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A model of trust in Fintech and trust in Insurtech: How Artificial Intelligence and the context influence it

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ABSTRACT

Finance and insurance are being transformed by Artificial Intelligence (AI). Nevertheless, the consumer is not passive in this process and there is some inhibition to trust. This research models trust in Fintech and trust in Insurtech. The two models are then compared to evaluate if trust in both is similar. Multigroup Structural Equation Modelling is used to evaluate if the model is equally valid for Fintech and Insurtech. The model presented here shows that trust in both Fintech and Insurtech are formed by (1) Individuals psychological disposition to trust, (2) Sociological factors influencing trust, (3) Trust in either the financial organization or the insurer and (4) Trust in AI and related technologies. The results of the multigroup analysis show that the model is equally valid for Fintech and Insurtech. This is particularly useful as these services are often offered by the same organization, or even the same mobile application.

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1. Introduction

Fintech and Insurtech are offering the consumer many new technology-centric services. Consumers are mostly positive towards these new technologies as they offer convenience and new capabilities (Kerényi and Müller, 2019). However, the role of consumer trust in the adoption of these new technologies is not entirely understood. The term Fintech refers to the specialized technology used in the financial industry while similarly, Insurtech is the specialized technology used in insurance. These terms are gaining popularity because technology is enabling more customized solutions and it has a more decisive role for finance and insurance (Alt et al., 2018; Lee and Shin, 2018). At its core, what is happening is that Artificial Intelligence (AI) is replacing the highly specialized, and highly skilled, human expert (Olivia and Smolnik, 2021). This transformation may be as fundamental to the nature of finance and insurance as the Internet was. The capabilities of AI and automation enable processes to be more scalable and effective. In finance, a loan can be approved in seconds based on behavioural data, to someone that was otherwise not creditworthy such as a student, e.g. Klarna (Venkataramakrishnan, 2021), while in insurance a consumer can be compensated for a loss they had very recently without them even having to make the claim, through the use of sensors and Internet of Things (IoT) devices (Krishnakanthan et al., 2021). While these changes are across the supply chain possibly the greatest transformation, at least the most visible one, is in the interaction and relationship between the financial organization or the insurer and their consumer. While the time of the travelling insurer going from door to door, often referred to colloquially in England as 'the man from the 'Pru'' (Prudential insurance) has long gone, we are now moving towards no human interaction at all, at least in B2C. As around 75% of Fintech and Insurtech are focused on retail (Catlin et al., 2017), the consumer's perspective is important. While finance and insurance have some differences in the nature of their relationship with their consumer there are also similarities, including the pivotal role of trust.

Trust is necessary whenever there is an interaction between two sides and at least one faces some kind of risk (McKnight and Chervany, 2002). This means it is more important in some contexts than others. While trust has been researched for many decades, it became a more prominent concern with the introduction and expansion of the Internet. The loss of face-to-face interaction raised the perceived risk and the importance of trust (Pavlou, 2003). Once solutions were found to reduce the risk, and build trust, this became a smaller challenge. Consumer trust has emerged as a challenge for new transformative technologies like blockchain, virtual worlds and AI. Organizations want to utilize these technologies in a way that does not reduce consumer trust. The importance of trustworthy AI is so significant that

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international legal frameworks have been created to give some broad guidance on what is, and is not, acceptable (European Commission, 2021).

Fintech and Insurtech, powered by AI, are another transformative phenomenon where concern about trust is important and is influencing adoption. Many Fintech and Insurtech companies are startups, while incumbents in finance and insurance may change beyond recognition. For example, chatbots or virtual assistants that utilize AI are widely used to interact with the person purchasing insurance or making an insurance claim (Zarifis et al., 2021). From the consumer's perspective there are some concerns. It is unclear if these AI powered systems are trusted, and how many interactions with the consumer they can replace. Anecdotal evidence of this pushback by some consumers are the many adverts that emphasize that their company will not force you to communicate with AI and will provide a real person to communicate with. Even pioneers of AI like Google are offering more opportunities to talk to a real person, seemingly hedging their bets (Johnson, 2017). Current literature does not sufficiently address trust in Fintech and Insurtech, and if they are sufficiently similar to be covered with one model. Therefore, the research questions are:

RQ1: What is the role of trust in Fintech?

RQ2: What is the role of trust in Insurtech?

In this research we outline the possible constituent factors that influence trust in Fintech and trust in Insurtech. We start with the psychology and sociology of trust, then discuss trust in other areas and trust in AI and data technologies. We then draw these issues together to propose a model of trust in Fintech and Insurtech. The model separates trust in a specific organization and trust in a specific technology like AI. This is an important distinction: Consumers have beliefs about the organization they bring with them, and other pre-existing beliefs on AI. Their beliefs on AI might have been shaped by experiences with other organizations. The validated model shows that trust in Fintech or Insurtech is formed by (1) Individuals psychological disposition to trust, (2) Sociological factors influencing trust, (3) Trust in either the financial organization or the insurer and (4) Trust in AI and related technologies. In addition to validating a model for trust firstly in Fintech and secondly in Insurtech, the two models were compared to see if they were the same, or if they had differences. For example, if one variable was more influential in one of the two models, this would suggest that the model of trust in one of them was not the same as in the other. The results of the multigroup analysis show that the model is equally valid for Fintech and Insurtech. Having a model of trust that is suitable for both Fintech and Insurtech is particularly useful as these services are often offered by the same organization, or even the same mobile application side by side.

The following section outlines the theoretic foundation and develops the research model. This is followed by the methodology section explaining the steps of the quantitative Multigroup Structural Equation Modelling (MGA-SME). The implementation of this analysis is then presented along with the results. Finally, the discussion and conclusion elaborate on the value of the model.

2. Theoretical foundation

The theoretic foundation must link trust to Fintech and Insurtech. Given this objective, we approach the literature review by looking at three areas: (1) the influence of psychology, sociology and different contexts on trust, (2) trust in financial organizations and insurers and (3) trust in AI and data technologies. These areas support the research model presented at the end of this section.

2.1. The role of psychology, sociology and context for trust

There is literature on trust spread across many different areas such as business, collaboration and education, but the fundamental principles they extend are usually from psychology and sociology (Aoki, 2020; McKnight et al., 2002). Each specific context such as business, and each specialized implementation like Fintech and Insurtech bring with them some idiosyncratic twists on the common themes from psychology and sociology. Each person has a different physiology and experiences that shape their psychological disposition. Therefore, many models of trust start with this variable (Aoki, 2020; McKnight et al., 2002). In most cases, creating a general model of trust that ignores the different individual disposition is hard to support with the data, so this should not be left out. This is because there usually is a range of responses from participants that is hard to fully explain without acknowledging their individualism and psychological differences. The sociological factors influencing trust are not as consistent as the psychological ones because they are influenced by the context to some degree. They are however often similar across similar contexts (McKnight et al., 2017; Schniter et al., 2020).

The influence of the context on trust can be low in some situations, due to certain factors such as common sociological influence but in other situations the context can be more decisive (Mou et al., 2017; Paolini et al., 2020). One prominent model of trust in e-commerce, widely considered to be the seminal paper bringing trust theory into e-commerce and information systems, showed how dispositions to trust combined with contextual factors created trust (McKnight et al., 2002). After trust was brought into e-commerce and information systems (McKnight and Chervany, 2002), it has been adapted to several contexts such as collaborative consumption (Möhlmann, 2015) and habits (Polites and Karahanna, 2012), so that it captures the consumer's perspective accurately in each context. Because of the relatively complex interplay of psychology, sociology, the context and trust, an empirically tested model is often the best way to understand and convey what is happening. A new model of trust should therefore build on the principles of psychology and sociology and adapt to the specific context. Because of the important role of the context, if research can focus a specific geographic region that has similar regulation and laws this will be conducive to more accurate results (Paolini et al., 2020).

2.2. Trust in financial organizations and insurers

The relationship between a consumer and their financial or insurance organization is different to their relationship with other organizations they purchase products or services from. Both finance and insurance usually involve large amounts of money over prolonged periods of time, often a lifetime. They require a higher involvement than the mundane or impulsive daily purchases we make (Johnson, 2017; Pitthan and De Witte, 2021). These more important purchases are therefore referred to as 'considered purchases' and can be seen as the opposite side of the spectrum from 'impulse purchases' (Johnson, 2017). The ability of the consumer to evaluate the service they are receiving is often less compared to simpler products, due to the complexity and volume of the transactions. This high risk, opaqueness and low transparency puts more weight on the importance of trust. This weight to build trust, traditionally fell on (1) staff, (2) technology and (3) institutions such as regulators. (1) Expert staff skilfully build professional relationships and embody professionalism through repeated interactions (Bapna et al., 2017). (2) Technology gives the consumer the ability to check what is happening with their finances and insurance cover on a mobile device. This immediate access a mobile app provides can reduce the uncertainty and perceived risk. This is, of course, as long as they can understand relatively easily what is happening. (3) Institutions like regulators that build institutional trust are perceived to be independent and fair (Fang et al., 2014).

While finance and insurance have several similarities, they also have some differences. They both involve a high level of risk, but the nature of the risk is different. In finance the primary risks are usually that the value of the consumer's assets will be reduced, or they will not be given the credit that they request. In insurance the primary risk is that the remedy provided to the consumer when they make a valid claim falls short of their expectations (Pitthan and De Witte, 2021). The remedy provided by the insurer is not always just financial but is often centred on reducing the period of disruption with practical solutions.

2.3. Trust in AI and data technologies

Research has shown that people trust human-like characteristics when interacting with people, but when interacting with systems, they can trust system-like characteristics that are different in some ways (Lankton et al., 2015). People's characteristics like integrity, benevolence, ability and competence are more human like, while reliability, functionality and helpfulness are more associated with technology (McKnight et al., 2017). Trust has these pillars that hold true in most contexts, but it should not be taken for granted that they work in all contexts. For example, in one study when the AI performed better than the human participant, this did not always reinforce the human's trust in it (Yin et al., 2019).

The consumer engaging in Insurtech already has some experience and beliefs in its constituent technologies (Zarifis et al., 2021). As we have seen in the second section the consumer's trust evolves depending on what technologies they interact with. For example, while purchasing insurance online with a chatbot may be a new experience, they may have interacted with chatbots before. Someone who uses a virtual assistant in their home and experiences the interaction, and how their data is used, will have some beliefs on this issue. The opaqueness of how AI is often applied is a concern (European Commission, 2021), that compounds the nature of some decisions in finance and insurance. While AI dominates the headlines, other data technologies are also important. Each technology raises different issues. For example, blockchain technologies were designed to build trust but there are people that distrust them more than the pre-existing alternatives. For some, blockchain technologies and a decentralized ledger reduce risk, while for others a traditional database controlled by one organization is less risky. The consumer's perspective on each of these transformative technologies may not be immediately obvious.

Therefore, we must understand the consumer's perspective on the constituent technologies of Fintech and Insurtech. Unfortunately, this is made harder by the different transparency of each of these technologies. Some are (1) largely transparent like a chatbot interacting with the consumer, (2) others are not transparent, but the consumer has some awareness of what they do, and (3) others are very opaque. The three levels of transparency (transparent, partially transparent and opaque) are illustrated in Fig. 1. The technologies that are transparent to the consumer and understood by them, are a small fraction of what is currently being used in Fintech or Insurtech, in processes like getting a loan or making an insurance claim.

2.4. Research model of trust in fintech/insurtech

The role of Fintech and Insurtech is increasing. This term only emerged recently but it is now widely used in the finance, insurance and technology sectors. AI driven automation, utilizing additional technologies such as big data, Internet of Things (IoT), blockchain and 5G is making the role of technology even more central than it was before. This research started by asking what the role of trust in Fintech and Insurtech is, and if it is different to other forms of trust. The first step to answering this question is to attempt to identify its constituent parts. The starting point is that trust in Fintech and Insurtech is formed by (1) Individuals psychological disposition to trust, (2) Sociological factors influencing trust, (3) Trust in the financial/insurance organization and (4) Trust in AI and related technologies. This relationship is illustrated in Fig. 2. The organization can think, and act independently, this is often referred to as agency. AI is also increasingly showing an ability to act independently and have its own agency. Therefore, the consumer must trust both the organization and AI with their respective independent agency. The hypotheses underpinning the model are presented below. The first two hypotheses cover how psychological disposition influences trust, first in finance and secondly in insurance:

H1: Individual's psychological disposition to trust, positively influences trust in a financial organization (H1a) and an insurer (H1b).

H2: Individual's psychological disposition to trust, positively influences trust in AI and related technologies used in finance (H2a) and in insurance (H2b).

The people around an individual and the communities that emerge around a technology often influence the individual's beliefs. The next two hypotheses cover how social factors influence trust, first in finance and secondly in insurance:

H3: Sociological factors influencing the individual's trust, positively influence trust in a financial organization (H3a) and an insurer (H3b).

H4: Sociological factors influencing the individual's trust, positively influence trust in AI and related technologies used in finance (H4a) and in insurance (H4b).

The literature review showed how trust in a technology is not a monolithic action. The literature shows that the consumer often brings with them some existing beliefs based on their experience. The first part of the fifth hypothesis covers how the consumer's trust in the financial organization will also influence their trust in the specialized financial technology, Fintech. The second part of the fifth hypothesis asserts the same for insurance:

H5a: Trust in a financial organization positively influences trust in Fintech.

H5b: Trust in an insurer positively influences trust in Insurtech.

The consumer has already heard many things about AI and in most cases interacted with it in some way. Therefore, they have some beliefs on the advantages, disadvantages and risks AI creates. The final hypothesis asserts that trust in AI influences trust, first in Fintech and secondly in Insurtech:

H6: Trust in AI and related technologies positively influence trust in Fintech (H6a) and Insurtech (H6b).

While there are broad procedural frameworks to give software developers some guidance when creating AI systems like CRISP-DM (Martinez-Plumed et al., 2021), this model is focused on the relationship with the consumer. Therefore, it is also suitable for financial organizations and insurers that do not develop AI systems but only apply them with limited customization. This research empirically tests this model in the following sections.

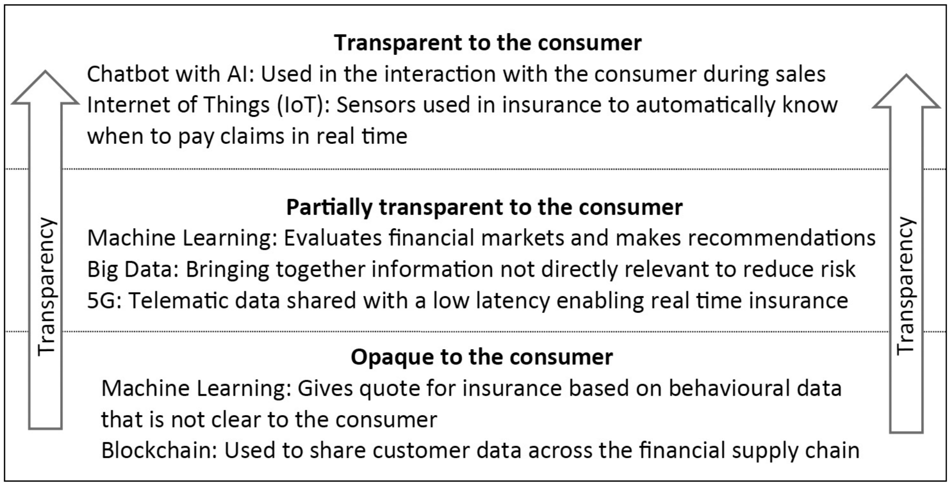

Fig. 1. The 3 levels of transparency of Fintech and Insurtech technologies for the consumer.

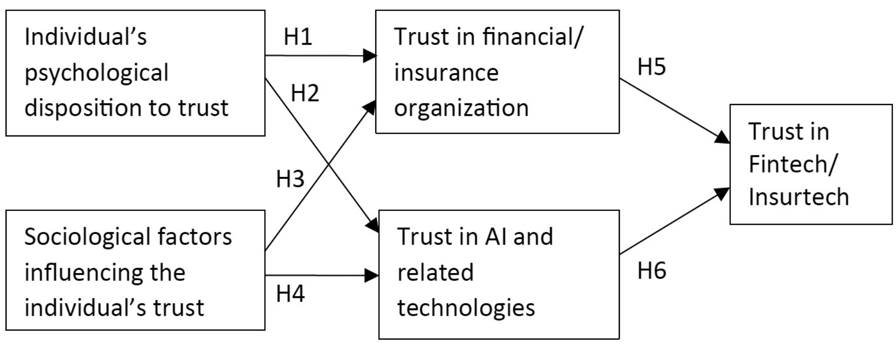

Fig. 2. The model of trust in Fintech and Insurtech.

3. Methodology

The methodology section will cover the data collection first and then the data analysis. The model has a strong theoretic foundation, but it is also evaluated with empirical data and a quantitative methodology.

3.1. Data collection

The data was collected with an online survey administered by SoSci Survey (www.soscisurvey.de). The survey questions are based on the constructs presented in Table 1. For each construct there were three questions in the survey. The first section related the five constructs to typical Fintech scenarios like taking a loan and receiving investment advice. The second section of the survey related the five constructs to typical Insurtech scenarios like acquiring insurance cover and making an insurance claim. Participants could respond to each question by making a choice on a Likert scale from 1 to 7, with 1 indicating a strong disagreement, and 7 a strong agreement. The participants had to have experience using Fintech and Insurtech. The data collection focused on EU countries as they have similar laws and regulations for finance and insurance. In total 283 responses were received. After the typical checks such as checking that all the questions are answered and removing responses that took an unreasonably short time to complete, the final number of valid and useable survey responses are 236. The participants came from Germany (56), Poland (50), Greece (42), Cyprus (28), France (18), Spain (11), Italy (8), Hungary (6), Sweden (4), Ireland (3), Netherlands (3), Austria (2), Malta (1), Romania (1), Bulgaria (1), Croatia (1) and Slovakia (1). Table 2 gives more detailed demographic information on the sample groups.

3.2. Data analysis technique

The model with five variables was tested with Partial Least Squares-Structural Equation Modelling (PLS-SEM), multi-group analysis (MGA) using SmartPLS 3.3.3, (Hair et al., 2014). This method was used primarily for two reasons: Firstly, variables like trust can be measured more accurately as a latent variable with several measured items. Secondly, MGA enables the comparison of two data sets with the same model. The analysis evaluated the validity of the model first for Fintech, then for Insurtech and lastly, if the model is equally representative for both. The multigroup analysis compared the model with the Fintech sample, to the Insurtech sample, to evaluate if they are sufficiently similar so that we can say the model represents both equally well. This is necessary as this research proposes that despite the differences between Fintech and Insurtech trust plays a similar role. Models of this complexity are usually evaluated in two stages in SmartPLS. First, this research analysed the measurement model that evaluates how well each of the observed variables capture their latent variables. The second stage was the structural model itself, the relationships between the five latent variables.

4. Analysis and results

This section starts with the measurement model and concludes with the structural model.

4.1. Measurement model

As PLS-SEM does not have a single measure that captures how well the model fits the data, so several measures were

Table 1
Constructs and their indicators.

Construct	Item	Source of construct items
Individual's psychological disposition to trust	PT1, PT2, PT3	McKnight et al. (2002) and Mou et al. (2017)
Sociological factors influencing the individual's trust	ST1, ST2, ST3	McKnight et al. (2002) and Mou et al. (2017)
Trust in financial organization or insurer	TO1, TO2, TO3	Hwong et al. (2017) and Lankton et al. (2015)
Trust in AI and related technologies	TAI1, TAI2, TAI3	Aoki (2020) and Zarifis et al. (2021)
Trust in Fintech/Insurtech	TFI1, TFI2, TFI3	Sleiman et al. (2021) and Zarifis et al. (2021)

Table 2
Demographic information of the survey sample group.

Measure	Item	Participants
Gender	Female	103
	Male	133
Age	Under 18	25
	18–24	88
	25–39	79
	40–59	31
	60 or older	13
Educational level	No high school education	0
	High school graduate	97
	University bachelor's degree	95
	University master or doctoral degree	44
Income (in Euro per month)	No regular income	14
	400–1200	41
	1201–3000	92
	3001–5000	54
	>5000	6

Table 3
Results of the measurement model analysis.

Items		Fintech/Insurtech						
		Loadings	CR	AVE	Discriminant validity (HTMT)			
					PT	ST	TO	TAI
PT	PT-1	0.943/0.950	0.911/ 0.903	0.773/ 0.757				
	PT-2	0.878/0.881						
	PT-3	0.812/0.770						
ST	ST-1	0.852/0.807	0.922/ 0.887	0.799/ 0.723	0.823/ 0.840			
	ST-2	0.925/0.888						
	ST-3	0.901/0.854						
TO	TO-1	0.853/0.793	0.911/ 0.893	0.775/ 0.736	0.780/ 0.740	0.798/ 0.774		
	TO-2	0.912/0.876						
	TO-3	0.934/0.869						
TAI	TAI-1	0.866/0.860	0.928/ 0.894	0.810/ 0.738	0.670/ 0.753	0.647/ 0.781	0.690/ 0.807	
	TAI-2	0.952/0.940						
	TAI-3	0.818/0.766						
TFI	TFI-1	0.853/0.837	0.900/ 0.884	0.749/ 0.717	0.842/ 0.788	0.820/ 0.774	0.801/ 0.818	0.759/ 0.833
	TFI-2	0.912/0.860						
	TFI-3	0.934/0.879						

Table 4
Effect sizes.

Path	Effect size (F^2)		Effect	
	Fintech	Insurtech	Fintech	Insurtech
PT-TO	0.158	0.083	Medium	Medium
PT-TAI	0.111	0.090	Medium	Medium
ST-TO	0.232	0.208	Medium	Medium
ST-TAI	0.056	0.214	Medium	Medium
TO-TFI	0.528	0.258	Strong	Medium
TAI-TFI	0.284	0.344	Medium	Medium

assessed. The reflective measurement model was evaluated by the methods illustrated in Tables 3 and 4, Hair et al. (2014). The reliability and validity of the construct were tested by the Composite Reliability (CR) and Average Variance Extracted (AVE). The Composite Reliability of the observed variables with the latent variable were all above the required threshold of 0.7, with the lowest at 0.749. The Average Variance Extracted (AVE) was above the required threshold of 0.5, with the lowest at 0.707. The lowest factor loading observed variables was 0.766 so they were all above the recommended level of 0.7. Discriminant validity was measured primarily by the Heterotrait-Monotrait Ratio of Correlations (HTMT), and none of the values exceeded the recommended limit of 0.90. HTMT is now the preferred method for discriminant validity (Hair et al., 2021), but other methods were also used and they returned similar results.

4.2. Structural model

Firstly, this stage analysed the relationship between the latent variables within the model and secondly it compared the model between the groups of Fintech and Insurtech. The coefficient of determination (R2) evaluated how well the endogenous variables represent the exogenous variables. All the values are moderate or high. For the Fintech group the R2 for TAI is 0.476 that is moderate as it is above 0.33, and for TO it is 0.683 and TFI it is 0.751, that are considered strong as they are above 0.67. For the Insurtech group R2 for TAI is 0.638, TO is 0.627 that are moderate as they are above 0.33 and for TFI it is 0.752 that is strong as it is above 0.67 (Chin, 1998).

The effect sizes on the endogenous latent variables are presented in Table 4. Values above 0.35 are considered strong, between 0.35 and 0.15, moderate, between 0.15 and 0.02 are believed to be weak and below 0.02 there is no effect (Chin, 1998). The effect sizes are significant in all cases.

The final stage of the analysis evaluated if the model applied to both Fintech and Insurtech equally well. The results of the non-parametric multigroup analysis method PLS-MGA are presented in Table 5. The multigroup analysis identified the difference between the groups and the probability that this difference is statistically significant (p-value). None of the p-values are below 0.05 or above 0.95, so none are statistically significant. This proves that the model does not have significant differences in Fintech or Insurtech. The equality of the two models is not rejected. Therefore, the model can be used in both of these related contexts.

5. Discussion and conclusion

This research modelled trust in Fintech and trust in Insurtech. The model of trust in Fintech and trust in Insurtech are then compared and it is proved that the model fits these two areas equally well. Therefore, the model can be used in both Fintech, Insurtech or services that include both. Technology is playing an increasing role in finance and insurance (Alt et al., 2018; Lee and Shin, 2018). These two areas involve risk for the consumer and therefore trust is needed. The new decisive role of Fintech and Insurtech is reforming the relationship with the consumer. In this period of digital transformation driven by AI, financial organizations and insurers need their consumers' trust. The theoretic contribution is discussed next, followed by the practical contribution.

Table 5
Multi-group comparison test results.

Path	Path Coefficient Difference (Fintech vs. Insurtech)	PLS-MGA: *p*-value (Fintech vs. Insurtech)	Hypotheses	Result
PT-TO	0.027	0.758	H1: Fintech = Insurtech	Non-rejected equality
PT-TAI	0.022	0.365	H2: Fintech = Insurtech	Non-rejected equality
ST-TO	0.020	0.830	H3: Fintech = Insurtech	Non-rejected equality
ST-TAI	0.120	0.365	H4: Fintech = Insurtech	Non-rejected equality
TO-TFI	0.066	0.312	H5: Fintech = Insurtech	Non-rejected equality
TAI-TFI	0.088	0.468	H6: Fintech = Insurtech	Non-rejected equality

5.1. Theoretic contribution

By extending widely validated models of trust (Lankton et al., 2015; McKnight et al., 2017; McKnight and Chervany, 2002), this research makes four main contributions to theory: (1) firstly it offers a model for trust in Fintech, (2) secondly it offers a model for trust in Insurtech and (3) it brings evidence that the same model is equally valid across Fintech and Insurtech. The third point is particularly important as these services are increasingly being offered together (Konopik et al., 2021). (4) It shows that the consumer brings with them some pre-existing beliefs on AI and related technologies. The consumer therefore does not trust Fintech and Insurtech just based on their direct experience with them, but they are also influenced by their existing beliefs on AI. This model ads to extensive research in other contexts, supporting the influence of pre-existing beliefs on technology use (Polites and Karahanna, 2012). These beliefs or habits can cause an inertia that is hard to change (Polites and Karahanna, 2012).

The model of trust in Fintech and Insurtech shows how an 'Individual's psychological disposition to trust' and 'Sociological factors influencing the individual's trust' influence 'Trust in financial or insurance organization' and 'Trust in AI and related technologies'. The last two variables then shape trust in Fintech or Insurtech. In addition to validating the model, this research shows how to operationalize the five variables in the context of Fintech and Insurtech.

An additional contribution is developing our understanding of Insurtech and linking it more extensively to the literature in business and information systems. Despite insurance contributing over 10 trillion euro per year to the European economy (Insurance-Europe, 2021), and technology playing an increasing role, our literature review indicates that it has not received sufficient attention by scholars. Just as Fintech carved out its own segment of dedicated research and experts in business and information systems (Lee and Shin, 2018), it is now overdue for Insurtech to receive similar attention.

5.2. Practical contribution

With AI permeating many aspects of our personal and professional lives it can be challenging for organizations to know what to focus on first. Whether the future of finance and insurance is a more efficient version of the model we have today, or more decentralized finance running on blockchains (DeFi), algorithms and AI are taking centre stage. The model this research develops enables an organization in finance or insurance to focus on the four variables that shape consumer trust in Fintech and Insurtech. An organization has more influence on the variable 'Trust in financial organization/insurer' than the other three psychological disposition, sociological factors, and trust in AI. The organization should however have an understanding of all four factors and try to compensate weaknesses in factors it has less influence on, by strengthening a factor where it does have more influence. The consumer may perceive these four variables differently in different contexts. Therefore, the organization must use experts in the technology, and business intelligence to optimize their relationship with AI and their consumers, in their context. The model presented here, can be informed and adapted to each organization's context with business intelligence utilizing context specific big data and machine learning (Park et al., 2020).

Broader frameworks that are used for AI development like CRISP-DM (Martinez-Plumed et al., 2021) do not focus on the relationship with the consumer directly so they can be supplemented with the use of this model. Additionally, an organization that is neither developing nor significantly customizing their AI solutions may benefit more by using a model targeted on their relationship with the consumer and the variables they can influence, like trust in their organization, rather than attempting to apply broader models. If an organization is engaged in software development and significant customization, they can use the trust model alongside broader procedural models.

Lastly, this research puts forward the three levels of transparency of AI and related technologies from the consumers perspective, as illustrated in Fig. 1. These are (1) transparent to the consumer, (2) partially transparent to the consumer, and (3) opaque to the consumer. The three levels give those applying Fintech and Insurtech a starting point to evaluate the consumers perspective of the transparency of their specific implementation. A more nuanced understanding will enable the targeted reduction of the opaqueness so that trust is elevated.

6. Limitations and future research

The contribution of this research should be seen in the light of some typical limitations that are caused by the topic and research methodology. The participants were from the European Union so this model should also be tested in other geographic regions. Another limitation is that the model is relevant to Fintech and Insurtech as we understand it today and not traditional, less technology-centric, approaches to finance and insurance.

The three levels of transparency of AI from the consumers perspective, can be further developed and evaluated. An experiment method could also be applied to further test the model and the causal relationships. The possible role of financial literacy can also be explored in relation to the model presented here. The simple and fast process offered to the consumer by Fintech and Insurtech mask the actual financial dimensions of what is happening to some degree. Despite this, higher financial literacy would probably lead to higher confidence in using Fintech and Insurtech.

This research also argues that more dedicated research on Insurtech is needed in business, information systems and finance. Future research can further clarify the similarities and differences to Fintech, particularly in areas such as the relationship with the consumer, how risk is calculated and how digital transformation is reshaping business models. It can also be explored if additional factors, like law and regulation, act like separate variables or moderate these relationships.

CRediT authorship contribution statement

Alex Zarifis: Ideas, Formulation or evolution of overarching research goals and aims, Development or design of methodology, Creation of models, Application of statistical, mathematical, computational, or other formal techniques to analyse or synthesize study data, preparation, creation and/or presentation of the published work by those from the original research group, specifically critical review, commentary or revision – including pre-or postpublication stages. **Xusen Cheng:** Ideas, Formulation or evolution of overarching research goals and aims, Development or design of methodology, Creation of models, Application of statistical, mathematical, computational, or other formal techniques to analyse or synthesize study data, preparation, creation and/or presentation of the published work by those from the original research group, specifically critical review, commentary or revision – including pre-or postpublication stages.

Declaration of competing interest

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

Ethics statement

The paper meets the requirements of the institutions of the authors for empirical papers. All the necessary permissions were taken for the data collection. A committee approval number is not applicable.

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