340		0.468		0.477		-0.004		0.017	
F stat.	7.96	***	12.12	***	14.87	***	41.90	***	0.90		5.66	***

Notes: Specifications marked with ‘b’ present the results after we ran the backward elimination (see Table 2 for a description of the explanatory variables). Robust standard errors are in parentheses. Statistical significance: ***$p < 0.01$, **$p < 0.5$, *$p < 0.1$.

We observe the strongest support for the positive association between the founder's banking experience and FinTech performance (H4). FinTechs founded by persons with banking experience demonstrate revenue growth 28 % and asset growth 36 % higher than that of founders with no such experience. The founder's age drops out of the backward eliminations, meaning that we have inconclusive results with respect to H2. The founder's gender is only statistically significant in the models that use ROA as a dependent variable. Interestingly, we find that FinTechs founded by men have a 26–28 % lower ROA than FinTechs founded by women. Considering that the latter estimations have very low explanatory power, this result should be interpreted with caution – still, it deserves further investigation in future studies if more data becomes available. In terms of the founder's previous education, we fail to observe any superiority of previous IT education (H3). Further, we observed that FinTechs established by persons with education other than IT and economics have slightly greater revenue growth than those established by persons with IT education.

Table 6 combines each founder's previous experience and education indicators.

Table 6: FinTech performance and combined founder characteristics

Dependent variable,	*Revenue growth*				*Asset growth*				*Return on assets*			
Model	4a		4b		4a		4b		4a		4b	
Constant	46.62	***	45.23	***	71.45	***	70.09	***	-66.74		24.15	***
	(14.30)		(12.10)		(16.24)		(13.69)		(66.50)		(8.34)	
f_age	3.43				1.96				1.06			
	(5.16)				(5.50)				(14.73)			
f_male	-3.35				-2.51				-24.66	*	-28.39	**
	(5.55)				(6.34)				(12.45)		(11.93)	
f_bank_ec	-15.19	***	-15.03	***	-20.32	***	-20.18	***	31.50			
	(4.17)		(4.23)		(6.35)		(6.42)		(33.95)			
f_bank_o	-6.19		-6.02		-11.27	*	-11.06	*	36.94			
	(3.78)		(3.81)		(6.75)		(6.63)		(32.45)			
f_nobank_it	-37.42	***	-37.21	***	-45.06	***	-44.91	***	31.88			
	(9.87)		(9.63)		(8.92)		(8.79)		(33.78)			
lnta	-2.19	***	-2.16	***	-2.62	***	-2.61	***	3.31			
	(0.72)		(0.71)		(0.78)		(0.76)		(3.00)			
No. of obs.	88		88		88		88		88		88	
Adj. R2	0.184		0.196		0.236		0.251		0.009		0.017	
F stat.	6.05	***	8.88	***	6.66	***	10.18	***	0.88		5.66	***

Notes: Specifications marked with 'b' present the results after we ran the backward elimination (see Table 2 for a description of the explanatory variables). Robust standard errors are in parentheses. Statistical significance: ***p < 0.01, **p < 0.5, *p < 0.1.

FinTechs having founders with previous banking experience and education in economics have 15 % lower revenue growth and 20 % lower asset growth than FinTechs established by persons with banking experience and IT education. Even more remarkable, FinTechs with founders with IT education and no previous banking experience have 37 % lower revenue growth and 45 % lower asset growth than FinTechs with founders who possess IT education combined with banking experience. This indicates that a key success factor in the field of FinTech is IT education, which helps founders to identify the most promising technologies and handle their implementation. However, without previous banking experience, it does not provide a competitive advantage. We also continue to observe a negative association between FinTech size and their revenue and asset growth.

When we added additional control variables (see Table 7), all the results concerning founder characteristics remain the same as in Tables 5 and 6.

Table 7: FinTech performance, founder characteristics and other FinTech characteristics

Dependent variable,	Revenue growth				Asset growth				Return on assets	
Model	5b		6b		5b		6b		5b	6b
Constant	-2.69		45.74	***	16.12		79.42	***	-4.52	-4.52
	(14.75)		(11.89)		(13.43)		(16.93)		(10.79)	(10.79)
f_edu_o	12.73	*								
	(6.57)									
f_edu_ec	4.07									
	(6.44)									
f_bank	26.21	***			34.97	***				
	(4.82)				(4.44)					
f_bank_ec			-13.07	**			-19.64	**		
			(5.80)				(7.89)			
f_bank_o			-3.99				-9.07			
			(6.43)				(8.57)			
f_nobank_it			-32.81	***			-43.56	***		
			(10.14)				(9.94)			
lnta	-1.37	*	-2.12	***	-1.65	**	-2.79	***		
	(0.74)		(0.74)		(0.68)		(0.79)			
b_market							-10.12	*		
							(5.65)			
b_b2bc			-0.25							
			(5.40)							
b_b2c			-16.23	**						

Dependent variable,	*Revenue growth*				*Asset growth*				*Return on assets*			
Model	5b		6b		5b		6b		5b		6b	
			(7.51)									
b_cust_p					-17.43	***			92.79	**	92.79	**
					(5.65)				(35.66)		(35.66)	
b_cust_isp					0.62				7.15		7.15	
					(4.53)				(14.43)		(14.43)	
b_r_app	-3.23		-7.49		-5.66		-8.66					
	(8.59)		(8.97)		(7.39)		(8.54)					
b_r_data	-7.33		-9.82		-8.96		-10.95					
	(10.28)		(9.42)		(8.44)		(7.57)					
b_r_interest	2.77		8.44		2.53		5.24					
	(5.20)		(6.00)		(5.42)		(6.67)					
b_r_license	14.96	***	13.67	**	10.59	**	14.27	*				
	(5.42)		(6.58)		(5.18)		(7.91)					
b_r_trading	8.05	*	15.01	**	7.31		14.84					
	(4.78)		(5.81)		(6.15)		(12.79)					
No. of obs.	88		88		88		88		88		88	
Adj. R2	0.344		0.278		0.477		0.303		0.020		0.020	
F stat.	6.72	***	5.09	***	12.96	***	6.02	***	3.39	***	3.39	***

Notes: Specifications marked with ‘b’ present the results after we ran the backward elimination (see Table 2 for a description of the explanatory variables). Robust standard errors are in parentheses. Statistical significance: ***p < 0.01, **p < 0.5, *p < 0.1.

In terms of other explanatory variables, we continue to observe a negative association between growth indicators and FinTech size. We also see that FinTechs focusing more on personal contact with a customer have 17 % lower asset growth compared to those concentrating on contact through an information system. FinTechs relying on license fees and trading fees also tend to exhibit greater growth indicators than FinTechs relying on commission fees.

5. Conclusions and Discussion

Our paper provides additional evidence in support of the RBV of entrepreneurship. We show that, in line with our expectations (H1), Russian FinTechs founded by other firms tend to exhibit superior performance compared to FinTechs founded by individuals. This result confirms and extends the results of previous empirical work on other types of firms (Shahveisi/Khairollahi/Alipour 2017). It supports the view that firms as founders have superior access to various resources (financing, competence, experience, etc.), and that as a result, the company as a founder can serve as a difficult-to-imitate asset. This explains why the company as a founder could be more successful in speeding a FinTech's growth more than an individual could. From the standpoint of FinTech customers and regulators, it implies that the type of FinTech founder may signal the FinTech's sustainability. As our dataset was restricted to two years of financial data, this aspect deserves attention in future studies focusing on Russian FinTechs as well as in the context of other countries. We also note that our dataset lacked information on the specialisation of the companies that founded FinTechs. Finally, it would be interesting to analyse the founding companies' previous interactions with the financial sector, and potentially, with innovative technologies.

In the context of FinTechs founded by individuals, several individual-specific founder characteristics matter for FinTech performance and tend to serve as difficult-to-imitate assets. The strongest support existed for the importance of founders' previous banking experience (H4). Russian FinTechs whose founders have banking experience exhibit significantly greater asset and revenue growth compared to FinTechs without such founders. This supports the results reported by previous studies for other types of firms (Soriano/Castrogiovanni 2012; Protogerou/Caloghirou/Vonortas 2017). As FinTechs operate in a specialised field, previous exposure to banking may help in market positioning, business model development and commercialisation of the business idea. This does not mean that persons with no previous banking experience cannot set up a successful FinTech; however, it suggests that if they do not have the adequate knowledge, they would need a team of experts with such knowledge supporting the FinTech's launch. Creating such a team usually requires resources that a founding individual might lack.

Previous studies on non-FinTechs have highlighted the relevance of key persons' education (e.g. Pozen 2010; Wai/Rindermann 2015; Arumona et al. 2019) and experience (e.g. Chen/Chang 2013; Protogerou et al. 2017) on corporate performance. We find that a founder's education does not influence the FinTech's performance. Contrary to our expectations, we fail to observe that FinTechs founded by persons with IT education perform better than others (H3). Instead, in some specifications, we observe that FinTechs founded by persons with education other than IT or economics perform better in terms of revenue growth. However, IT education proves to be valuable in combination with previous experience. We find strong evidence that Russian FinTechs with founders who have education in economics as well as previous banking experience have lower growth indicators than FinTechs created by founders with IT education and previous experience in the banking sector. At the same time, FinTechs with founders who have IT education and no banking experience have lower growth indicators than FinTechs with founders who have IT education and banking experience. This indicates that to reap the benefits of IT education in the field of FinTech, the founder must have some exposure to the banking sector. One potential reason for this is that FinTech lies at the intersection of finance and technology. It also indicates that having a background in economics may not be sufficient in the field of FinTech, even if this is coupled with prior banking experience. In order to boost FinTech development, it may be worth including specialised IT courses (e.g. artificial intelligence, big data) in traditional business and economics programs. Our findings provide additional insight into the RBV, indicating that a specific combination of founder education and experience may form a strong basis for a competitive advantage. The patterns we observe in the FinTechs in our study might also hold for other high-growth, technology-driven sectors.

Regarding the founder's age (H2), our results are inconclusive. This could be due to the very arbitrary 40-year threshold chosen to divide founders into age groups or multifaceted impact of age, which is more clearly observable in the context of previous work experience and educational background. However, this result is in line with Kautonen's (2008) findings concerning small- and medium-sized enterprises in Finland.

The results reported above are subject to several limitations. First, our analysis is limited by the relatively short history of the FinTech sector and the related short period of the dataset. Due to this short timeframe, we were unable to control for survivorship bias, which can only be overcome once more data become available. Second, our dataset could be somewhat biased due to our hand-gathered information on company founders from Facebook and LinkedIn. The data on founder experience and education presented in the social networks are not formally verified and could therefore contain subjective interpretations. Official data on the mentioned characteristics would benefit future studies and could potentially allow researchers to differentiate between levels of education. Third, we overlooked companies created by a group of individuals. As the number of such companies in our dataset was low, this does not have a strong influence on the results reported above. Fourth, due to the limited availability of individual-specific data, we overlook the potential impact of the founder's main source of income on FinTech performance. If such data were available, this founder-specific aspect would merit consideration. Fifth, the results could be impacted by Russia's historical, institutional and cultural background. The first two could affect the results reported for the founding entity and age, and the latter may influence founders' risk-taking behaviours (Illiashenko/Laidroo 2020), all of which correspond to FinTech performance. As our dataset was based only on Russian data, we could not control for such factors. Therefore, our results cannot be generalised to other countries. Still, future similar studies in other countries could shed some light on their potential impact on the reported associations.

Despite the above-mentioned limitations, and due to the increasing role of FinTechs, our results are beneficial to regulators, venture capitalists, customers and other stakeholders interacting with FinTechs and other similar technology-oriented companies. FinTechs founded by other firms or founded by individuals with IT education and previous banking experience have greater chances of succeeding in the Russian context. As this paper is the first to consider the role of founders in FinTech performance, future studies are needed to verify these results over longer periods and in broader sets of countries.

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Keelteoskus

Vene keel	emakeel
Inglise keel	kesktase

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