The International Journal of Business and Finance Research
Vol. 13, No. 2, 2019, pp. 83-105
ISSN: 1931-0269 (print)
ISSN: 2157-0698 (online)

IBFR
www.theIBFR.com

EVIDENCE ON USAGE BEHAVIOR AND FUTURE ADOPTION INTENTION OF FINTECHS AND DIGITAL FINANCE SOLUTIONS

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ABSTRACT

Financial Technology Companies are gaining popularity and becoming more relevant within financial services industries worldwide. This growth can be encouraged by the EY FinTech Adoption Index, which indicates a global average FinTech Adoption of 33.0% in 2017. With regard to Financial Technology Companies and Digital Finance Solutions, this figure emphasizes the importance of this study's objective to identify potential determinants of current use behavior and future usage intention. To both theoretically and empirically address this research question, we conducted a questionnaire-based survey with 381 participants from three German universities. Because our study bases on both the theory of reasoned action and the unified theory of acceptance and usage of technology 2, we contribute not only to the general understanding of Financial Technology Companies and Digital Finance Solutions but also to the existing literature on behavioral intention and technology acceptance. Thus, we contribute to several strands of literature. However, based on this study's results, we defined certain fields of interest and derived corresponding strategic and managerial implications from the viewpoint of traditional financial institutions. Moreover, we contribute to the practical solution of the current challenges faced by traditional financial services providers. Finally, based on our analyses, we identify future research opportunities regarding these important issues.

JEL: G10, G20, G21, G22, G23, G24, M13, M31, O33

KEYWORDS: Fintech, Digital Finance Solutions, Technology Adoption, Current Use Behavior, Future Usage Intention, Behavioral Intention, Consumer Behavior, Theory of Reasoned Action (TRA), Unified Theory of Acceptance and Usage of Technology 2 (UTAUT2)

INTRODUCTION

Currently, Financial Technology Companies (FinTechs) are gaining popularity and overall attention. Customers of financial services are changing expectations and increasing their usage of financial technologies. Further, a general shift in utility and usability can be observed. Based on the EY FinTech Adoption Index, the percentage of FinTech users increased significantly from 16.0% in 2015 to 33.0% in 2017 and may increase to a global average of 52.0% (Ernst & Young, 2017). These developments emphasize the importance of identifying potential drivers of FinTech adoption. Furthermore, the development of strategic and managerial implications from the viewpoint of traditional financial institutions is inevitable. Moreover, traditional banks are currently having evolving discussions on how to address FinTechs as new competitors, either co-operative or competitive (Gomber et al., 2017). However, leaving FinTechs or digital movers unchecked could be dangerous for traditional financial institutions, because customer out-migration poses significant risks. Consequently, this study's aim is to identify potential determinants of current use behavior and future usage intention. Moreover, gaining knowledge about whether and how these drivers affect decision-making is of great relevance. This raises the question of whether and how customers of traditional financial institutions are likely to shift to FinTechs as alternative service providers. Therefore, this paper investigates, with regard to FinTechs and Digital Finance Solutions, how customers behave currently and intend to behave in the future. In doing so, this paper contributes to several strands of literature. First, we contribute to the general understanding of FinTechs and Digital Finance Solutions. Second, we improve the understanding of the adoption, readiness and behavior of customers regarding the theory of reasoned action (TRA) and the unified theory of acceptance and usage of technology 2 (UTAUT2) (Venkatesh et al., 2012, Ajzen and Fishbein, 1977). These theoretical frameworks produce a comprehensive set of variables that concern the circumstances and perceived benefits and risks that drive decision-making, usage intention and expectations. To achieve this paper's objective, we conducted a questionnaire-based study with 381 participants from three German universities.

To provide a systematic and clear understanding of the addressed topics, the remainder of this paper is structured as follows: First, in the next section, a literature review illustrates the theoretical foundation. The following section defines the collected dataset as well as the research methodology, i.e., represented by a questionnaire-based survey, a descriptive analysis and a logistic regression approach. Afterwards, the results section provides comprehensive analyses and discussions. This is enhanced by the derivation of strategic and managerial implications and a proof of robustness. The final section offers concluding comments and highlights limitations as well as future research opportunities.

LITERATURE REVIEW

First, we build our definitional foundations regarding FinTechs and Digital Finance Solutions, which represent the basis of our research approach and are associated with the dependent side of our empirical model design. According to previous research, we state that – so far – no unique definition of "FinTech" has been established (Dorfleitner et al., 2016, Ryu, 2018a, Schueffel, 2016, Gerlach and Rugilo, 2018, Zavolokina et al., 2016). However, albeit the lack of agreement, there is consensus that "FinTech" being a composition of the words "financial" or "finance" and "technology" (Arner et al., 2016, Dorfleitner et al., 2016, Gomber et al., 2017, Kim et al., 2016, Kuo Chuen and Teo, 2015, Ryu, 2018a, Zavolokina et al., 2016). Anyhow, regarding the question of how to define "FinTech", some authors propose a functional (i.e., product or service oriented) view, whereas others follow an institutional approach. For instance, Arner et al. (2016) refer to FinTech as technology-based financial solutions and speak about a new marriage of information technology and financial services. Similarly, Kim et al. (2016), Kuo Chuen and Teo (2015) and Ryu (2018a) focus their understanding on the use of new technology that enables the development of innovative, disruptive and differentiated financial services or products. These services and products have the potential to disrupt existing industry structures and boundaries (Philippon, 2016). Contrariwise, other authors follow an institutional approach to defining "FinTech" and refer to FinTechs as companies or entities, both start-up or established, that develop and offer innovative financial services by the use of new technology. As a consequence, FinTechs usually represent some kind of innovator or disruptor (Dorfleitner et al., 2016, Gomber et al., 2017). According to Deloitte (2014), AGV Banken (2015) and Christensen et al. (2015), those entities threaten established competitors by developing revolutionary products and services with powerful displacement potentials. Because this paper addresses the adoption of FinTechs as new and – compared to traditional financial institutions – alternative service providers, it follows the institutional approach to defining FinTechs.

Based on offered products and services as well as the underlying technological concepts, there are different approaches to systemizing FinTechs. However, even though we can find numerous proposed systemization approaches (He et al., 2017, Maume, 2017, Philippon, 2016, Brummer and Gorfine, 2014, Dorfleitner et al., 2016, Bank for International Settlements, 2017), we must state that all of them are similar. For the purpose of this study, the paper follows the comprehensive "Digital Finance Cube-concept" by Gomber et al. (2017). This systemizes FinTechs along the Digital Finance Business Functions, i.e., Digital Financing, Investments, Money, Payments, Insurances and Financial Advice. Moreover, a second dimension of the

Digital Finance Cube distinguishes FinTechs based on the technological concepts used. Since this paper addresses the adoption of financial institutions as well as their products and services, the technological perspective is disregarded. However, Digital Finance Solutions are defined as products and services (independently of the supplier) that fall within the scope of the abovementioned Digital Finance Business Functions. Thus, as Table 1 depicts, we derive six Digital Finance Solutions, which build the basis of our further research:

Table 1: Definitional Foundations of Digital Finance Solutions

Digital Finance Solutions	Definition
Digital Financing Solutions (DFS)	Traditionally, banks act as suppliers for financial resources. Thus, corporates and individuals who are seeking financial resources contact banks. However, Digital Financing Solutions enable corporations and individuals to become independent from these traditional methods, since the necessary financing can be acquired by using the internet. For the purposes of this study, all digital types of financial resources are considered as Digital Financing Solutions. This implies, for instance, platforms that offer digitalized solutions in the area of crowdfunding, factoring, leasing or invoicing (Gomber et al., 2017).
Digital Investment Solutions (DIS)	Digital Investment Solutions embrace products and services that support both individuals and institutions in making investment decisions as well as, by the use of the respective devices and technologies, in arranging required investment transactions on their own. In the B2C context, this phenomenon includes mobile and social trading as well as online brokerage and online trading. Within the B2B area, high-frequency and algorithmic trading account for Digital Investment Solutions (Gomber et al., 2017).
Digital Money Solutions (DMS)	For the purpose of this study, Digital Money Solutions are considered as newly established digital, virtual or cryptocurrencies that exist only electronically and are used mainly on the internet. The best-known Digital Money Solution in this context is bitcoin, which was introduced in 2008 (Gomber et al., 2017, Nakamoto, 2008).
Digital Payment Solutions (DPS)	In contrast to Digital Money Solutions, Digital Payment Solutions refer to electronic payments that use traditional currencies such as EUR or USD (fiat currency). Moreover, Digital Payment Solutions imply mobile payment transactions (smartphone involved), P2P payments (e.g., PayPal) and e-wallets or digital wallets that are used to store money digitally (Gomber et al., 2017).
Digital Insurance Solutions (DInS)	Digital Insurance Solutions are digital products and services in the area of insurance. For instance, friendsurance.com provides a digital platform on which individuals can ally in order to reduce insurance costs at a constant level of protection (Gomber et al., 2017).
Digital Financial Advice Solutions (DFAS)	Digital Financial Advice Solutions embrace the provision of investment proposals, which are – in contrast to traditional financial advice – designed to work with no or minimal human intervention and are based on algorithms and a digital onboarding process that considers pre-defined parameters concerning investment goals, financial background and risk aversion. Presently, these so-called robo advisors focus on portfolio management services and utilize investment strategies, which base on established theories such as modern portfolio theory. A well-known supplier in Germany is Scalable Capital (Gomber et al., 2017).

This table outlines the definitional foundations of all six derived Digital Finance Solutions from the comprehensive "Digital Finance Cube-concept". This systemization of several digital financial services contributes to this paper's further research approach.

In terms of this study, we aim to identify both past and current use behavior as well as future (continuous) usage intention (Ryu, 2018b, Lee, 2009, Cheng et al., 2006). Therefore, the actual and future usage intentions of both FinTechs and Digital Finance Solutions are associated with the dependent side of our empirical model design. In doing so, we investigate how experience as well as expectation about FinTechs and Digital Finance Solutions determine the decision to use or to continue the usage. Following Venkatesh et al. (2012), Brown and Venkatesh (2005) and Venkatesh et al. (2003), experience applies to all past and current users, while expectation addresses future consumers and those who intend to continue usage. In order to identify potential drivers, a theoretical framework built on decision-making and acceptance has been reviewed. Since decisions are often made on incomplete and imperfect information, potential users build expectations. Various approaches aim to model users' intention on current and future behavior (Venkatesh et al., 2002, Limayem et al., 2007, Pikkarainen et al., 2004).

For this study, the theoretical framework of usage decisions in general is grounded on the theory of reasoned action (TRA) (Ajzen and Fishbein, 1977). Regarding the net valance framework, which is based on the TRA, users (of technology) face a certain degree of benefit and risk when making decisions (Ryu, 2018b, Peter and Tarpey Sr, 1975). Assuming that the continuous usage of a service, good or technology is based on negative and positive attributes, the net valence theory combines those attributes (Ajzen and Fishbein, 1977, Lewin, 1943). However, perceived risks are represented through the variables of financial, legal, security and operational risks. Incentivization through perceived benefits is expressed by economic benefits, seamless transactions and convenience. By modeling a multi-dimensional benefit-risk framework in accordance with the technological components of usage and behavior, considerable studies have examined the benefit-risk framework for the adoption and usage process of financial IT services (Ryu, 2018b, Abramova and Böhme, 2016, Zhou et al., 2010, Lee, 2009, Liu et al., 2012). While Lee (2009) and Liu et al. (2012) proposed a single dimension for the perceived benefit side and a multidimensional construct for the perceived risk side, this study follows Ryu (2018b) and Abramova and Böhme (2016) by modeling both a multi-dimensional benefit and risk framework.

After making a decision, consumers need to accept a product or service to adopt and continue using it. Therefore, we extended the set of variables by technology acceptance drivers to model a future continuance intention. Regarding technology acceptance, there have been many developments in theories, evolving from the technology acceptance model (TAM) (Davis, 1989), TAM2 (Venkatesh and Davis, 2000), to the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) and its modifications (Brown and Venkatesh, 2005, Venkatesh et al., 2012). However, this study is grounded on the theoretical framework of UTAUT2 (Venkatesh et al., 2012), as it represents the latest version and combines various contributions since then (Morosan and DeFranco, 2016, Raman and Don, 2013, Yang, 2013). Following UTAUT, originally modeled to explain employee technology acceptance, UTAUT2 focuses on the consumer use context (Venkatesh et al., 2012), which matches the aim of our study. In doing so, UTAUT2 addresses whether and how behavioral intention is affected by performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit.

Finally, this study combines both the classical acceptance research as mentioned in UTAUT2 and the net valence concept of TRA to identify a theoretical overlap and therefore possible drivers of current use behavior and future adoption intention. Although extending the mentioned theories to a financial context is not novel, our proposition is different from previous research, as we state that this approach – to the best of our knowledge – is the first study to model both the UTAUT2 variables and the net valence framework with regard to FinTechs and Digital Finance Solutions. Thus, based on the abovementioned literature, we identified a comprehensive set of 15 potential determinants, which were clustered into 11 variables due to intersections. Moreover, these were enlarged by socio-demographic variables to consider potential effects on the previously mentioned constructs. Table 2 outlines a detailed explanation of these systematically derived variables.

Table 2: Definitional Foundations of Potential Determinants

Variable	Definition
Performance expectancy (PE)	The degree to which using a technology provides benefits to consumers in performing certain activities (Venkatesh et al., 2012).
Economic benefit (EB)	The consumers' cognitive trade-off regarding cost reductions and financial gains resulting from the usage of FinTechs or Digital Finance Solutions (Venkatesh et al., 2012, Dodds et al., 1991, Ryu, 2018b, Kuo Chuen and Teo, 2015, Mackenzie, 2015, Lewin, 1943, Bilkey, 1953, Bilkey, 1955, Peter and Tarpey Sr, 1975).
Convenience (C)	The degree of ease, portability, accessibility and flexibility associated with consumers' use of technology (e.g., in terms of time and location) (Venkatesh et al., 2012, Ryu, 2018b, Kuo Chuen and Teo, 2015, Sharma and Gutiérrez, 2010, Okazaki and Mendez, 2013, Lewin, 1943, Bilkey, 1953, Bilkey, 1955, Peter and Tarpey Sr, 1975).
Social influence (SI)	The extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology (Venkatesh et al., 2012).
Technical conditions (TC)	Consumers' perceptions of resources and support available to perform a behavior (e.g., organizational and technical infrastructure, speedy and simple processes) (Venkatesh et al., 2003, Brown and Venkatesh, 2005, Venkatesh et al., 2012, Ryu, 2018b, Chishti, 2016, Zavolokina et al., 2016, Lewin, 1943, Bilkey, 1953, Bilkey, 1955, Peter and Tarpey Sr, 1975).
Hedonic motivation (HM)	The fun or pleasure derived from using a technology (perceived enjoyment) (Brown and Venkatesh, 2005, Venkatesh et al., 2012).
Habit (H)	The extent to which an individual believes the behavior to be automatic, depending on the extent of interaction and familiarity that is developed with a target technology. Thus, habit is a perceptual construct, which reflects the result of prior experiences (Venkatesh et al., 2012, Limayem et al., 2007).
Financial risk (FR)	The potential financial losses resulting from the usage of FinTechs or Digital Finance Solutions (Ryu, 2018b, Forsythe et al., 2006, Lewin, 1943, Bilkey, 1953, Bilkey, 1955, Peter and Tarpey Sr, 1975).
Legal risk (LR)	The users' distrust and anxiety arising from unclear legal status and the lack of regulations (e.g., regarding suffered financial losses and security issues) resulting from the usage of FinTechs or Digital Finance Solutions (Ryu, 2018b, Lewin, 1943, Bilkey, 1953, Bilkey, 1955, Peter and Tarpey Sr, 1975).
Security risk (SR)	The potential losses arising from fraud or hacking resulting from the usage of FinTechs or Digital Finance Solutions (Ryu, 2018b, Lewin, 1943, Bilkey, 1953, Bilkey, 1955, Peter and Tarpey Sr, 1975).
Operational risk (OR)	The potential losses, distrust and dissatisfaction arising from failed or inadequate internal processes, employee behavior and systems resulting from the usage of FinTechs or Digital Finance Solutions (Ryu, 2018b, Barakat and Hussainey, 2013, Lewin, 1943, Bilkey, 1953, Bilkey, 1955, Peter and Tarpey Sr, 1975).
Socio-demographics (SD)	n/a

This table outlines the definitional foundations of all systematically derived potential determinants of usage behavior and future adoption intention of FinTechs and Digital Finance Solutions. The full set of variables is derived from the two baseline theories, i.e., UTAUT2 and the benefit and risk framework of the TRA. EB, TC and C represent the clustered variables.

DATA AND METHODOLOGY

In order to investigate how users of financial services currently behave and intend to behave in the future as well as which factors determine their use behavior regarding FinTechs (institutional level) and Digital Finance Solutions, we developed an English-language questionnaire. The questionnaire bases on the systematically derived comprehensive set of potential determinants that results from the above-described literature review. It contains four questions per construct, including one control question. All measures were – unless otherwise noted – evaluated with a 6-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree) (Carifio and Perla, 2007, Jacob et al., 2013, Klopfer and Madden, 1980). The questionnaire was structured as follows: each participant received a three-page questionnaire. Thereof, one page featured questions related to the former and future use behavior and intention regarding FinTechs and one page related to one out of the six Digital Finance Solutions. Regardless, the questions related to FinTechs and Digital Finance Solutions were, except for slight adjustments to their wording, equivalent to each other. Finally, to gather data to control for individual differences and key characteristics, each participant received one page of socio-demographic and personal questions. Appendix A provides an overview of the set of variables as well as its related questionnaire items and literature. However, prior to the final data collection, we performed a pre-test, which included 34 participants. Following this pre-test, the final data collection was conducted from November 26th to December 21st, 2018, in business-, economics- and banking-related lectures at three German universities. Thus, the target group used is of particular interest because we derive our implications from the traditional financial institutions' point of view, and the participants represent future high net worth individuals. As a result, we count 381 participants, which ultimately led, based on the above-described structure of the questionnaire as well as inevitable deletions, to a dataset of 300 evaluable observations. Table 3 shows the final dataset, subdivided by FinTechs and the six Digital Finance Solutions. Additionally, a detailed overview of the socio-demographics and key characteristics of the dataset is provided in Appendix B.

Table 3: Numbers of Observations, Deletion Process and Final Dataset

Variable	Numbers of Observations	Inconsistencies		Evaluable Observations / Final Dataset
FinTech (institutional level)	381	81	(26.3%)	300
DFS	65	17	(26.2%)	48
DIS	64	15	(23.4%)	49
DMS	61	19	(31.1%)	42
DPS	64	16	(25.0%)	48
DInS	62	20	(32.3%)	42
DFAS	65	18	(27.7%)	47

The above table summarizes the number of observations, inconsistencies and the resulting final dataset for both the institutional level (FinTech) and all six Digital Finance Solutions.

Since we collected data regarding the former use behavior and future usage intention of FinTechs as well as six Digital Finance Solutions, we gathered data for 14 potential dependent variables. However, for the purpose of the empirical part of this paper, we focus on the future usage intention regarding FinTechs as alternative service providers to traditional financial institutions. This approach implies the application of one empirical model specification, which uses the binary constructed dependent variable "future usage intention (FinTechs)". In this respect, participants were asked whether they intend to use or continue to use FinTechs within the next years. To investigate which factors determine future usage intention, the comprehensive and systematically derived set of 11 potential determinants represents the independent side of the empirical model specification. Finally, we insert socio-demographics as well as key characteristics to control for unobserved effects and to limit and forestall endogeneity issues. Consequently, the following regression equation was estimated to identify determinants of the future usage intention of FinTechs:

$$Future\ usage\ intention\ (FinTechs) = \beta_0 + \beta_1(PE) + \beta_2(EB) + \beta_3(C) + \beta_4(SI) + \beta_5(TC) + \beta_6(HM) + \beta_7(H) + \beta_8(FR) + \beta_9(LR) + \beta_{10}(SR) + \beta_{11}(OR) + \beta_{12}(SD) + \varepsilon \quad (1)$$

RESULTS AND DISCUSSION

The following section of this paper first delivers insight into the descriptive statistics of the sets of dependent and independent variables. In contrast to the empirical analysis, the descriptive results are neither limited to FinTechs (institutional level) nor to one specific Digital Finance Solution, nor to the former use behavior or future usage intention. Subsequently, we introduce the key results of our logistic regression model from traditional financial institutions' point of view. In doing so, potential opportunities and threats that banks face – due to the customers' attitude regarding the eventual usage of FinTechs and Digital Finance Solutions – are taken into account. Moreover, the following discussion considers only positive and negative significant outliers because we aim to draw valid implications. Nevertheless, this approach does not postulate that average and inconspicuous results as well as – in this dataset – non-significant effects do not have any influence on strategic and managerial decision-making. Finally, this section concludes by conducting several robustness checks for the dataset and the regression approach.

RESULTS

The descriptive results show that 54.3% of all respondents had – to date – never used FinTechs instead of or parallel to traditional financial institutions as service providers. However, the results also show that more than 70.0% intended to do so in the future. Notwithstanding, there are great differences regarding the former use behavior and future usage intention between the respective Digital Finance Solutions. For instance, DFAS were used by less than 15.0% of all respondents. Moreover, DInS and DMS were used by less than 20.0% of all respondents. In contrast, DPS reached, with almost 90.0%, the greatest past adoption rate. Anyhow, regarding all dependent variables, the data show that the future usage intention outweighs the current use behavior. This indicates a positive attitude toward FinTechs as alternative service providers and toward the currently observable digitization process of the financial services industry. Nevertheless, there are huge differences in future usage intentions ranging from 38.1% for DMS to 97.9% for DPS. This finding, however, implies great differences regarding prospective customer needs and expectations. Table 4 summarizes the descriptive results for the 14 dependent variables:

Table 4: Descriptive Results for the Dependent Variables

Use Behavior	Fintechs (Institutional Level)	DFS	DIS	DMS	DPS	Dins	DFAS
Former use behavior							
Yes	137 (45.7%)	26 (54.2%)	15 (30.6%)	8 (19.0%)	43 (89.6%)	7 (16.7%)	7 (14.9%)
No	163 (54.3%)	22 (45.8%)	34 (69.4%)	34 (81.0%)	5 (10.4%)	35 (83.3%)	40 (85.1%)
Future usage intention							
Yes	215 (71.7%)	37 (77.1%)	31 (63.3%)	16 (38.1%)	47 (97.9%)	19 (45.2%)	20 (42.6%)
No	85 (28.3%)	11 (22.9%)	18 (36.7%)	26 (61.9%)	1 (2.1%)	23 (54.8%)	27 (57.4%)
Correlation (former use behavior / future usage intention)	0.55	0.59	0.41	0.62	0.43	0.49	0.49
N	300	48	49	42	48	42	47

The above table shows the descriptive results for the former use behavior and the future usage intention for both the institutional level (FinTech) and all six Digital Finance Solutions. In doing so, the table outlines the huge gap between former use behavior and future usage intention, which implies a high customer out-migration potential for traditional financial institutions.

The great differences in descriptive results emphasize the importance of questioning the determining factors of past and future use behavior. In doing so, we identified the above-described comprehensive set of potential determinants. However, the following descriptive results regarding the potential determinants were obtained: First, the data show that for the institutional level and – apart from DPS – across all Digital Finance Solutions, the determinants FR, LR, SR and OR were rated, compared to the other variables, relatively low. This finding indicates a general uncertainty about how to evaluate these risk factors when conducting a decision behavior. Furthermore, at the institutional level, the respondents rated the independent variables PE, C and TC relatively high, which indicates that these determinants are quite important for individuals' use behavior and intention. For DFS, DIS, DInS and DFAS, we find the same variables, and EB was rated – compared to the other determinants – relatively high. Finally, within DMS and DPS, both PE and TC were rated relatively high, whereas – again compared to other determinants within the respective Digital Finance Solutions – EB seems to be relatively important to DMS and C to DPS. Comparing the responses of the determinants not within but rather across the Digital Finance Solutions, we find PE, C, SI, TC, HM and H were rated highest for DPS. Moreover, EB was rated highest for DFS. However, there is almost no difference compared to its rating for DPS and DFAS. Finally, Table 5 reports the descriptive results of the independent set of variables.

Table 5: Descriptive Results for the Independent Variables

Variable	FinTechs (Institutional Level)	DFS	DIS	DMS	DPS	DInS	DFAS
PE							
Mean	4.42	4.35	3.89	3.48	5.09	3.74	3.78
Median	4.67	4.67	4.00	3.33	5.33	3.67	4.00
Std. deviation	1.07	1.29	1.26	1.36	1.07	1.06	1.17
EB							
Mean	3.90	4.17	3.90	3.53	4.10	3.78	4.13
Median	4.00	4.33	4.00	3.67	4.17	4.00	4.33
Std. deviation	0.96	0.91	1.04	1.20	1.17	1.19	1.06
C							
Mean	4.16	4.12	3.62	3.25	4.79	3.62	3.84
Median	4.33	4.00	4.00	3.17	5.00	3.67	4.00
Std. deviation	1.04	1.14	1.08	1.26	1.10	1.10	0.84
SI							
Mean	3.11	3.28	2.69	2.53	4.33	2.21	2.61
Median	3.33	3.33	2.67	2.00	4.42	2.00	2.67
Std. deviation	1.38	1.38	1.13	1.36	1.43	1.13	1.09
TC							
Mean	4.12	4.13	3.76	3.48	4.79	3.87	3.84
Median	4.00	4.33	3.67	3.67	5.00	3.83	4.00
Std. deviation	1.17	1.37	1.05	1.34	1.10	1.13	0.98
HM							
Mean	3.44	3.49	3.21	3.30	3.70	2.66	3.22
Median	3.42	3.50	3.00	3.33	3.67	2.83	3.33
Std. deviation	1.10	1.22	1.26	1.30	1.17	1.18	1.12
H							
Mean	3.66	3.64	3.14	2.74	4.53	2.99	2.94
Median	3.67	3.67	3.33	2.67	4.67	3.00	3.00
Std. deviation	1.13	1.22	1.05	1.41	0.95	1.11	1.21
FR							
Mean	3.00	2.88	2.84	2.79	3.57	3.04	2.80
Median	3.00	3.00	3.00	2.67	4.00	3.00	2.67
Std. deviation	1.25	1.21	1.20	1.31	1.44	1.25	1.15
LR							
Mean	3.23	3.23	3.03	2.86	3.51	3.21	3.12
Median	3.33	3.00	3.00	3.00	3.50	3.00	3.00
Std. deviation	1.17	1.14	1.18	1.41	1.41	1.30	1.06
SR							
Mean	3.08	3.13	3.02	2.76	3.17	3.19	2.99
Median	3.00	3.00	3.00	2.67	3.00	3.17	3.00
Std. deviation	1.34	1.29	1.21	1.26	1.41	1.26	1.30
OR							
Mean	3.11	3.23	2.85	2.81	3.30	3.07	2.97
Median	3.00	3.00	3.00	3.00	3.67	3.00	3.00
Std. deviation	1.17	1.28	1.05	1.15	1.39	1.25	1.11
N	300	48	49	42	48	42	47

This table summarizes the descriptive results for the potential determinants. With regard to the institutional level (FinTech) and all six Digital Finance Solutions, the table contains information regarding the mean, median and standard deviation of the participants' ratings. Finally, for each Digital Finance Solution and the institutional level (FinTech), the number of observations (N) is indicated in the last row.

Utilizing the comprehensive dataset, we built a logistic regression model specification that appropriately addresses this paper's research question concerning factors that potentially determine users' behavior regarding the adoption of FinTechs as alternative service providers. In doing so, we included all 11 systemically derived potential determinants. However, for several methodological reasons, we did not include the full set of available socio-demographics and key characteristics. Due to the homogeneity of all respondents, we excluded age, field of study and target degree. Moreover, with regard to multi-collinearity issues, we excluded the respondents' digital experience, which is highly correlated with digitization knowledge. For the same reason, we needed to exclude the importance of personal interaction (provider and service). Finally, due to a lack of additional value regarding potential implications, we excluded the former banking and finance app usage, which, compared to online banking usage, has little difference in its descriptive results. Based on the remaining set of variables, the logistic regression approach leads to the following results: PE, EB, C, SI, TC and H positively affect the future usage intention. Thus, increasing perceived PE, EB, C, SI, TC and H ceteris paribus implies an increasing probability of future FinTech usage. However, this effect is significant for PE, SI and TC at the 10.0% level. Contrariwise, the data show a negative ceteris paribus effect of HM on the probability of future FinTech usage. Yet, one must note that this effect remains insignificant. Furthermore, ceteris paribus, FR, LR and SR seem to positively influence the probability of future FinTech usage. In this respect, it is important to mention that due to the questions' wording, a lower perceived FR, LR and SR positively influence future usage decisions (Appendix A). Anyhow, these effects are not significant at the 10.0% level. In contrast, the data show a significant and negative ceteris paribus effect of OR on the probability of future FinTech usage. Moreover, the higher the users' disposable income is and the lower the total liquid wealth is, the higher the probability of future FinTech usage, ceteris paribus. Finally, former online banking usage significantly increases the probability of future FinTech usage. Although some of the identified ceteris paribus effects are not significant at the 10.0% level, the McFadden R^2 of 0.393 indicates a satisfactory model design. Thus, the independent variables collectively explain the variance in the dependent variable quite well (McFadden, 1973, Veall and Zimmermann, 1996). However, Table 6 summarizes the R-Output of our logistic regression approach:

Table 6: Logistic Regression Output

Variable	Estimate	Std. Error	z Value	Pr(>|z|)
(Intercept)	-9.470	1.805	-5.245	0.001***
PE	1.146	0.227	5.052	0.004***
EB	0.241	0.213	1.131	0.258
C	0.003	0.213	0.015	0.988
SI	0.268	0.151	1.771	0.077*
TC	0.353	0.192	1.845	0.065*
HM	-0.086	0.206	-0.419	0.675
H	0.267	0.204	1.311	0.190
FR	0.090	0.175	0.516	0.606
LR	0.231	0.194	1.190	0.234
SR	0.143	0.172	0.829	0.407
OR	-0.523	0.213	-2.459	0.014**
sd.genderfemale	0.386	1.072	0.360	0.718
sd.gendermale	0.100	1.089	0.092	0.927
sd.risk.attitude	-0.027	0.144	-0.191	0.848
sd.disposable.income	0.186	0.108	1.721	0.085*
sd.total.wealth.liquidity	-0.136	0.075	-1.803	0.071*
sd.online.bankingyes	1.397	0.506	2.760	0.006***
sd.digitization.knowledge	0.183	0.174	1.051	0.293
Null deviance:	357.64 on 299 degrees of freedom			
Residual deviance:	217.14 on 281 degrees of freedom			
AIC: 255.14				
Number of Fisher scoring iterations: 6				
McFadden R2:	0.393			

*The above table shows the R-output of the estimated logistic regression approach. In this respect, the effect of all systematically derived potential determinants as well as of some socio-demographics on the future usage intention of FinTechs as alternative service providers is estimated. Finally, ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.*

Due to the binary formulation of the dependent variable, we conducted a logistic regression approach. Thus, it is only able to interpret the direction of the independent variables' effects, but not their extent. To find the latter, we calculated the average marginal effects of all independent variables of the above model specification. As Table 7 shows, the results indicate, for instance, that if the independent variable PE increases marginally, the probability of future FinTech usage increases – on average, for all 300 observations – by 13.14 percentage points. Because the estimated coefficient of the determinant PE is highly significant, the average marginal effect is also highly significant. Moreover, the calculations indicate a highly significant average marginal effect of 16.00 percentage points for the independent variable of online banking. Thus, the likelihood of online banking customers to use FinTechs as alternative service providers increases by 16.00 percentage points compared to non-online banking customers. Additionally, the data show that a marginal increase of SI and TC raises the probability of future FinTech usage by 3.07 and 4.05 percentage points. Finally, these differences indicate the importance of the calculation of average marginal effects prior to the discussion and interpretation of the results. However, Table 7 summarizes the estimated coefficients as well as the calculated average marginal effects for all included independent and control variables:

Table 7: Average Marginal Effects of Independent Variables

Variable	Estimate	Average Marginal Effect
(Intercept)	-9.470	-1.085
PE	1.146	0.131
EB	0.241	0.028
C	0.003	0.000
SI	0.268	0.031
TC	0.353	0.040
HM	-0.086	-0.010
H	0.267	0.031
FR	0.090	0.010
LR	0.231	0.026
SR	0.143	0.016
OR	-0.523	-0.060
sd.genderfemale	0.386	0.044
sd.gendermale	0.100	0.012
sd.risk.attitude	-0.027	-0.003
sd.disposable.income	0.186	0.021
sd.total.wealth.liquidity	-0.136	-0.016
sd.online.bankingyes	1.397	0.160
sd.digitization.knowledge	0.183	0.021

This table indicates the calculated average marginal effects of the independent variables, i.e., all potential determinants and some socio-demographics. The average marginal effect is shown in the column on the right-hand side of the above table.

Discussion

On the institutional level, the descriptive results show that more than 70.0% of the participants intend to make use of FinTechs in the future. This indicates that a customer shift from traditional service providers to FinTechs is possible. Moreover, this shift may interfere in the relationship between the principal banks and their customers, which has – particularly in Germany – a long tradition (the house bank principle). Furthermore, the comparison of the identified future usage intention of FinTechs with the already mentioned EY FinTech Adoption Index – which indicates an adoption rate of 35% in Germany in 2017 – points out a huge gap and thus great potential for customer out-migration for traditional financial institutions (Ernst & Young, 2017). This finding further emphasizes the motivation and importance of research on future usage intentions as conducted in this study. Additionally, on the Digital Finance Solutions level, we identify – across all solutions apart from DMS and DPS – a gap of more than 20.0 percentage points between the current FinTech usage and its future intention. Since DPS is already used by 89.6% of all participants, the future usage intention could increase by only a maximum of 10.4 percentage points. These results again validate that traditional financial institutions need to be aware of potential customer out-migration in all areas of financial services. An extension of consciousness in this issue should therefore be of high priority for traditional service providers.

How current and potential customers rate the different drivers that might determine a usage decision and intention is of major interest. We investigated positive customer expectation drivers of former and future FinTech usage considerations. On the institutional level, the participants rated PE, C and TC highest, which indicates that these determinants have a major impact on the future usage intention, perceived as positively inherent in FinTechs. Banks need to be aware of the degree to which using technology provides benefits. In addition, C, as an extrinsic factor, seems to determine the future usage intention positively in terms of technological flexibility in time and location. Moreover, the ease of use drives a decision. For banks, this phenomenon implies the need for improvements of customer applications as well as flexible time and location availability of products and services to avoid customer out-migration. TC, as a third factor of FinTech success, addresses the technological and organizational infrastructure of FinTechs. Customers intend to make use if they understand the process (Zhou et al., 2010) and have faith in the organizational resources to operate properly.

Two important implications for traditional financial institutions follow these results: First, a certain base of confidence must be created. Second, technological knowledge and background must be imparted. Otherwise, customers' lack of trust in technology may ultimately cause potential out-migration. Furthermore, C (effort expectancy and convenience) and TC (facilitating conditions and seamless transaction) are clustered variables that again emphasize the idea of combining the TRA and UTAUT2 variables. Moreover, this finding underlines the importance of those variables for banks as a main driver of potential customer out-migration. In summary, on the institutional level, the three determinants of PE, C and TC outline potential losses for traditional financial institutions. Thus, it is inevitable to strengthen a positive perception of those three determinants in strategic and managerial decision-making.

Regarding the individual Digital Finance Solutions, the descriptive results also show that for DFS, DIS, DInS and DFAS, participants rated PE, C and TC relatively high. The resulting practical implications can be associated with those on the institutional level, as discussed before. Moreover, EB – clustered of price value and economic benefit – was rated relatively high, too. What stands out most when focusing on EB is the expected cost-performance ratio. With consideration of financing, investment, money, insurance and financial advice solutions, customers are focused on potential gains and savings potential. Since the potential gains are sometimes not controllable directly (e.g., exogenous shocks), the focus for banks should be on the conditions and cost structure to ensure that customers expect a satisfactory cost-performance ratio and thus are willing to demand the respective products or services. Furthermore, for DMS and DPS, we observe a relatively high rating for PE and TC. Hence, the previously derived implications regarding those determinants are also valid for DMS and DPS. Moreover, for DPS, the variable C turns out to be of great importance. This indicates that – according to the importance of C on the institutional level – flexibility in time and location as well as general convenience drive customers' willingness to use DPS.

In addition, with regard to the risk variables (FR, LR, SR, OR), we identify outliers, too. In this regard, it is important to mention again that due to the questions' wording, lower-rated and thus perceived FR, LR, SR and OR imply a greater importance of those risk factors. On the institutional level as well as for DMS, we did not find any outliers within the participants' rating. This may be explained by a lack of both the providers' and customers' internal influence on DMS. For DFS, we observe a relatively lower rating for FR. This means that the risk of making a loss – due to mistakes by the customer itself or by a counterparty – is critical for future usage intention. In general, all fields of tailspin determine a usage consideration. For DIS, we also identified FR as a relatively important determinant. This follows the interpretation and implications previously drawn for DFS. Moreover, with regard to DIS, the participants' ratings of OR indicate that customers perceive a relatively high risk of uncontrollable internal processes. On the Digital Finance Solution level, this finding implies that traditional banks need to build up security and trust on the inside and project it to the outside because customers do not typically fear operational risks when using DIS. Solely for DPS, SR is observed to have greater importance. This can be explained by the required security of transactions for both personal and financial data. Thus, customers fear hacking and fraud as well as personal uncertainty. This fear may not be a threat but rather an opportunity for traditional banks to strengthen DPS, because data security may be communicated and perceived as a competitive advantage of traditional financial institutions. When stating that security, especially transaction and data security, is an important factor for Digital Finance Solutions, we find that FR is rated relatively important for DFAS. As for the previously mentioned security risks, this finding may be due to the technical fear of misunderstanding algorithmic processes and the resulting fear of losing money. A lack of knowledge in the functioning of DFAS (e.g., robo advisory) and an ascribed missing rationality of the system may overweight a high interest and cause customers to refuse to use it. At this point, for traditional banks, the opportunity to create a hybrid solution is arising. Merging a digital solution with traditional banking security and the banks' employees' great expertise in this sensitive field could be a good way to attract and hold that group of customers.

As this survey attempts to explain behavioral intention as a dependent variable, the empirical results indicate several fields of interest for traditional banks, where they may suffer potential customer out-migration. The strong positive effect of PE implies that if a FinTech is able to improve its perceived performance, customers' future usage intention increases significantly. The expected benefit in daily usage improvement and time efficiency is of great importance for customers' usage intention. Thus, banks need to strengthen their appearance as beneficial and their competitive advantage in creating effectiveness and benefits in daily usability and acceptance. Moreover, SI is also identified as a significant positive driver. This implies great multiplier and network effects (Katz and Shapiro, 1994, Bertrand et al., 2000), because both the private and professional surroundings positively influence the future usage decision. In addition, group influence has a major impact on risk-taking behavior (Wallach et al., 1962). The intention to use digitized financial services, which are – due to their novelty – perceived to be more risky, increases within a certain group. To strengthen this aspect, traditional banks need to focus on the group behavior of customers. Communities and platforms as well as a transformation in private surroundings may be potential instruments to empower customer relationships and to prevent the loss of market share to FinTechs.

Furthermore, traditional banks' customer churn management should focus on technical aspects of function, time and location flexibility as well as process improvement. This is represented by a positive effect of TC on the future FinTech usage intention. According to the descriptive results on TC, for the institutional level as well as for the individual Digital Finance Solutions, this finding matches the implication of a change in technical conditions. If FinTechs succeed in creating efficient technical processes, customers intend to increase their usage.

Finally, we find that OR negatively influences future usage intention, which means – due to the questions' wording – that a lower perceived OR leads to a decreasing future usage intention. Anyhow, this result is not interpretable intuitively and needs to be taken into account in more detail. A potential explanation may be that – so far – from the users' point of view, there is a lack of experience regarding OR in FinTechs. Consequently, this lack of experience may imply that users feel unable or unsecure to appropriately evaluate the OR associated with FinTechs.

Among the socio-demographic variables, online banking is the strongest factor, significantly affecting future usage intention positively. This indicates that customers who already use online banking tend to be more open-minded towards using FinTechs as alternative service providers. Primarily, their inhibition level is lower, which might also lower their perceived risk of using FinTechs. This group of customers represents the most important one to observe for traditional financial institutions, as they may have a relatively high risk of potential out-migration. The behavioral intention of usage is affected not only by the way the technology is used or the money is spent but also by the source and amount of money possessed. Disposable income has a significant positive effect on the future usage intention of FinTechs. With an increasing regular disposable income, customers are more willing to take higher risks (Shaw, 1996, Kanbur, 1979). Apparently, this willingness includes increasing readiness regarding the usage of new technologies and alternative service providers. This relates to the simple effect of more possibilities with an increasing amount of money. Hence, the opportunity to use alternative financial services providers becomes more tangible. Therefore, the intention to use them would, depending on the expectations, increase. Moreover, former research indicates that less mature decision makers tend to take higher risks, while more mature customers tend to be more risk averse (MacCrimmon and Wehrung, 1990). As our sample focuses on students, this finding entails that students who begin increasing their disposable income tend to take higher risks when making financial decisions.

Therefore, if FinTechs manage to create the previously mentioned network effects within customer groups of rising disposable income, traditional banks may encounter a higher loss potential. Thus, the latter should try to motivate and incentivize these customers by using hold and push strategies. In contrast, the empirical results show that wealth has a vice versa negative effect on the future usage intention of FinTechs. This depicts that usage intention is decreasing with increasing wealth. This behavioral intention may be ascribed to a traditional attitude towards wealth. Students usually have a certain income, which does not yet provide great wealth. Thus, it usually takes a student longer to earn or save a certain amount of money than it does for middle-aged employees. Consequently, any wealth a student has – if having so – is likely to be provided by others (e.g., parents, grandparents).

According to previous research, this implies a greater fear of loss compared to a monthly returning income (Slovic, 1964). This phenomenon may explain the identified negative effect of wealth on FinTech usage, which is perceived to be more risky. Hence, if the fear of losing a saved amount increases with rising wealth, the willingness to take risks decreases. To conclude, this group of customers represents a very important one for traditional financial institutions, since they may be less likely to out-migrate. Ultimately, these studies' results indicate that customers are willing to and expect to use innovative and reinvented financial products and services, thus, Digital Finance Solutions.

It is important to once again state that there is a general acceptance and future usage intention of FinTechs as alternative service providers. Thus, from traditional financial institutions' point of view, integrating Digital Finance Solutions into their product portfolios is inevitable. Otherwise, banks are likely to experience great customer out-migration to FinTechs, because these servicers offer the expected and demanded innovative Digital Finance Solutions. To summarize the above-discussed results, Table 8 outlines the systematically derived strategic and managerial implications for traditional financial institutions.

Table 8: Strategic and Managerial Implications

Field of Interest	Strategic and Managerial Implications…
FinTechs (institutional level)	…derived from the descriptive results: Generally: Be aware of the great potential of customer out-migration and strengthen customers' positive perception of, especially, the determinants PE, C and TC PE: Strengthen technology since customers expect them to improve performance and provide benefits C: Improve customer applications and their time- and location-flexible availability TC: Create a base of confidence and impart technological knowledge and background …derived from the empirical results: PE: Strengthen technology since customers expect them to improve performance and provide benefits. Customers' intention to use FinTechs increases if they expect to be able to improve time efficiency and daily usage experience TC: Create a base of confidence and impart technological knowledge and background. Focus on efficient processes as well as time- and location-flexible availability of products and services SI: Make use of private and professional network effects. For instance, build up communities and platforms in order to empower customer relationships and to prevent the loss of market share to FinTechs Online banking: Focus on technically affine customers since they have a higher probability of out-migrating to FinTechs as alternative service providers Disposable income/total liquid wealth: Be aware of differing risk attitudes of customers, make use of customers' data analysis in order to implement target-group-specific marketing activities
Digital Financing Solutions (DFS)	…derived from the descriptive results: Generally: Be aware of customers' high future usage intention of DFS PE/C/TC: See FinTechs (institutional level) EB: Focus on conditions as well as cost structure in order to ensure that customers expect a satisfactory cost-performance ratio FR: Lower customers' fear of losing money due to mistakes and counterparties' failure
Digital Investment Solutions (DIS)	…derived from the descriptive results: Generally: Be aware of customers' high future usage intention of DIS PE/C/TC: See FinTechs (institutional level) EB/FR: See DFS OR: Improve customers' trust in internal security and processes
Digital Money Solutions (DMS)	…derived from the descriptive results: Generally: Be aware of customers' high future usage intention of DMS PE/TC: See FinTechs (institutional level) EB: See DFS
Digital Payment Solutions (DPS)	…derived from the descriptive results: Generally: Be aware of customers' high future usage intention of DPS PE/C/TC: See FinTechs (institutional level) SR: Focus on transactional security for both personal and financial data and communicate this as a competitive advantage
Digital Insurance Solutions (DInS)	…derived from the descriptive results: Generally: Be aware of customers' high future usage intention of DInS PE/C/TC: See FinTechs (institutional level) EB: See DFS
Digital Financial Advice Solutions (DFAS)	…derived from the descriptive results: Generally: Be aware of customers' high future usage intention of DFAS PE/C/TC: See FinTechs (institutional level) EB: See DFS FR: See DFS + focus on hybrid solutions in order to merge the DFAS advantages with the banks' great expertise in this sensitive field

This table summarizes all derived strategic and managerial implications from the viewpoint of traditional financial institutions. The left column of the above table shows the respective field of interest (i.e., the institutional level (FinTech) and the six Digital Finance Solutions), the right column summarizes the strategic and managerial implications. These implications were derived from both the descriptive and empirical results.

Robustness

To ensure the best possible data quality, we conducted several robustness checks regarding the dataset as well as the regression approach. As already mentioned, the questionnaire contains four questions per construct, including one control question with (partly) reversed wording. All measures – apart from the dichotomous dependent variables – were evaluated on a 6-point Likert scale. Thus, we were able to ensure the respondents' understanding of the questions by calculating the correlations of every three questions per construct with their corresponding control question. In doing so, we obtained – as expected – negative correlations. This finding indicates a great understanding of the questions by the participants and thus that this study's dataset is of high quality. Moreover, we double-checked our control questions by implementing a reverse wording for the OR's control question. In this case, we obtained a positive correlation, which reconfirms the high quality of the dataset. All correlation results are provided in Appendix C of this paper.

Furthermore, we checked our regression approach for multi-collinearity issues by examining the correlations between the independent variables as well as calculating the variance inflation factors. However, as mentioned earlier, we excluded several variables from the model specification (e.g., the respondents' digital experience) to prevent multi-collinearity. After doing so, the correlation coefficients and variance inflation factors indicate no further multi-collinearity issues. All calculated variance inflation factors are provided in Appendix D. Moreover, we analyzed the reliability by calculating Cronbach's alpha. Because all numeric variables have a Cronbach's alpha above 0.75, referred to Gliem and Gliem (2003) and Peterson (1994), the questionnaires' reliability is satisfactory. Furthermore, to check for autocorrelation and heteroscedasticity issues, we calculated resistant standard errors. This did not lead to any significant changes. Finally, even though we derived the set of independent variables systemically and clustered the potential determinants carefully, it is impossible to prevent all endogeneity issues for sure. Nonetheless, with regard to potential endogeneity issues, we do not expect certain coefficients to be overestimated or underestimated.

CONCLUDING COMMENTS

This paper investigates the customers' current use behavior and future usage intention of FinTechs and Digital Finance Solutions. Its objective is to identify and evaluate potential adoption drivers and to develop strategic and managerial implications for traditional financial institutions. To both theoretically and empirically address this research question, a survey of students at three German universities was conducted. This ultimately led to 300 evaluable observations. Consequently, in addition to the descriptive analysis, a logistic regression approach for "future usage intention (FinTechs)" was used to estimate the effect of 11 potential determinants on the behavioral intention.

Finally, the results of this study show that customers are willing and expect to use innovative and reinvented financial products and services, thus, Digital Finance Solutions. At the same time, the results indicate a huge gap between the customers' current use behavior and future usage intention not only with regard to the Digital Finance Solutions but also to FinTechs. Thus, we state that from the traditional financial institutions' point of view, integrating Digital Finance Solutions into their product portfolios is inevitable. Otherwise, banks are likely to experience great customer out-migration to FinTechs, since these servicers offer the expected and demanded innovative Digital Finance Solutions. Moreover, building on the diffusion of the benefit-risk framework of TRA and UTAUT2, we identified several potential determinants of customers' use behavior regarding both FinTechs and Digital Finance Solutions. However, these findings enabled us to define certain fields of interest and to derive corresponding strategic and managerial implications for traditional financial institutions. To attract customers, build up competitive advantages and thus prevent customer out-migration, the implications particularly but not exclusively focus on determinants such as PE, EB, C, SI and TC. Furthermore, this study contributes to several strands of literature. We contribute not only to the general understanding of FinTechs and Digital Finance Solutions but also to the existing literature on behavioral intention and technology acceptance in clustering TRA and UTATUT2 variables. However, one should outline that traditional financial institutions still hold competitive advantages, such as a high level of acceptance, good market positions and financial resources as well as a strong customer base. Nevertheless, the current digitization tendencies with corresponding changes in both competitive and market landscapes seem to be of a disruptive nature and of great relevance. Managers should not only be aware of the resulting challenges but – in order to remain competitive – also implement strategic and managerial measures in a timely manner.

Notwithstanding, it is important to outline that – due to the sample's structure as well as its geographic scope – one should be careful in generalizing the results and implications to more heterogeneous customer groups. However, because we derive our implications from the traditional financial institutions' point of view, the underlying sample is of particular interest because these participants represent future high net worth individuals. Moreover, even though the set of potential determinants was derived systematically and carefully, it is impossible to completely avoid the lack of further important variables. This may ultimately cause endogeneity issues. However, we do not expect endogeneity issues in this study. Furthermore, the results and implications are limited to the conducted methodological approach. Thus, even though several robustness checks were conducted, remaining methodological issues may affect both the results and implications of these studies. Partly derived from the limitations, we identify requirements for future research. First, future research approaches should address the above-stated limitations to verify this study's results and implications. This implies, for instance, addressing the research question with a more heterogeneous national or even international sample as well as with alternative methodological approaches. Moreover, this paper's research questions should be concretized regarding the individual Digital Finance Solutions. This would qualify research to identify and evaluate differences. In addition, this would deliver additional value in terms of the derivation of specific practical implications. Furthermore, since we clustered variables from different strands of literature, the set of potential determinants can be further reviewed. In particular, the great relevance of the clustered variables postulates that further research should consider the individual sample and the isolated Digital Finance Solutions.

APPENDIX

Appendix A: Variables, Questionnaire Items and Related Literature

Variable/Construct	Items	References
Overall Usage/ Behavioral Intention	1: Did you ever make use of FinTechs? 2: Do you intend to use (continue the usage of) FinTechs within the next years?	Cheng et al. (2006), Lee (2009), Venkatesh et al. (2012), Ryu (2018b)
PE	1: The use of FinTechs (might) improve(s) my daily usage of financial services. 2: The usage of FinTechs is (might be) less time intense. 3: Using FinTechs is (might be) more efficient. 4: I see no advantages in using FinTechs. (control)	Venkatesh et al. (2012), Featherman and Pavlou (2003), Lee (2009)
EB	1: The usage of FinTechs is (might be) less cost intense. 2: The usage of FinTechs (might) offer(s) savings potentials. 3: I do (might) expect financial gains from the usage of FinTechs. 4: I see no benefit in using FinTechs. (control)	Yiu et al. (2007), Lee (2009), Ryu (2018b)
C	1: FinTech interaction is (might be) clear, understandable and easy. 2: The usage of FinTechs is (might be) easy for me. 3: The usage of FinTechs is (might be) possible at any time very quickly and easily. 4: The use of FinTechs is not clear and understandable. (control)	Venkatesh et al. (2012), Ryu (2018b)
SI	1: People who influence my behavior use FinTechs. 2: In my private surrounding, I know many people who use FinTechs. 3: In my professional surrounding, I know many people who use FinTechs. 4: I do not know people in my private/professional surrounding who use or may use FinTechs. (control)	Self-worded
TC	1: I have the resources and technological infrastructure to use FinTechs. 2: The whole process of using FinTechs is (might be) simple for me. 3: I have the technological knowledge to use FinTechs. 4: I do not have the technological knowledge and the resources to use FinTechs. (control)	Venkatesh et al. (2012), Brown and Venkatesh (2005)
HM	1: It is (might be) fun and entertaining to use FinTechs. 2: Using FinTechs is (might be) enjoyable. 3: It (might) give(s) me pleasure to use FinTechs. 4: I do (might) not enjoy using FinTechs. (control)	Venkatesh et al. (2012)
H	1: The use of FinTechs is (might become) a habit for me. 2: The use of FinTechs is (might be) natural to me. 3: I will (would) try to use FinTechs in my daily usage of any financial solutions. 4: I will (would) never get used to FinTechs within my daily life. (control)	Venkatesh et al. (2012)
FR	1: I am (might) not (be) worried to lose money due to a counterparty failing when using FinTechs. 2: I am (might) not (be) worried about a financial risk due to mistakes I could make. 3: I am (might) not (be) worried to lose money due to transaction errors. 4: I do (might) fear financial risks when using FinTechs. (control)	Abramova and Böhme (2016), Lee (2009), Featherman and Pavlou (2003)
LR	1: I am (might) not (be) worried about the legal status and restrictions of FinTechs. 2: I am (might) not (be) worried about the uncertainty of regulation. 3: I am (might) not (be) worried about a restriction of use of FinTechs. 4: I do (might) fear legal risks when using FinTechs. (control)	Ryu (2018b), Abramova and Böhme (2016)
SR	1: I am (might) not (be) worried about security when using FinTechs. 2: I am (might) not (be) worried about data security when using FinTechs. 3: I am (might) not (be) worried about financial information security when using FinTechs. 4: I do (might) fear security risks when using FinTechs. (control)	Ryu (2018b)
OR	1: I am (might) not (be) worried about potential losses due to internal processes out of my field of control. 2: I am (might) not (be) worried about losses due to technological vulnerabilities of FinTechs. 3: I am (might) not (be) worried about the compensation of potential losses or information leakages. 4: I do (might) not fear any operational risks when using FinTechs. (control)	Abramova and Böhme (2016), Self-worded
Construct	6-point Likert scales, unless otherwise noted, with 1 = strongly disagree and 6 = strongly agree.	Jacob et al. (2013), Carifio and Perla (2007), Klopfer and Madden (1980)

This appendix summarizes, for each variable, the questionnaire items as well as their related literature. The first row represents the dependent side of the logistic regression approach. All following rows are related to the independent side of the estimation. Items regarding the socio-demographics are not included here.

Appendix B: Socio-Demographics and Key Characteristics of the Final Dataset

Variable		Absolute Frequency	Relative Frequency (%)
Gender	Male	155	51.7
	Female	137	45.7
	Diverse	8	2.7
	Total	*300*	*100*
Age	Under 20	36	12
	20-22 147		49
	23-25	81	27
	26 and older	36	12
	Total	*300*	*100*
Field of Study	Banking and Finance	11	3.7
	Business Administration	151	50.3
	Business Chemistry	23	7.7
	Economics	100	33.3
	Finance and Actuarial Mathematics	10	3.3
	Mathematics	4	1.3
	Others	1	0.3
	Total	*300*	*100*
Target Degree	Bachelor	211	70.3
	Master	89	29.7
	Total	*300*	*100*
	<250	53	17.7
Disposable Income	250-500	82	27.3
	501-750	59	19.7
	751-1,000	55	18.3
	1,001-1,250	25	8.3
	1,251-1,500	6	2
	1,501-1,750	2	0.7
	1,751-2,000	4	1.3
	2,001-2,250	3	1
	>2,250	11	3.7
	Total	*300*	*100*
Total Wealth (Liquidity)	<1,000	58	19.3
	1,001-2,500	54	18
	2,501-5,000	46	15.3
	5,001-7,500	38	12.7
	7,501-10,000	30	10
	10,001-15,000	21	7
	15,001-20,000	14	4.7
	20,001-30,000	12	4
	30,001-50,000	14	4.7
	>50,000	13	4.3
	Total	*300*	*100*
Online Banking Usage	Yes	265	88.3
	No	35	11.7
	I don't know	0	0
	Total	*300*	*100*
Banking / Finance App Usage	Yes	204	68
	No	95	31.7
	I don't know	1	0.3
	Total	*300*	*100*
Risk Attitude	Mean	3.21	
	Median	3	
Digital Experience	Mean	4.65	
	Median	5	
Digitization Knowledge	Mean	4.41	
	Median	5	
Importance of Personal Interaction (Provider)	Mean	3.72	
	Median	4	
Importance of Personal Interaction (Services)	Mean	3.84	
	Median	4.00	

This appendix summarizes the absolute and relative frequencies of the socio-demographics and key characteristics of the participants in the final dataset. This information is, in addition to the potential determinants, partly used in this paper's logistic regression approach.

Appendix C: Correlations of Questionnaire Items with Their Corresponding Control Questions

Questionnaire Item	Correlation
PE, PE.control	-0.448
EB, EB.control	-0.311
C, C.control	-0.423
SI, SI.control	-0.563
TC, TC.control	-0.607
HM, HM.control	-0.335
H, H.control	-0.398
FR, FR.control	-0.255
LR, LR.control	-0.107
SR, SR.control	-0.313
OR, OR.control	0.431

This appendix summarizes the correlations between the questionnaire items and the respective control questions. Since all correlation coefficients show the expected algebraic sign, it is possible to state that the participants had a great understanding of the questionnaire. This finding can be reconfirmed, since the control questions were double-checked by a reverse wording for the control question for the variable OR.

Appendix D: Calculated Variance Inflation Factors

Variable	GVIF	Df	GVIF^(1/(2*DF))
PE	1.273	1	1.128
EB	1.228	1	1.108
C	1.448	1	1.203
SI	1.210	1	1.100
TC	1.389	1	1.179
HM	1.463	1	1.210
H	1.387	1	1.178
FR	1.469	1	1.212
LR	1.465	1	1.210
SR	1.597	1	1.264
OR	1.937	1	1.392
sd.gender	1.544	2	1.115
sd.risk.attitude	1.234	1	1.111
sd.disposable.income	1.256	1	1.121
sd.total.wealth.liquidity	1.270	1	1.127
sd.online.banking	1.131	1	1.063
sd.digitization.knowledge	1.159	1	1.076

This appendix shows the calculated variance inflation factors, which are used to identify potential multi-collinearity issues. However, the results indicate no further issues in this respect.

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ACKNOWLEDGEMENTS

The authors would like to emphasize their gratitude to the journal editor Terrance Jalbert as well as the two anonymous reviewers for their valuable and helpful comments. These really helped us to considerably enhance and refine the substance of our paper. Moreover, the authors would like to thank the participants of both the 27th Global Conference on Business and Finance in San José, Costa Rica and the research seminar of Financial Markets and Financial Management in Duesseldorf, Germany. Finally, the authors thank their doctoral advisor Prof. Dr. Christoph J. Börner, for his helpful comments and general support.

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