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FinTech services from BigTech companies

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Abstract

The so-called BigTech companies Amazon, Alphabet, Apple and Meta and are constantly attempting to grow into new business areas. Due to their expertise in data analysis, they have managed to quickly establish themselves in many industries as digital ecosystems and, as part of this strategy, are also expanding their footprint in financial services. However, the biggest challenge that BigTech companies are facing in financial services is customer acceptance. This paper contributes to the emerging field of digital ecosystems and the acceptance of sensitive services by users. Although the BigTech firms have gained much attention, only little empirical analysis is available. This paper aims to shed light on the determinants of customer acceptance of BigTech banking services. Based on a survey in Switzerland this research develops an analytic model to identify and test the relevant determinants. The results indicate that the strongest significant influences were found in subjective risk and trust which clearly demonstrates the still-existing incumbents' advantage over the BigTech companies.

KEYWORDS

banking services, BigTech, customer behaviour, FinTech

1 | INTRODUCTION

The term financial technology (short FinTech) addresses the digitisation of financial services which is mainly driven by technology innovation, process disruption and service transformation (Gomber et al., 2018). As an umbrella term, it encompasses innovative solutions that are enabled by IT and that is often used for start-up companies who deliver those solutions, although it also includes the incumbent financial service providers like banks. The Economist already back in 2015 wrote that the 'magical combination of geeks in T-shirts and venture capital that has disrupted other industries has put financial services in its sights. From payments to wealth management, from peer-to-peer lending to crowdfunding, a new generation of start-ups is taking aim at the heart of the industry (...)' (Economist, 2015). Particularly, in the aftermath of the global financial crisis of 2008, the financial industry has been shaken up by more agile and cost-effective FinTech start-ups that are able to address customers' needs more compellingly and comprehensively. However, new competition is not solely restricted to the start-up field. The BigTech companies (also often referred to as 'Big Data' companies), which, in particular, often refer to Amazon, Apple, Alphabet (and here specifically Google) and Meta are currently threatening the business of traditional financial institutions (as Microsoft is not specifically providing any financial services it is not part of this research). In contrast to the FinTech start-ups, they already possess masses of data from many customers and the capital to invest in innovative solutions which might qualify the BigTech companies to be the true competitors for banks. These companies have a market capitalisation of more than $8.63 trillion (as of June 19th, 2024) which is almost double the size of of the gross domestic product of the world's third largest economy Germany with a predicted volume of $4.59 trillion in 2024. The examples of innovative banking services that the BigTech companies provide range from mobile payment applications like Apple Pay and Google Pay and Amazon Lending to digital currencies like Meta's former Diem initiative, which was not pursued further. But for all of them, one can identify that their solutions are still isolated and focusing on single areas. This contrasts with the Chinese companies Baidu, Alibaba and Tencent, which have already developed entire digital ecosystems offering a realm of financial services in payments, investments and financing. Even though the BigTech companies have not yet developed clear strategies for the banking business, banks are aware of their enormous potential. One reason for the rather hesitant entry of the BigTech companies into the banking market is the customer acceptance of financial solutions offered by them, especially as financial services are very closely related to trust as a critical success factor. For example, a survey among 2,000 U.S. banking customers identified that 89% of them are concerned about data privacy and sharing (The Clearing House, 2018), which clearly paves the way for banks which are viewed as the most trustworthy institutions in the same survey. In the banking sector, this is regarded as the greatest challenge for innovative services from other providers than banks.

In this context, FinTech has emerged as a strategic area for both the incumbent organisations as well as the start-ups. For the incumbents, much research has been conducted on mobile payment and the use of internet banking (e.g., Baptista & Oliveira, 2015; Kesharwani & Bisht, 2012; Lee, 2009; Mallat et al., 2004), research on start-ups only appeared over the past few years (e.g., Caragea et al., 2023; Dhar & Stein, 2017; Gomber et al., 2018). However, research has not yet examined the intersection of BigTech and FinTech from a strategic point of view, although the relevance of these companies in all economic areas and especially in FinTech has grown enormously over the past years (Carstens, 2019). But the differences between the two are significant. BigTechs have an already existing big customer base and can leverage network effects even across different sectors. For example, a customer might qualify for a loan if she always pays her bills for ordered products on time. Additionally, they have access to more capital, a higher regulatory expertise and a higher growth potential.

This paper aims to close this research gap and focuses on the question of whether customers of the BigTech companies would be willing to use banking services or whether customer acceptance of such services would remain rather low. For example, one question that many central banks are currently challenged with is, whether the introduction of private digital currencies (so-called stablecoins) as a novel digital payment instrument would undermine the role of central banks in the financial system. To deal with this research question, namely the customer acceptance of BigTech banking services, this paper develops a model of technology acceptance based on the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2, Venkatesh et al., 2012), which is adapted to banking services regarding independent and control variables. The model is fed by the results from a customer survey in Switzerland (see Appendix 1). The research chose Switzerland for three reasons: (1) The country is ranked in the top five countries in IMD's digital ranking (IMD, 2023); (2) Switzerland has large numbers of customers using products and services from BigTech companies like Alphabet (95.51%), Amazon (46%), Meta (41%) and Apple (44%) (see www.statista.com for more details); and (3) the authors have access to a large number of customers living in Switzerland. The target group was defined as the total population of Switzerland, which already has a banking relationship in one way or another (Creswell, 2009). In Switzerland, 98% of the entire population with an age above 15+ has a bank account, and 94% of young adults (15–24 years old; see more details here: https://datatopics.worldbank.org/financialinclusion/country/switzerland). The aim is to identify the influences of the determinants on the acceptance of the BigTech banking solutions and their effect magnitude.

The paper is structured along the following sections. Section 2 of this paper reviews the relevant literature on banking services offered by non-banks as well as on customer acceptance. Section 3 develops a hypothesis model, and Section 4 discusses the data used for the empirical analysis. Section 5 tests the data and presents a discussion of the results. Section 6 summarises the results, shows implications of the study, and its limitations along with potential directions for future research.

2 | THEORETICAL BACKGROUND

2.1 | Existing research on FinTech of BigTech companies

The BigTech companies Alphabet, Amazon, Apple and Meta today make up four of the seven most valuable companies in the world. Together, these tech companies employ around 800,000 persons and generate a turnover of more than $1.3 trillion. These figures alone show how dominant the BigTechs are today. Almost no industry has been spared from the activities of these four companies so far. Examples are telecommunications (e.g., Google fiber), healthcare (e.g., Apple HealthKit), entertainment (e.g., Meta Oculus) and IT (e.g., Amazon Cloud). In some industries, they even are industry leaders (e.g., Amazon in providing cloud services). Despite the many scandals, such as the Cambridge Analytica Facebook faux pas, BigTechs are still very popular among users. The financial sector is one such market in which the BigTechs extended their activities in recent years which is specifically driven by more flexible regulatory requirements in many countries. Surprisingly, not much research has been conducted on this topic, except for a few considerations with regard to financial regulation (Mano & Padilla, 2018), a specific focus on lending (Karim & Lucey, 2024; Stulz, 2022) as well as some practice surveys from consulting companies (e.g., Du Toit & Burns, 2017; McKinsey, 2019). Academic research-based analysis is still rare. While research on FinTech and customer acceptance has grown over the past years, these results cannot be transferred to BigTechs, as they have more customers, a network of providers, more capital, more customer data, higher regulatory expertise and a higher growth potential. In contrast, traditional financial institutions have constantly growing amounts of data but make limited use of them. The banks could independently offer innovative products based on the smart linking of data with the help of artificial intelligence and data science. With the new Payment Services Directive (PSD2), which came into force in Europe in January 2018, traditional financial institutions were forced to grant certified third-party providers access to their customer data (Access to Account [XS2A]) via standardised interfaces (APIs)—if customers agree. With this new regulation in place, the EU wishes to intensify competition in payment transactions (and in the future also to other financial services) and thus to promote innovation. Accordingly, data giants such as the BigTechs are among the beneficiaries as well. Nonetheless, this development also poses threats as the BigTech may monopolise certain areas like loans for consumers and small and medium enterprises (SMEs), which could force the incumbents to be reduced to 'low-cost manufacturers', which merely fund the loans intermediated by the BigTechs (Mano & Padilla, 2018).

On the other hand, consumers' willingness to use BigTech's services increases. In a survey among consumers in the United States, 65% of the respondents were willing to purchase financial products from Amazon, 58% from Google, 56% from Apple and 35% from Meta (McKinsey, 2019). These numbers are even exceeded by another survey that showed that 73% of Americans aged 18–34 would purchase financial products from BigTech and that Amazon enjoys the highest level of customer confidence (Du Toit & Burns, 2017). On the one hand, the switching numbers of customers in banking remain relatively low in many countries due to the fact that many processes are still manual and paper prone. Another reason is that the business is based on trust, and traditional financial institutions continue to enjoy a high level of trust among customers. For technology companies, however, access is not a hurdle that is too difficult to overcome, as they already have a huge customer base. The biggest challenge for them is therefore the complexity of financial products combined with customer acceptance. The latter depends on various factors which will be explored in the next section.

2.2 | Ecosystems, systems theory and UTAUT

With the emergence of ecosystems, which can be broadly described as network configurations between hierarchy and market (Jacobides et al., 2018, p. 2261), a convergence across industries can be observed. In such ecosystems, organisations from different industries work together to achieve a common goal. In general, ecosystems hold different design options for companies regarding (1) the extent to which a company wants to control the value chain (vertical integration) or drive or be part of an ecosystem that delivers on the end customer's needs and (2) the extent to which they know about their end customer's goals (partial or complete) (Weill & Woerner, 2015, p. 29). However, these design options increase the complexity for the providers in such ecosystems, whereas they reduce them for the user. Following systems theory, one major strategy to reduce complexity is 'integration'. In systems theory, integration is defined as the inter-connection of different elements to a system (Maier & Rechtin, 2002), yet another strategy contrary to integration would be to reduce the number of elements and/or their interrelationships (Benbya & McKelvey, 2006). This approach is central to BigTech companies, as they reduce the number of providers and aim at providing all services over a single platform. This perspective also reflects the evolution of complexity science as a special field of systems theory where the focus of systems thinking has shifted from stable network structures to dynamic network configurations (Merali & Allen, 2011). When applied to ecosystems, complexity theory can, for example, help to better adapt to changing environments. However, one important factor for this is the user perspective and its acceptance of new technologies and services.

In previous work, the terms 'acceptance' and 'adoption' were not always differentiated properly but were partly used as synonyms (Nabih et al., 1997). This distinction of terms is nowadays the starting point for most studies, which are divided into acceptance and adoption research. Acceptance research is predominantly concerned with the positive attitude towards (determinants of attitude formation) and the subsequent use of innovation by potential customers. A major difference in adoption research lies in the fact that the causes for the success or non-success of technological innovations are pursued. In contrast to adoption research, acceptance research focuses exclusively on the individual level. Adoption research, however, deals with the identification of takeover determinants and the time of the takeover of an innovation. The following empirical investigation is based on the former. The term 'acceptance' can be mapped against different interpretations: (1) acceptance as attitude, (2) acceptance as willingness to act, (3) acceptance as behaviour and (4) acceptance as attitude and behaviour. In the context of this work, it is stipulated that the acceptance of attitudes alone is sufficient for a positive acceptance. In summary, the objective of acceptance research can be outlined as identifying reasons for acceptance or rejection of an application.

The UTAUT approach according to Venkatesh et al. (2003) combines the findings of the eight most widely used acceptance models at the time. The following theories were merged as follows: the 'Theory of Reasoned Action' (TRA), the 'Theory of Planned Behavior' (TPB), the 'Theory Acceptance Model' (TAM), the 'Motivational Model' (MM), the 'combined TAM/TPB-Model' (C-TAM-TPB), the 'Model of PC Use' (MPCU), the 'Innovation Diffusion Theory' (IDT) and the 'Social Cognitive Theory' (SCT) (Oshlyansky et al., 2007; Venkatesh et al., 2003). In the newly developed model, four independent core factors influence the behavioural intention to actually use an innovation (Venkatesh et al., 2003): (1) the performance expectancy, (2) social influence and (3) the effort expectancy, as well as (4) facilitating conditions.

On top of that, four moderation variables, which influence the four core factors, are taken into account in the model: (1) experience, (2) voluntary application, (3) gender and (4) age. The first three independent factors have a moderating effect on behavioural intention and actual use, while the 'facilitated conditions' have a direct effect on behavioural use. In opposition to previous studies, a meta-analysis by King and He (2006) has shown that the moderating variables have a strong influence on research. Since, despite the complementary factors, many complex research projects cannot be fully captured, additional factors are added depending on the research design. Min et al. (2008), for example, include trust and convenience as supplementary factors in their study. Since the UTAUT model has been considered highly relevant in research and has also been used outside the organisational context, Venkatesh et al. (2012) revised the model for the use of technology acceptance by consumers, which was originally designed for the organisational context. In this sense, the four core factors mentioned above were supplemented by three additional ones for consumers (Venkatesh et al., 2012). In the following, the core factors are presented, as they are elementary for the remainder of this paper:

1. Performance expectancy: This factor defines to what degree a person assumes that the innovation will help them to achieve a profit in their performance (professional or academic).
2. Effort expectancy: It describes the effort that the consumer puts into using the innovation. The abbreviation of the factor is somewhat negative, although in the studies it ultimately measures the perceived user-friendliness, or in other words the simplicity of use.
3. Social influence: This factor measures the degree to which an individual is put under pressure by important reference groups or persons to use the innovation.
4. Facilitating conditions: They describe to what extent an individual feels that the prevailing framework conditions support the use of an innovation.
5. Hedonic motivation: This perceived pleasure describes the joy that an individual feels during or shortly after the use of an innovation.
6. Price value: The comparison between the perceived benefits and the monetary effort that results for a consumer is defined under the price value factor.
7. Experience and habit: Experiences and habits trigger learning processes in most people. For this reason, this factor describes the extent to which an individual tends to perform an action based on learning processes.

In addition, individual and demographic variables have been incorporated as moderators. UTAUT2 is employed as the basic construct for the empirical part of this work but was extended to the specific circumstances of FinTech services from BigTech companies.

3 | HYPOTHESIS DEVELOPMENT

To apply the UTAUT2 model in the context of financial services from BigTech companies, adaptions have been made (Figure 1). In particular, the benefit aspects are defined differently in the area of acceptance of banking services than in other types of technology applications. According to (Chai & Kim, 2010), especially the risk and benefit perspective plays a major role. The former is associated with the acceptance and use of banking services in almost every empirical study. This shows the great importance of the security aspect in financial services. The perception of benefits, on the other hand, consists of the following elements: user-friendliness, compatibility, distribution and additional features. It is assumed that the independent variables do not influence each other.

Trust plays a major role in people adopting new technologies (Todd, 1998). Especially when it comes to internet-based applications or services, trust is one of the largest concerns for users (Chai & Kim, 2010). Depending on the purpose of this research, different definitions of trust can be found in the literature. Bashir and Madhavaiah (2015) for example define trust in the context of online banking services as the assured confidence that a consumer has in the provider's ability to provide reliable services through the internet. The relationship of trust in financial services, therefore stems, above all, from loyalty and honesty (Morgan & Hunt, 1994). Trust excludes opportunistic action by the provider (Walter et al., 2003). Since trust can counteract uncertainty, it is a key element for BigTech banking services (Lee et al., 2011).

The *effort expectancy* describes the expenditure the consumer associates with the use of the application. Gilaninia et al. (2012) paraphrase that the ease-of-use factor is the mental effort an individual must make to understand and use a technology. Several studies have found a strong positive effect on a customer's intention to adopt an easy-to-use new product (Bashir & Madhavaiah, 2015; Jaruwachirathanakul & Fink, 2005; Schierz et al., 2010; Thakur, 2014; Yu et al., 2015). Since the BigTechs already have a relatively high number of users, the ease of use would be high in most cases, as many customers already consult these platforms. The construct is often described as the user-friendliness of an application. However, since it is grasped as a very important factor, it is also included in this research model.

A further factor this research accounts for is the *perceived performance expectancy* of an application. As already stated above, Venkatesh et al. (2003) define it as the degree to which a person assumes that the innovation will help him or her achieve a profit in their job, hobby or school, etc. Since it has emerged as the most

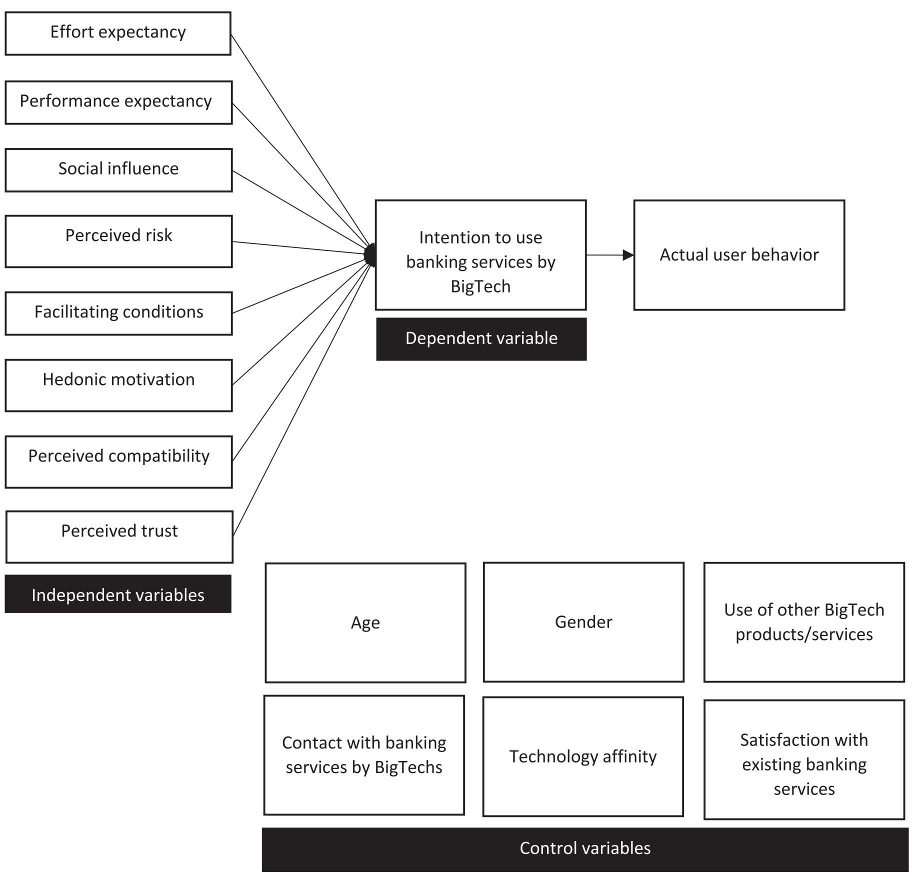

FIGURE 1 Hypothesis model based on the extended UTAUT2 model.

stable construct in previous studies, it is also integrated into the model used in this research. However, since the factor still originates from the UTAUT model, it is interpreted somewhat differently for the following purposes. In the consumer context of banking services, the construct is understood as the degree to which consumers think that the application fits into their daily routines and creates added value for them (Kleijnen et al., 2004). On the one hand, technology compatibility, and on the other hand, the dissemination of an application appear to be of central importance. It is important for the customer that the solution can be used as widely as possible. Isolated or partial solutions have a negative effect on the benefit aspect. For this reason, the distribution of an application is an important factor for the perception of the benefit and thus also the behavioural intention.

The *facilitating conditions* capture to what extent a person feels that the prevailing framework conditions or circumstances support him/her in using the application. The factor is adjusted to explore user acceptance of banking services provided by non-banks. On the one hand, technology compatibility, and on the other hand, the spread of an application appear to be of central importance. It is key for the customer that the solution can be used as widely as possible. As stated previously, the benefits of an application also depend strongly on its compatibility with other products and services (Lin, 2007).

The *social environment* plays a very central role in the acceptance of technologies (Bandura, 1991). As seen above, the factor 'social influence' covers the degree to which an individual feels pressure from important reference groups or individuals to use an innovation (Venkatesh et al., 2003). Narayan (2013) points out that the virtual world also belongs to the social environment. Some studies emphasise that applications that promote interaction between individuals have a positive influence on the acceptance of this application (Preece, 2000; Sorooshian et al., 2013). For this reason, it is argued that especially social networks such as Facebook, where users can interact with each other, have a positive influence on the use of banking services of such platforms.

The *hedonic motivation*, which is also circumscribed as the perceived pleasure of a person, describes the joy that the user feels while using an application. This factor is adopted without change, as this construct can be used universally for various innovations (Venkatesh et al., 2012).

The *price value* factor is not incorporated into this analysis. It compares the perception between the advantages of an application and its monetary cost. Venkatesh et al. (2012) consider this variable to be crucial in the consumer context because, unlike the organisational context, customers must bear the costs of an application themselves. However, since most banking services differ only marginally from each other regarding costs, this factor is not taken into account in this empirical analysis.

Another factor not considered in our modified model is *experience and habit*. The reason for this is that this factor points to the extent to which a person tends to perform an action based on learning processes or educated habits. Since the financial services offered by BigTech are still a quite new phenomenon, this factor is negligible (Figure 1).

In the following empirical study, age, gender, whether the respondent has already had contact with the banking services of the BigTech, the use of other products and services of the BigTech (such as social media channels), technology acceptance and satisfaction with existing banking services are examined as control variables. The latter is based on research findings to date, which have shown that many potential customers are not willing to embrace BigTech banking services because they are satisfied with the existing services of traditional banks (see Section 2 as well as [Lin et al., 2005]). Any existing contact with BigTech banking services and the use of other BigTech products/services (e.g., social media) have been included as a control variable, as it has made a significant contribution to the explanatory content of the results in previous studies (Santouridis & Kyritsi, 2014). Many studies have concluded that an already existing use of similar services or an already existing relationship with a brand has an influence on the acceptance of the new services (Karjaluoto et al., 2002). A person's technology affinity is treated as a control variable in many studies based on technical innovations or applications and describes the basic attitude of a person towards technologies (Lassar et al., 2005). Based on these considerations, the following hypotheses are developed for the application of the UTAUT2 model for financial services used by BigTech:

> Effort expectancy: The perceived user-friendliness captures the ease a person associates with the application of a technology. It has been shown that this factor has a strong positive effect on a person's behavioural intention, especially in the case of innovations (Chiao-Chen, 2013). On top of that, the effect is stronger if the application is self-service in which consumers must get by without a lot of external help, which is the case for online and mobile banking (Alalwan et al., 2015; Park et al., 2007). It can therefore be assumed that the simpler and user-friendlier a BigTech banking service is, the greater the behavioural intention to use this application. This results in Hypothesis 1:

Hypothesis 1. Effort expectancy has a significantly positive influence on the behavioural intention to use the banking services of BigTechs.

Performance expectancy: In many studies, this criterion has emerged as a significant determinant of behavioural intention and is also regarded by many researchers as the most stable construct (Fakhoury & Baker, 2016; Luo et al., 2010; Oliveira et al., 2014). For this reason, a consumer of BigTech banking services would be able to use them if he felt that they would improve his overall performance compared to other banking services (Tan & Lau, 2016). Consequently, it can be assumed that the greater the individual's perceived performance expectancy, the greater his willingness to adopt the application would be (Mbrokoh, 2016). It has been verified that this effect is very strong for both internet-based and mobile applications, as they increase flexibility and adaptability and thus also increase perceived performance expectancy (Yang & Forney, 2013). Since these points also apply to the banking services offered by the BigTechs, the following hypothesis can be stated:

Hypothesis 2. The perceived performance expectancy has a positive significant influence on the behavioural intention to use banking services of the BigTechs.

Social influence: With new technologies on the rise, the influence of the social environment is particularly strong, as there are hardly any norm values according to which the consumer can orientate himself, and for this reason, uncertainty prevails (Mbrokoh, 2016; Patel, 2016). This also applies to the banking services of BigTechs. Since BigTech solutions are very often embedded in social networks, the effect is intensified (Preece, 2000; Sorooshian et al., 2013). Thus, it is argued that the social influence will have a significant positive impact on the use of the banking services of BigTechs:

Hypothesis 3. The social influence significantly affects the behavioural intention to use the banking services of the BigTechs in a positive manner.

Perceived risk: Following Kalaiarasi and Srividya (2012), a high perceived risk positively affects the reluctance to use an application. The risk factor in the financial services market is presumably extremely relevant regardless of the object of the study. Lee (2009) shows that perceived risk plays a greater role in banking services than in other service domains, as personal data and financial resources are involved in the financial services sector on the one hand and are very often transmitted online and/or via a mobile device on the other (Kazi & Mannan, 2013). Accordingly, the risk of data misuse is given priority (Arcand et al., 2017). Various studies point out that software problems and hacker attacks are also perceived as risks in the financial services business (Tai & Ku, 2013). Therefore, the following hypothesis is derived:

Hypothesis 4. The perceived risk has a significant negative influence on the behavioural intention to use the banking services of the BigTechs.

Facilitating conditions: In terms of investigating the customer acceptance of banking services provided by non-banks, facilitating conditions are interpreted as the available financial resources, the skills needed to use the application and external conditions such as a functioning internet connection (Chemingui & Hajer, 2013). Since these circumstances can facilitate the use of an application and thus make it more pleasant, the hypothesis is as follows:

Hypothesis 5. Facilitating conditions have a significant positive influence on the behavioural intention to use the banking services of the BigTechs.

Hedonic motivation: Malaquias and Hwang (2016) demonstrate that not only functional motivation (e.g., to complete a transaction quickly) but also the hedonic motivation plays an important role in banking services. The fact that the banking services of the BigTechs are self-service technologies reinforces the influence of hedonic motivation (Curran & Meuter, 2007). Since most of the products offered by the BigTechs are associated with joy and pleasure, this feeling could also be transferred to banking services. In addition, the visual design (design, colours, layout, animations etc.) of an application can increase pleasure and enjoyment (Hausman & Siepke, 2009). As the BigTechs are very experienced in designing applications for consumers, it is assumed that their banking services are likely to be very appealing to customers. Thus, the following hypothesis is derived:

Hypothesis 6. Hedonic motivation has a significant positive influence on the behavioural intention to use the banking services of the BigTechs.

Perceived compatibility: Yu (2012) showed that perceived compatibility is an important factor for the behavioural intentions of potential users. The more the banking services offered by the BigTechs correspond to the everyday life and values of the consumer, the higher is the intention to use them. If an application does not correspond at all with the consumer's values, this compatibility, which is perceived as low, has a negative effect on the consumer's intention to use it (Yu, 2012). This leads to the following hypothesis:

Hypothesis 7. The perceived compatibility has a significantly positive influence on the behavioural intention to use BigTech banking services.

Perceived trust: In this research model, perceived trust is included as a supplementary variable since it is of great importance for people with new technologies and influences acceptance (Todd, 1998). Three elements stand out: the smooth application, the ethical nature of the service and the good reputation of the provider (Koksal, 2016; Xin et al., 2015; Zhou, 2011). Especially when it comes to novel self-service applications or services, trust is one of the main concerns for users, as there is little or no personal contact at all (Chai & Kim, 2010). In banking services, this effect is even stronger, as financial matters are generally perceived as more sensitive (Alalwan et al., 2015). If trust is not present, it increases customer concern, which has a negative impact on their behavioural intentions (Koksal, 2016). Liebana-Cabanillas et al. (2013) as well as Lee et al. (2011) stated in their studies that trust is a crucial determinant of the acceptance and usage of banking services. For this reason, the eighth hypothesis is as follows:

Hypothesis 8. Perceived trust has a significantly positive influence on the behavioural intention to use the banking services of the BigTechs.

4 | RESEARCH CONTEXT AND DATA

To test the model and hypotheses empirically, an online-based survey in which 361 persons participated was designed (see Appendix 1). The meta-analysis by King and He (2006), in which 88 technology acceptance studies were analysed, showed that a modest sample is sufficient to achieve significant results. For simpler constructs, a sample of just over 40 participants proved sufficient to demonstrate the underlying correlative effects. The target group of this research was defined as the total population of Switzerland, which already has a banking relationship (Creswell, 2009). The limitation of the target group can be regarded as marginal as the aim of the survey is to reflect the Swiss population's characteristics as closely as possible. All responses were collected by the online survey and then analysed using SPSS software. This type of survey was chosen to obtain as much (random) data as possible and thus to be able to gain more reliable estimates. In addition, the risk of socially desirable answers could be reduced by the guaranteed anonymity. The structure of the questionnaire (see Appendix 1) was then examined with the help of an exploration factor analysis to check if items should be grouped or left as single factors.

The study focuses on three main findings. The first is whether the independent variables have an impact on the dependent variable. Second, the ANOVA table is used to determine whether the whole model is significant in itself and therefore suitable for the analysis of the individual variables. Third, the strengths of the respective influences are shown and used for interpretation (Anderson et al., 2010). Multiple regression is primarily used to find a linear function that best adapts to the overall trend of all empirical points in a sample. This research uses the method of the fewest squares which is also the objective function of multiple regression. Since the multiple regression model is more complex than the simple regression model, some prerequisites must be met. In particular, all six Gauss-Markov assumptions are satisfied. Therefore, the least squares estimator is the best linear estimator for the model adopted. In particular, these conditions are as follows (Berry & Feldman, 1985):

The *first condition* is met if the regression coefficients are linear. If this assumption is violated, this leads to a distortion of the estimated values. For this purpose, partial scatter plots were created and analysed in SPSS. Due to this graphical representation, this assumption can be considered fulfilled in the present model. The *second condition* is met if the sample of the survey was randomly 'chosen', which is the case in this research. The *third condition* points to the exogeneity of the independent variables. The graphical representation does not provide any exact information about the predominance of autocorrelation, which is why the Durbin-Watson test was applied. A value of 1.830 was determined. Therefore, autocorrelation is excluded since a value between 0.7 and 2.3 can be regarded as a good proxy. The *fourth* *condition* presupposes that there is no perfect collinearity between the independent variables. In other words: A linear independence of the variables is assumed. Violating this assumption would be problematic since the estimates of the regression parameters become less accurate with increasing multicollinearity. This would mainly result in increased standard errors. With perfect multicollinearity, an estimate of the various regression coefficients would no longer be possible. In order to check the whole, the correlation matrix, for example, can be considered. However, the VIF values are described as more reliable and better. The results show that the VIF values are between 1.042 and 5.076 (see Table 1). Since a critical value of 10 applies to the VIF factor, it is safe to say that multicollinearity in the present model is not critical for further action and that the fourth assumption is therefore also fulfilled (Berry & Feldman, 1985). Analogous to the VIF, the tolerance factor can also be paid attention to, which is calculated from the reciprocal of the VIF.

The *fifth condition*, the *Gauss–Markov condition*, forms the constancy of the variance of the sturgeon terms. A graphical representation in a scatter diagram did not provide a clear result for the classification of homoscedasticity or heteroscedasticity either, which is common with large amounts of data; therefore a statistical test had to provide clarity. Homoscedasticity (equality of variances) of residuals shows that a model makes equally good predictions across all values. If this is not the case, heteroscedasticity prevails and there is a possibility that the model will not produce equally good predictions for all values. In order to make a clear statement on the fifth condition, a complex White test was performed, in which the independent variables were multiplied crosswise. The 109 newly created variables were then used for the white test. The main difference to the Breusch–Pagan–Godfrey test, which is also used frequently, is that the cross products and the squares of all explanatory variables are additionally formed and taken into account for auxiliary regression (White, 1980). The null hypothesis of the White test is that homoscedasticity prevails (Pindyck & Rubinfeld, 1991). Obs*R^2 statistics was employed to test this null hypothesis. Since in the present work, a p-value of 0.000 was obtained, which is smaller than the error probability $\alpha = 0.05$, the null hypothesis had to be rejected and the alternative hypothesis assumed, which states that heteroscedasticity of the residuals predominates. The largest problem with a lack of variance homogeneity (homogeneity elasticity) is the standard errors, which are not calculated correctly. Since in the worst case these can lead to false results in the hypothesis tests, robust standard errors should be used. The *sixth and final condition* is the normal distribution of error terms. These should be approximately normally distributed.

Two graphical methods are suitable for checking the distribution assumption. On the one hand, a histogram of the standardised residuals can be generated in which the deviations from the normal distribution curve, which is also displayed, can be recognised (see Figure 2).

On the other hand, a probability–probability plot can also be helpful to test for normal distribution. The standard case is that the larger the sample, the more likely a normal distribution can be assumed. The graph shows the cumulative frequency distributions of the residuals with the cumulative normal distribution. Figure 3 shows that these are fairly identical and that a normal distribution can therefore be derived.

TABLE 1 VIF values.

Coefficients[a]							
	Non-standardised coefficient		**Standardised coefficient**			**Collinearity statistics**	
	Regression coefficient	**Standard error**	**β**	**T**	**Sig.**	**Tolerance**	**VIF**
Constant	2.007	.923		2.175	.030		
Effort expectancy	0.153	0.030	0.148	50.084	0.000	0.0228	4.377
Performance expectancy	0.033	0.022	0.033	1.497	0.135	0.284	3.526
Social influence	0.153	0.038	0.104	3.976	0.000	0.201	4.973
Perceived risk	−0.270	0.036	−0.234	−7.527	0.000	0.201	4.973
Facilitating conditions	0.144	0.027	0.148	5.335	0.000	0.255	3.926
Hedonic motivation	0.122	0.035	0.083	3.490	0.001	0.340	2.937
Perceived compatibility	0.095	0.025	0.099	3.854	0.000	0.298	3.355
Perceived trust	0.271	0.038	0.223	7.086	0.000	0.197	5.076

[a]Dependent variable: behavioural intention.

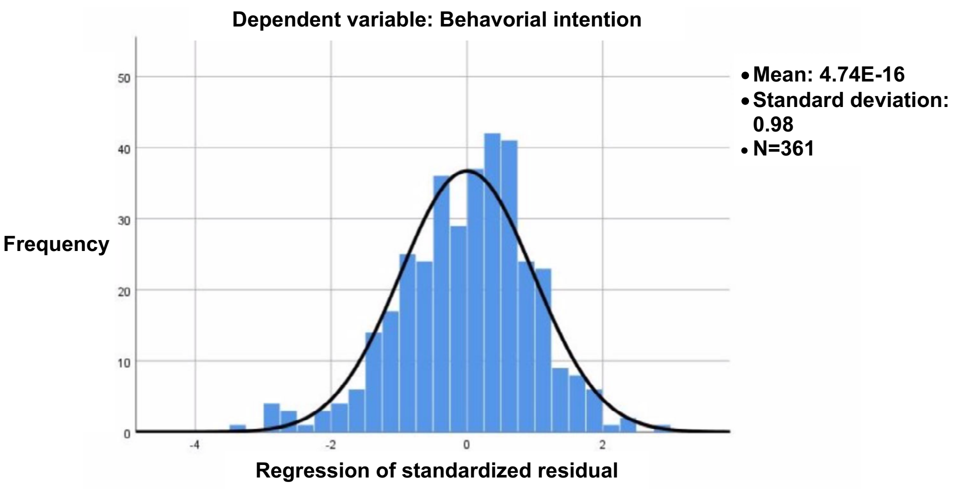

FIGURE 2 Normal distribution. [Colour figure can be viewed at wileyonlinelibrary.com]

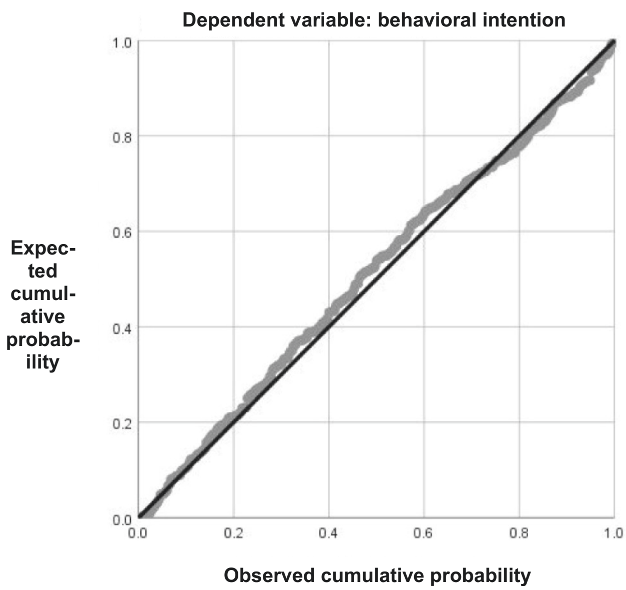

FIGURE 3 *Q-Q* test.

5 | EMPIRICAL ANALYSIS AND RESULTS

Since there is no gross violation of the Gauss–Markov conditions, multiple regression is suitable for the analysis of the results. For this purpose, the analysis methods already presented are applied to test the formulated hypotheses. In particular, this research first checks the descriptive characteristics of the sample and the model quality. Second, the mean values, the standard deviations, the correlation matrix and the models created are outlined and analysed.

5.1 | Overview of the sample

Data were collected by means of a survey, which consisted of two parts (see Appendix 1). In the first part, demographic characteristics (such as age and gender) and other control variables (technology affinity, existing contact with BigTech banking services and use of other BigTech products/services [e.g. social media channels]) were surveyed. The gender was coded with 0 = female and 1 = male. The affirmation of the statements on the existing contact and on the use of other BigTech services was coded with = 1—the negation thus with zero (=0). In the second part of the questionnaire, statements on the individual factors (independent variables) were addressed, which were subjectively accepted and assessed by the test persons with the help of a seven-point Likert scale from 1 = 'I do not agree at all' to 7 = 'I fully agree', complemented by a control question (where simply 4 had to be clicked to identify how many participants went through the whole questionnaire). Out of 407 participants, seven were excluded because the control question was not clicked and 39 did not complete the survey so the final survey contained 361 valid test subjects.

Our sample shows a high proportion of young people under 30 as well as older people (over 51 years). As can be seen in Table 2, middle-aged people are also represented, so that our sample well reflects the population of the Swiss population. It turned out that there is a surplus of male participants, who are represented with 54.6%. The proportion of male participants also increases, especially with increasing age. For example, the group of over 51-year-olds consists of 58.8% male participants and 41.2% female participants.

TABLE 2 Sample features age and sex.

Features of sample	Total number	Male	Female
Under 30 years	135 (37.4%)	69 (51.1%)	66 (48.9%)
31–50 years	141 (39.1%)	78 (55.3%)	63 (44.7%)
More than 51 years	85 (23.5%)	50 (58.8%)	35 (41.2%)
Total	**361 (100%)**	**197 (54.6%)**	**164 (45.4%)**

TABLE 3 Cronbach's alpha.

Measurement instrument	Cronbach's alpha
Technology affinity	0.900
Effort expectancy	0.912
Performance expectancy	0.849
Social influence	0.927
Perceived risk	0.918
Facilitating conditions	0.846
Hedonic motivation	0.758
Perceived compatibility	0.799
Perceived trust	0.960
Behavioural intention	0.976

5.2 | Quality control of the models

Apart from the tests above, reliability and validity must also be guaranteed to check the quality. The validity can be regarded as given since on the one hand questions/statements from earlier studies were used (content validity and reliability) and the factor analysis showed the validity of the measuring instrument (all minimum values reached).

To provide further evidence for the reliability of the questionnaire scientifically, Cronbach's alpha was tested for the individual measuring instruments. Cronbach's alpha mainly determines the internal consistency of the measuring instrument and can therefore make statements about random measurement errors. According to George and Mallery (2003), a Cronbach's alpha of >0.9 can be regarded as excellent. Values between 0.7 and 0.9 are generally classified as good. Table 3 summarises the calculated Cronbach's alpha. It can be seen that the values are between 0.758 and 0.976 and the reliability is thus guaranteed (Nunnally, 1967).

5.3 | Descriptive results

The descriptive results contain the mean values, the standard deviations and the correlations between the variables. The dependent variable is the first variable and the variables two to nine are the independent variables. Variables 10–15 represent the control variables. Table 4 analyses whether the variables (apart from the dependent variable: the behavioural intention) have a critical correlation value of over 0.9 (or 0.7 in other studies) (Bagozzi et al., 1991). Since none of the correlations have a value above neither 0.7 nor 0.9, it can be concluded that no methodological bias prevails. Of the eight independent variables, effort expectancy (16.42) has the highest mean value, and social influence (10.11) has the lowest mean value.

The model also shows correlations between the independent and dependent variables. The independent variables should normally have a correlation value of at least 0.3 with the dependent variable. This is consistently fulfilled. Of the independent variables, perceived trust shows the strongest significant correlation to the dependent variable ($r = 0.902$, $p < 0.01$). The effort expectancy also possesses a strong positive correlation with the behavioural intention ($r = 0.871$, $p < 0.01$). Contrary to other research, performance expectancy in the present study reveals the weakest correlation with behavioural intention for the use of BigTech banking services (Kim, 2014; Lee, 2009). From the independent variables, only the perceived risk turns out to have a significantly negative correlation ($r = -0.837$, $p < 0.01$) with the dependent variable, as hypothesised.

To account for multicollinearity, the average VIF values (Sinan & Alkan, 2015) were given in the presentation of the models (see Table 4). Since the values range between 1.31 and 3.66, multicollinearity does not play a significant role in the models described below, although this cannot be completely excluded due to the values of the descriptive statistics (Curto & Pinto, 2011).

5.4 | Results and analysis of multiple regression

Table 5 summarises the models with which the hypotheses can be tested. The first model is the complete (modified) model used for the analysis. This forms the basis for the hypothesis tests and is presented in more detail following the brief explanations of Models 2–11. The second model analyses the determinants identified and already established by Venkatesh et al. (2012). The third model,

TABLE 4 Means (*M*), standard deviations (*SD*) and correlations for all variables.

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Behavioural intention	11.63	6.662															
2. Effort expectancy	16.42	6.468	0.871**														
3. Performance expectancy	16.04	6.531	0.745**	0.387**													
4. Social influence	10.11	4.538	0.843**	0.196**	0.399**												
5. Perceived risk	11.75	5.782	−0.837**	−0.127*	−0.393**	−0.451**											
6. Facilitating conditions	16.56	6.837	0.865**	0.389**	0.301**	0.252**	−0.344**										
7. Hedonic motivation	10.83	4.564	0.808**	0.269**	0.195**	0.153**	−0.201**	0.138**									
8. Perceived compatibility	16.14	6.887	0.833**	0.381**	0.208**	0.180**	−0.348**	0.246**	0.225**								
9. Perceived trust	10.94	5.469	0.902**	0.301**	0.327**	0.229**	−0.561**	0.262**	0.162**	0.274**							
10. Technology affinity	15.90	6.570	0.906**	0.428**	0.233**	0.153**	−0.390**	0.295**	0.315**	0.214**	0.127**						
Age	37.59	14.22	−0.44**	−0.54**	−0.47**	−0.42**	0.381**	−0.44**	−0.38**	−0.41**	−0.36**	−0.52**					
Sex	0.55	0.499	−0.51**	−0.43**	−0.32**	−0.50**	0.525**	−0.41**	−0.46**	−0.42**	−0.50**	−0.42**	0.078				
Contact with banking services by BigTechs	0.13	0.340	0.087	0.063	0.066	0.032	−0.075	0.085	0.067	0.099	0.060	0.081	−0.033	−0.003			
Use of other BigTechs products	0.78	0.412	0.240**	0.301**	0.229**	0.207**	−0.21**	0.248**	0.203**	0.215**	0.216**	0.297**	−0.39**	−0.006	0.027		
Satisfaction with current banking services	0.67	0.470	−0.022	−0.022	0.008	−0.034	0.029	−0.029	0.011	0.031	−0.025	−0.045	0.032	0.076	−0.127*	−0.065	

Note: Variable 12 coding: 0 = male, 1 = female; Variables 13–15 coding: 0 = No, 1 = Yes.
**The correlation is significant at the level of 0.01 (two-sided).
*The correlation is significant at the level of 0.05 (two-sided).

TABLE 5 Results of the multiple linear regression.

Models		1 All variables	2 Variables according to (Venkatesh et al., 2012)	3 Control variables	4 Effort expectancy	5 Performance expectancy	6 Social influence	7 Perceived risk	8 Facilitating conditions	9 Hedonic motivation	10 Perceived compatibility	11 Perceived trust
Independent variables	Effort expectancy	0.11312***	0.27997***	-	0.27803††	-	-	-	-	-	-	-
	Performance expectancy	0.02626	0.08411**	-	-	0.1422***	-	-	-	-	-	-
	Social influence	0.08936***	0.22113**	-	-	-	0.27178***	-	-	-	-	-
	Perceived risk	−0.20609***	-	-	-	-	-	0.44236***	-	-	-	-
	Facilitating conditions	0.13240***	0.29597***	-	-	-	-	-	0.33173***	-	-	-
	Hedonic motivation	0.07207**	0.16606***	-	-	-	-	-	-	0.22680***	-	-
	Perceived compatibility	0.08915***	-	-	-	-	-	-	-	-	0.27580***	-
	Perceived trust	0.21251***	-	-	-	-	-	-	-	-	-	0.44746***
Control variables	Technology affinity	0.125081**	-	0.8434***	0.60047***	0.73250***	0.64271***	0.50297***	0.57305***	0.67961***	0.63356***	0.50186***
	Age	0.01346	0.04206*	0.01327	-	-	-	-	-	-	-	-
	Sex	−0.01695	−0.05654**	−0.15573***	−0.13735***	−0.15617***	−0.10254***	−0.06528***	−0.13102***	−0.11996***	−0.12584	−0.07615
	Contact with banking services by BigTechs	0.01249	-	0.02192	-	-	-	-	-	-	-	-
	Use of other BigTechs products	−0.00693	-	−0.00565	-	-	-	-	-	-	-	-
	Satisfaction with current banking services	0.030404	-	0.02974†	-	-	-	-	-	-	-	-
Characteristics	Number of participants	361	361	361	361	361	361	361	361	361	361	361
	Constant	1.16349	−5.4861***	−1.40887†	−1.706.620	−1.3621**	−2.0110***	9.9925***	−1.9998***	−2.0314***	−1.9669***	−1.8608***
	−2 log-likelihood	1476.863	1620.917	1743.954	1706.620	1739.509	1687.503	1615.827	1663.063	1698.152	1677.66	1739.509
	Average VIF	3.45	2.73	1.31	3.66	2.03	2.33	3.01	2.67	2.15	2.27	2.69

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; ††$p < 0.10$;
†$p < 0.20$.

however, only captures the control variables used and serves to identify the significant control variables. The remaining models (4–11) map the respective independent variables individually, taking into account the significant control variables.

Starting with the second model, it can be stated that the factors of the proposed model have a significant influence on the behavioural intention to use BigTech's banking services. The factors effort expectancy, social influence, facilitated conditions and hedonic motivation have a positive influence on the behavioural intention at the significance level of $p < 0.001$. The greatest effect in the second model with a value of $\beta = 0.29597$ is shown by the facilitated conditions. According to Cohen (1992), this value can be regarded as relatively high, since a change of the facilitated conditions by the value $+1$ increases the behavioural intention by the (rounded) value $\sim$0.3. Surprising is the performance expectancy. This factor is 'only' significant at the level $p < 0.01$ and has a relatively modest influence ($\beta = 0.08411$) even though this factor is said to have the strongest influence on behavioural intention.

The third model, which only encompasses the control variables, tests the significance of the individual control variables. It turns out that only gender and technology affinity have a significant impact. For this reason, these two variables are integrated into Models 4–11. The fourth model shows the effect of the independent variable effort expectancy in isolation, taking into account the two control variables described. A rather similar value ($\beta = 0.27803$, $p < 0.001$) was found as in the second model, which represents a significant positive influence on behavioural intention. The fifth model takes a closer look at the influence of performance expectancy. It can be seen that the analysed factor in this model has a slightly stronger effect ($\beta = 0.14222$) on the behavioural intention than in the second model. In model six it can be seen that the social influence has a strong ($\beta = 0.27178$, $p < 0.001$) significant influence on the dependent variable. The perceived risk, to which attention is paid in the seventh model together with the control variables gender and technology affinity, shows the second strongest effect among the individually considered independent variables. This relationship is negative and therefore in line with our expectations. This means that if the perceived risk increases by $\sim$2.3, the intention to use BigTech banking services decreases by -1. This correlation is significant at the significance level of $p < 0.001$. Models eight to ten furthermore indicate all significantly positive correlations to the dependent variable. The last model considers the effects of perceived trust. The analysis observes from the model that the perceived trust at the significance level of $p < 0.001$ has a very strong positive influence on the intention to use the banking services of the BigTechs (Cohen, 1992). In simplified terms, it can be stated that an increase in perceived trust has a very strong positive influence on behavioural intentions. The dependent variable changes by almost half ($\beta = 0.44746$) of the change in the independent variable (perceived trust). In summary, the Models 4–11, in which an independent variable and the two significant control variables (gender and technology affinity) are considered, the independent variables always have a significant ($p < 0.001$) influence on the dependent variable.

In the following, the model is investigated in its entirety to support or falsify the hypotheses. It could be found that the overall model (Model 1) possesses an R^2 of 0.934. However, since many variables are taken into account in the model, the corrected R^2 was also included. This has a similarly high value of 0.933. The R^2 thereby describes the coefficient of determination of the model used (Chin, 1998). This means that 93.3% of the total variance of the dependent variable is explained by the variables used. This value can be conceived of as high as only 6.7% of the variance cannot be explained by the model about the behavioural intention to use banking services of the BigTechs. This is not surprising as the model is based on an intensive literature search and both factors from general technology acceptance research and (possible) specific factors from the financial sector have been exploratively integrated into the model. To assess whether the R^2 value is random or not, the F-value was accounted for. The ANOVA (see Table 6) shows a highly significant F-value, indicating that the relationship between the independent and dependent variables is not random. Since the model is thus suitable for further analysis as a whole, the individual hypotheses are now tested.

5.4.1 | Testing Hypothesis 1

The first hypothesis states that effort expectancy has a significantly positive influence on the behavioural intention to use the banking services of the BigTechs. This statement is supported by the first model. The term 'effort expectancy' is somewhat misleading as it points to the perceived simplicity of an innovation in the model used. It is important to note that this factor is positively referenced, which means that if the value is high, the innovation is assumed to be easy to use. For this reason, it can be clearly stated that in the case of an increasing value of effort expectancy, the behavioural intention to use banking services increases. The effect strength can be regarded as medium due to the value ($\beta = 0.11312$, $p < 0.001$) (Cohen, 1992). The effect of the effort

TABLE 6 ANOVA.

ANOVA[a]					
Model	**Square sum**	**df**	**Middle of the squares**	**F**	**Sig.**
Regression	14915.120	14	1065.366	347.55	0.000[b]
Non-standardised residuals	1060.614	346	3.065	-	-
Total	15975.734	360	-	-	-

[a]Dependent variable: Behavioural intention.

[b]Impact variables: Satisfaction with current banking services, contact with banking services by BigTechs, Use of other BigTech products, sex, age, hedonic motivation, perceived compatibility, social influence, facilitating conditions, perceived risk, performance expectancy, perceived trust and technology affinity.

expectancy is also confirmed in the fourth model described earlier. These findings coincide with other studies already published (Alalwan et al., 2015; Chitungo & Munongo, 2013; Luarn & Lin, 2005).

Since the effort expectancy in the present study has a medium-strong positive influence on behavioural intention, this factor should not be neglected by the BigTechs. Providers may focus on bringing user-friendly services to the market. One option could be to integrate banking services into existing services/applications, as the survey has shown that many participants are already familiar with the current services/applications of BigTechs (such as social media channels). Through integration into existing structures, the perceived simplicity of using innovative banking services could be significantly increased as consumers do not have to invest much time or effort in learning the banking services. In addition, attention should be paid to an attractive and clear design so that consumers can find their way around quickly and all functions are easy to find. In order to ensure simplicity of use, it may also prove to be helpful to introduce new customers to the various functions of the banking service after installation with the help of instructions or self-tutorials.

5.4.2 | Testing Hypothesis 2

The second hypothesis states that the perceived performance expectancy has a significant positive influence on the behavioural intention to use BigTech banking services. It could not be confirmed by the first model and is therefore rejected. The model indicates a relatively small effect of ($\beta = 0.02626$), which, however, is not significant ($p > 0.20$). The result is interesting and not in line with previous findings where a significant and mostly strong influence on behavioural intention is noted (e.g., Bhatiasevi & Yoopetch, 2015; Kim, 2014; Lee, 2009; Luarn & Lin, 2005; Santouridis & Kyritsi, 2014).

Surprisingly, the performance expectancy variable could not generate any significant impact in our setting. On the one hand, this could be related to geographical reasons concerning data collection, as many digital and innovative banking services are already offered in Switzerland by start-ups and also by traditional banks. This is confirmed by another study which suggests that the banking services of the data giants are considered less useful in countries where digitisation is well advanced (which is the case in Switzerland; Du Toit & Burns, 2017). Despite the fact that the influence is not significantly emphasised, the BigTechs would not be ill-advised to advertise the services and the added value of their own services. In concrete terms, this could mainly be the speed with which the service can be carried out. However, since the effect has not been shown to be significant, the BigTechs would have to consider their opportunity costs and compare carefully (in terms of both where to invest time and money) whether they aim to influence performance expectancy through targeted measures.

5.4.3 | Testing Hypothesis 3

The third hypothesis analyses if the social influence significantly amplifies the behavioural intention to use BigTech banking services. Our empirical investigation suggests verifying this hypothesis. The first model shows a positive effect of $\beta = 0.08936$ ($p < 0.001$) of the social influence on the intention to use BigTech banking services. According to the Cohen subdivision (1992), the effect strength can be assessed as rather weak to medium.

The verification of the third hypothesis implies that the opinions of other customers or friends have a weak to medium influence on the individual's intention to use BigTech banking services. This means that customers are influenced by their social environment when using or not using these banking services. This is a very interesting finding for the BigTechs. Especially for Meta, where customers are linked to each other in terms of a social community, this determinant seems to be crucial. Thus, a great deal of importance can be attached to network effects. For Facebook, for example, it is advantageous to connect existing users with each other, by enabling users to send money among friends. By creating such networks among friends and acquaintances, social influence can be stimulated positively, and the so-called social pressure to use novel services can be increased (Venkatesh et al., 2003; Yu, 2012), (Preece, 2000; Sorooshian et al., 2013). In addition, Narayan (2013) identified that these effects not only work in the real world but also hold very strongly in the virtual world. For this reason, there are many possibilities for the BigTechs to steer and optimize social impact.

5.4.4 | Testing Hypothesis 4

The perceived risk has a significant negative influence on the behavioural intention to use BigTech banking services. This hypothesis can also be verified by the data. As already described in the theoretical part, many studies have shown that perceived risk is a central determinant of the acceptance of financial services (e.g., Luarn & Lin, 2005; Mallat et al., 2004), which is now in consonance with our findings. Analogous to other prior work (e.g., Luo et al., 2010; Rawashdeh, 2015), a significant ($p < 0.001$) negative influence ($\beta = -0.20609$) on the behavioural intention to use banking services of the BigTechs was identified, indicating a medium to strong influence (Cohen, 1992).

Perceived risk has the second strongest influence on the dependent variable. This strongly suggests a key determinant to watch out for and steer to enhance customer acceptance. As the perceived risk increases, so does the reluctance to use banking innovations of the BigTechs (Kalaiarasi & Srividya, 2012). The main reason for this strong effect is mainly due to the fact that personal and financial data are involved in the area of financial services, which per se are regarded as risky to handle (Kazi & Mannan, 2013). Clearly, these would have a negative impact on behavioural intentions via spill-over effects (Arcand et al., 2017).

5.5 | Testing Hypothesis 5

The fifth hypothesis is fulfilled and facilitated conditions have a significant positive influence on the behavioural intention to use the banking services of the BigTechs. In the multiple regression performed, the facilitated conditions factor has a positive significant influence ($\beta = 0.13240$, $p < 0.001$) on the behavioural intention.

The facilitated conditions describe internal and external factors that can positively influence the behavioural intention when fulfilled. These include some factors that cannot be directly influenced by the BigTechs (such as the financial capabilities of the individual), but also external factors play a major role. The latter include, for example, a functioning internet connection or a secure and functioning application. These circumstances would already have a medium influence on the acceptance of the offered banking services (Chemingui & Hajer, 2013).

5.5.1 | Testing Hypothesis 6

The sixth hypothesis is empirically confirmed as well. Therefore, hedonic motivation has a significant positive influence on the behavioural intention to use BigTech banking services. This could be verified using the value ($\beta = 0.07207$, $p < 0.01$) from the first model, although the effect can be regarded as rather weak (Cohen, 1992).

Even though hedonic motivation is a significant determinant according to model 1, its effect can be classified as rather modest. In addition, the significance level is somewhat weaker than for the other factors. From the result, however, it can be concluded that it is not only the functionality of an offered banking service that is important for the behavioural intention to use it but also the convenience that an individual perceives when using it. This conclusion is also consistent with other studies (e.g., Alalwan et al., 2015; Hausman & Siepke, 2009). However, convenience is just one part, whereas trust remains one of the major requirements (Malaquias & Hwang, 2016).

5.5.2 | Testing Hypothesis 7

To test the seventh hypothesis, namely that perceived compatibility has a significant positive influence on behavioural intention, the first model is examined more closely. The resulting value indicates that the hypothesis can be accepted. A positive and significant ($\beta = 0.08915$, $p < 0.001$) connection to the behavioural intention to use BigTech banking services is found.

In prior work, perceived compatibility proved to be a significant positive factor for the behavioural intention of banking services (Yu, 2012). This is also confirmed in the present study. However, the effect that is measured in this frame turned out to be rather weak to moderate (Cohen, 1992). For the BigTechs, this nevertheless means that this factor ultimately has an influence on the acceptance of the banking services offered. Thus, it seems important to identify those individuals for whom the use of their solutions is compatible with their specific lifestyle. This phenomenon can be observed very strongly at

Apple (e.g., the credit card offered together with Goldman Sachs). This example shows that the BigTechs are already attempting to affect the perceived compatibility of other products on offer. Therefore, it is not far off to do the same by establishing its banking services in the form of clever marketing activities. The easiest way to do this is to address existing customers. However, potential customers for whom the innovative banking services are compatible with their values/lifestyle but who have not yet the intention to use the new banking services due to a lack of information should also be actively addressed (if backed up by a corresponding cost analysis).

5.5.3 | Testing Hypothesis 8

The last hypothesis tested in this research is the influence of perceived trust on the behavioural intention to use BigTech banking services, which was reasoned to be significantly positive. This hypothesis is supported by the model. The perceived trust has even the strongest significant influence ($\beta = 0.21251$, $p < 0.001$) on the behavioural intention. This factor furthermore plays a crucial role in earlier studies as well (e.g., Lee et al., 2011; Liebana-Cabanillas et al., 2013). The multiple regression of the model reveals that the behavioural intention increases by one unit when the perceived confidence increases by ~4.7 units. This influence is interpreted as relatively strong (Cohen, 1992).

Since the perceived trust has the strongest impact on the intended use of banking services by BigTechs and thus on their acceptance, this factor is of central importance. This includes, for example, the reputation of the provider or ethical factors (Koksal, 2016; Xin et al., 2015; Zhou, 2011). In addition, trustworthy cooperation partners can further be integrated to increase the perceived trust.

5.6 | Theoretical implications

The BigTech companies have gained great interest in recent years as they demonstrated the emergence of new digital ecosystems as a novel field (Jacobides et al., 2018). Currently, most banks are primarily working in vertically integrated value chains covering the complete knowledge of end customer goals. But banks are increasingly evolving into digital ecosystems that are constructed of networks, customers, (non-)banks and providers. This may also include the provision and or (out)sourcing of services from companies from other industries which increasingly leads to blurring industry sector borders. These digital ecosystems require a clear understanding of consumer preferences, and, as especially the BigTech companies stepped into this field very early, the analysis of consumer preferences in a sensitive field like financial services, is relevant for other domains as well. Thus, this research contributes to the discussion of consumer preferences for digital ecosystems

A second relevant field to which this research contributes new knowledge, is the area of technology acceptance of consumers. Since there is up to date little to no literature on the acceptance of banking services by the BigTech firms, contributions from related research fields were considered in the context of this work. Thus, a relatively large number of studies dealing with the technology acceptance of mobile payment solutions and other FinTech services could be found. Apart from that, since the Technology Acceptance Model and the UTAUT2 model on which the research was built on, has so far rather been used for such studies, this work pioneered on uncharted terrain by helping establish the UTAUT2 model for this context and extending it to the specific requirements in this area. Thus, this work closes a gap in acceptance research where technology acceptance of BigTech banking services has not yet received much attention. One major contribution of this research is the extension of existing literature on technology acceptance. Based on the empirical investigation, the factors 'effort expectancy', 'social Influence', 'facilitated conditions' and 'hedonic motivation' were confirmed as key elements for the acceptance of banking services in the context of digital ecosystems. In addition, a comprehensive literature analysis was carried out to identify further possible determinants that exploratively complement the existing UTAUT2 model. It could be shown that the factors 'perceived risk', 'perceived compatibility' and 'perceived trust' play a crucial role in the intention to use banking services as well. Thus, it can be concluded that the determinants around risk perception and trust in the financial sector ought to be strongly weighted.

6 | CONCLUSION

Even though the four BigTech companies Alphabet, Amazon, Apple and Meta are increasingly entering the financial services market, not much research has been conducted on the acceptance of their digital finance solutions yet. Put differently, little is known about the determinants influencing customer acceptance of BigTech's banking services. To shed light on this, the determinants of the customer acceptance of such new banking services of the BigTechs were examined in the context of this work. Based on a literature search, the current efforts of the BigTechs to enter the banking market and the resulting current challenges were pointed out. The latter subsequently served to adapt the technology acceptance model (UTAUT2), from which eight hypotheses were derived. With the help of a survey, the hypotheses were tested. For this purpose, a total of 361 completed questionnaires were evaluated and analysed using multiple regression. Seven of the eight hypotheses were confirmed and the factors 'effort expectancy', 'social influence', 'perceived risk', 'facilitated conditions', 'hedonic motivation', 'perceived compatibility' and 'perceived trust' were classified as relevant for the intended use of BigTech banking services. The 'performance expectancy' could not be identified as a significant influencing factor. Overall, 93.3% (corrected R^2) of the total variance could be explained with the help of the model presented, which proved to be significant overall. The model has shown that the perceived trust, followed by the perceived risk, has the greatest significant impact. This is surprising, as the BigTech firms often state that the performance expectancy is the one that supports their competitive advantage over the incumbent financial institutions.

Although the analysis shows a significant impact, it also has some limitations. On the one hand, the results are not generally transferable to other countries. Since only Swiss citizens were interviewed, the findings apply to Switzerland and may be different in other countries. A further limitation is an actual model as it does not directly measure the acceptance/use of BigTech banking services, but the influence on the behavioural intentions. This is stated in this connection but does not represent a major limitation, since such a model design is used in most research on technology acceptance and a strong correlation has been found between acceptance/use and behavioural intention for use. Finally, the survey was carried out in the initial phase of BigTech's broader entry into the banking sector, which is why it is a research context of future-oriented technologies. It can also be considered a limitation that the BigTechs were presented as a group in terms of data collection since it could very well be that the individual companies (Alphabet, Amazon, Apple and Meta) would have been evaluated differently in terms of technology acceptance. For this reason, it would certainly be interesting for future work to examine the companies separately and, above all, to account for the business-to-business view, for example by interviewing Amazon retailers. As the literature research suggests, the BigTechs (especially Amazon) grow strongly into the business-to-business sector as well. Consequently, it would be interesting to take up these findings in future research.

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APPENDIX: SURVEY

Sex

female male

Age

I have already come across BigTech banking services.

yes no

I use other existing products/services from BigTechs (e.g., social media channels).

yes no

4.I am currently satisfied with my existing banking services.

yes no

The following questions were answered using a 7-point Likert scale:

Do not agree at all 1 2 3 4 5 6 7 Totally agree.

Technology affinity

TA1: I think most technologies are easy to learn.

TA2: I feel comfortable learning new technology.

TA3: I know how to deal with technological malfunctions and problems.

TA4: I feel at the cutting edge of technology.

Effort expectancy

EE1: Learning how BigTech banking services work would be easy for me.

EE2: The use of BigTech banking services is clear and understandable to me.

EE3: I think BigTech banking services would be easy to use.

EE4: It would be easy for me to acquire skills to master BigTech banking services.

Performance expectancy

PE1: Banking services from BigTechs could be meaningfully integrated into my everyday life.

PE2: BigTech banking services would increase my chances to achieve those that are important to me.

PE3: BigTech banking services would help me get banking done faster.

PE4: Using BigTech banking services would increase my productivity increase.

Social influence

SI1: People who are important to me think that I should use banking services by BigTechs.

SI2: People who influence my behaviour think that I should use BigTech banking services.

SI3: People whose opinion I weight would like it if I would use BigTech banking services.

Perceived risk

PR1: I would not feel protected enough using BigTech banking services.

PR2: The likelihood that something will go wrong when using BigTech banking services is high.

PR3: I would be concerned about my data when using BigTech banking services as it could be misused.

Facilitated Conditions

FC1: I have the resources to use BigTech banking services.

FC2: I have the knowledge to use BigTech banking services.

FC3: BigTech banking services are compatible with other technologies that I use.

FC4: I could get help from someone if I have trouble using it.

Hedonic Motivation

HM1: Using BigTech banking services is fun.

HM2: The use of BigTech banking services is pleasant.

HM3: The use of BigTech banking services is entertaining.

Perceived compatibility

PC1: I do not need to change anything to use BigTech banking services.

PC2: The use of BigTech banking services fits perfectly with the way I like to use banking services.

PC3: BigTech banking services fit well into my everyday life.

PC4: BigTech banking services are compatible with my values.

Perceived trust

PT1: I would feel safe using BigTech banking services.

PT2: I think that BigTech can be trusted as a banking service provider.

PT3: In my opinion, the BigTech try to protect my interests.

Behavioural intention

BI1: I intend to use BigTech banking services in the future.

BI2: I will try to integrate BigTech banking services into my everyday life.

BI3: I plan to use BigTech banking services regularly in the future.