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Factors That Influence the Intention to Use Alternative Finance Fintech: An Application of Structural Equation Model to The Case of Small Service Sector Businesses in Metropolitan Lima

Juan Luis Peñaloza F.[a], Fátima Ponce R.[b], Andrey Santiago Dolores V.[c], Carlos Alonso Vásquez L.[c]

[a] Department of Financial Economics and Actuarial Science and Statistics. Complutense University of Madrid[b] Management Sciences Department. Pontifical Catholic University of Peru. [c] Faculty of Management and Senior Management. Pontifical Catholic University of Peru

Abstract

This paper applies structural equation modelling (SEM) to investigate the determinants of the intention to adopt alternative financing mechanisms, with a specific focus on Micro, Small, and Medium-sized Enterprises (MSMEs). The central objective is to identify and measure the latent variables that explain MSMEs' intention to use Fintech-based financing platforms. Drawing on the Technology Acceptance Model (TAM), the study highlights the relevance of perceived usefulness, defined as the degree to which firms value alternative financial technologies as effective tools for investment and business growth. The empirical findings suggest that the adoption of Fintech financing is primarily driven by MSMEs' recognition of its potential to enhance liquidity, expand access to credit, and overcome structural barriers to financing. By linking behavioural intention with technological acceptance in the financial domain, this paper contributes to a better understanding of Fintech adoption in developing economies and offers insights for policymakers and financial institutions seeking to foster greater financial inclusion.

Keywords: Fintech adoption, alternative financing, MSMEs, structural equation modelling, Technology Acceptance Model (TAM), financial inclusion, liquidity constraints, entrepreneurial finance

JL: G10, G11, G15, G17, G21, G23, G24, G28

Introduction

In today's knowledge society, traditional and digitised financial institutions (banks, microfinance institutions, cooperatives, insurance companies, etc.) are responsible for efficiently channelling resources for productive investment from agents with saving capacity to those who need financing. With the particularity that they must be focused on satisfying the financial needs of their customers, not only in the traditional credit segments, but also in the neglected segments due to lack of profitability and/or elevated risk (measured in the traditional way), such as micro-enterprises, family businesses or Small and Medium Enterprises (SMEs).

The incorporation of modern technologies in the productive activity of MSMEs has changed the financing source's structure and the risk management forms of Fintech. This new scenario has led to the development of alternative ways of accessing investment, working capital resources, and reaching a wide variety of businesses: small businesses, micro-enterprises, and fast-growing firms. All of them are aimed at creating an incentive structure that promotes productivity growth and achieves greater financial inclusion.

Despite their importance in the productive structure of developing countries and particularly in the Metropolitan Lima city (Peru), MSMEs face serious problems and obstacles to their growth and development. One of the major challenges Peruvian companies' faces is the lack of liquidity or financing to be able to make the necessary investments and thus improve its growth in order to continue in the market.

The disruptive role of latest information and communication technologies in the financial sector has led to the development of Fintech associated with big data, artificial intelligence, cryptography, and mobile internet. However, not every technological innovation in the financial sector can be classified as Fintech (e.g., online banking).

For the study of this topic, we have used the Technology Acceptance Model (TAM), which has been adapted to many different technologies and it has proven to be especially useful in a research context. For this and based on the original TAM model a review of its developments has been carried out with the specific objective of applying it to the study of the intention to use financial platforms (Fintech), in this case alternative financing platforms.

The results obtained provide useful information on the importance of the different potential benefits, suggesting that intention to use Fintech is influenced by perceived usefulness, access to financial resources and diversification of use. Furthermore, the model used suggests that a good fit of how people are, rather than what they want, should be of particular importance for usage.

The present paper is divided into five sections. The first section introduces the topic of financial technologies related to Fintech. The second section addresses the issue of alternative financing and its relevance for decision making and access to alternative capital markets. The third section presents the review results of developments and advances in the specialised literature, including an empirical perspective on Fintech use. The fourth section deals with methodological issues in the application of structural equations to model the use of technology platforms for accessing investment and financial resources, what we know about Fintech. This will be done from an analysis of the causes that influence the intention to use these innovative technologies in business activity. The fifth section is devoted to the analysis of the results obtained with the application of the measurement and structural model to explain the causality of the concepts related to the intention to use Fintech. Finally, we point out the limitations of this research with some conclusions and a bibliography.

Problem Statement

In today's knowledge-based society, risk and uncertainty are inherent in all financial activities. The cyclical tendency of economies, and the natural appetite of financial institutions for business models that prioritise short-term profit optimization, have a negative impact on society. The unpredictable evolution of financial innovation driven by technology, and the growing international interdependence between financial institutions and markets can lead all economies into difficult situations, with serious consequences for the overall functioning of the productive system. This especially affects those related to the long-term management of micro, small and medium-sized companies (MSMEs).

In this context, all related to small and medium-sized enterprises (SMEs) and MSMEs has a great deep impact on the progress and development of national economies, in particular, the Peruvian economy. This is due to this type of company accounting for more than 98% of the country's whole business network (INIEI, 2019). Therefore, essential aspects such as job creation, poverty reduction or gross domestic product (GDP) growth, etc., depend on them.

However, despite their huge importance, MSMEs have serious problems and barriers to their growth and development. One of their main problems is the lack of liquidity or financing to be able to make the necessary investments that favour its growth to continue in the market. Added to this is the lack of knowledge and culture in terms of organisational development, lack of clarity on how to bring their products or services to the final consumer and lack of knowledge of digital business techniques to strengthen their commercial and sales area.

In developing economies, the gap to available financial resources remains a serious problem affecting a wide range of companies and micro-enterprises. Especially the access to those resources managed by banks and traditional capital markets (inflexible and poorly configured), which impose limits on the amounts demanded and high restrictions on access to such funds.

Thus, in the Latin American context, the financial gap was estimated at USD 1.2 trillion in 2017, making it the second largest gap in the world, only behind the East Asian region. Furthermore, according to the Inter-American Development Bank (IDB), MSMEs in the region receive only 12% of total credit, and only 17% of SMEs in the region use bank loans to finance short-term working capital, compared to 29% of large companies. In the Peruvian case, the existing financing gap is similar to that of the region, since only 6% of MSMEs have access to the regulated financial system.

The consequences for companies of these restrictions are the high capital cost, the excessive requirements for granting credit, or the widespread culture of distrust and, therefore, the lack of credit habits. All these factors have a negative impact on the MSMEs results since they cannot cover their financial needs throughout the life cycle of their companies.

However, we are experiencing a fourth technological revolution that has affected the financial services industry. Thus, financial institutions are immersed in a digital transformation process in which their own survival is at stake. In recent years, technology companies have emerged with highly disruptive value propositions in the financial products and services area. These companies make up the well-known Fintech, Techfin or neobanks sector, whose names are related to the "Finance" and "Technology" terms.

Although alternative financing methods to major banks and organised capital markets have almost always existed, the appearance of the Internet and recent technologies speed the process and now, the new modes have acquired notable relevance within the financing processes of all kinds of business projects. These online platforms have become competitors to the traditional financial system and attempt to disintermediate the financial function by directly connecting supply and demand for capital or investment funds (Diaz and Ramírez, 2000). The decision to receive funds through a Fintech platform was strongly influenced by the speed and better customer service offered by these new financial institutions (Ziegler, et al. 2022).

The relevance of use alternative financial instruments in developing economies, understood as platforms that facilitate online credit to individuals or companies with funds from individual investors or institutional investors (Cuya, 2020), is based on the following facts:

First, the existence of a financial gap in access to formal market credit for MSMEs, due to information asymmetry, high transaction costs and corporate governance forms of SMEs. Moreover, the diversification of the financial offer oriented to SMEs has not been able to reduce this financial gap that small enterprises suffer in their medium and long-term decisions.

Second, MSMEs generally do not depend on the credit flow from traditional banks. Moreover, they do not have the minimum funds to access financing from banks or capital markets. Many of these companies do not have a good credit rating, or simply they do not have the required rating.

Third, the perception that the transformation of the current financial system offers new business opportunities, which has given rise to Fintech, linked to the possibility of individualising the services provided to customers, this being one of the main factors of demand-driven digitisation. In addition, a range of new business models and niche markets are opening with the intensive use of technology.

Fourth, the Fintech ecosystem in Latin America has grown significantly, along with the global level (Ernst and Young, 2021). In the Peruvian case, Fintech companies have been growing considerably in recent years. In the 2019-2021 period, the number of Fintech corporations increased from 130 to 171. Over the last 7 years, the average annual growth of the Peruvian Fintech sector has been 20%.

Fifth, the lack of access to formal financing generates many related problems that have become characteristic in the region and in developing countries, such as prominent levels of informality, high interest rates, and high business closing rates.

It is important to highlight that the MSMEs financing is one of the key points for their survival. Not only from the point of view of medium and long-term financing, but also from the point of view of financing current assets and adjusting operational funding requirements.

Similarly, the results show that there is an inefficient allocation of credit in Latin America, which has created an undesirable distortion of the financial system to the detriment of MSMEs. Small and medium-sized enterprises (SMEs) cannot easily replace bank financing by capital market financing. Therefore, Fintech has a relevant role to play in correcting this financial distortion generated by the formal financial system.

Among financial Fintech we can find Crowdfunding (digital platforms where people contribute their economic resources to individuals, projects, or companies). However, the present research is focused on Lending Fintech (platforms that facilitate online credit to individuals or companies with funds raised from individual investors or institutional investors) according to classification of Cuya (2020) and discussed in more detail in Dolores and Vásquez (2022).

The main objective of this paper is to determine the factors that influence the intention to use Fintech alternative financing by small businesses in the service sector in Metropolitan Lima, through a quantitative approach methodology, based on a structural equation model. For this purpose, a modified Technology Acceptance Model (TAM) is used, as explained below, where the underlying variables are:

Perceived Usefulness, Perceived Ease of Use, Brand Image, Risk Perception and Government Support.

The hypotheses related to the intention to use new technologies to access financial resources available on the web are:

H1: Risk perception has a negative influence on the intention to use Fintech among small service companies.

H2: Perceived Usefulness, Perceived Ease of Use, Brand Image, Perceived Risk and Government Support significantly influence Fintech usage intention among small service companies.

The theoretical relevance of the research object is based on the fact that Fintech companies are here to stay, and their presence and relevance will continue to increase. In this way, we are driving an increasingly strong ecosystem that will act as a driver of change and transformation in the financial sector, particularly as an element of financial inclusion for MSMEs.

State of the Art

Intentionality is one of the central problems in research on the behaviour of economic and social agents, with the advantage of bringing together epistemological, ontological, anthropological, and ethical aspects. However, there is some confusion between the phenomenological concept of intentionality and the semantic concept of intentionality (widely used).

Thus, the “Real Academia de la Lengua Española” (2014) provides clarity by conceptualising "intention" as the will towards an end, that is, an idea that is pursued with a certain action or behaviour or thing that one intends to do.

The words "Intent to use" constitutes an expression form of demand for certain services, which are necessary for the functioning of economic and/or business activity. It is focused on the use of non-conventional financial services such as Fintech (financial technologies).

Fintech are an effective alternative to the limitations of the formal financial system (given the limitations of bank credit and the conventional capital market) to meet the financing needs of the self-employed, micro, small and medium-sized enterprises (Martincevic et al., 2020; Ziegler, et al., 2022).

In other words, a Fintech should not only be understood as an IT and technological support to facilitate access to banking or other financial services, but as a new particularised financing system, based on trust and accountability, offering various types of services such as: savings, investment, money transfer and payments, loans and insurance (Jiwasiddi, Adhikara, Adam, and Triana, 2019).

In addition to providing services similar to those of traditional banks, Fintech has innovated other service areas, including crowdfunding, treasury management, foreign exchange, securities investments, mutual fund investments, and more recently in areas such as big data or Bitcoin and blockchain technologies (Perez, 2019).

Under this generic perception of Fintech and due to the speed at which technological innovations are occurring (mobile devices, microprocessor capacity expansion, the low cost of obtaining and processing data and internet), Fintech are shaping a new digital financial architecture that surpasses the analogical format.

Among the characteristics identified by Funcas' "Observatorio de digitalización financiera" - KPMG (2017) - we have selected the following: the offer of online financial products, disruptive technologies, flexible structures and purposeful methodologies, a customer-centric approach, a mono-product offer, financial inclusion, and greater efficiency, with the consequent cost reduction.

The Fintech rise is just the latest wave of innovation in the banking industry. This innovation wave encompasses artificial intelligence (AI) (Teigens, et al. 2020), machine learning, advanced data analytics, distributed log technology (DLT) (Hueso Ibañez, 2015), application programming interfaces (APIs) (Hernández-Quintero and Esteban, 2020). Innovative technologies offer opportunities, but they are also risk sources.

However, unlike other phases of technology-driven innovation that banking has experienced in the past, Fintech has the ability to lower the barriers to entry into the financial services market and make data more relevant as a key raw material. Fintech also has the ability to promote the start of new business models and stands out for the expectations of transformation of the financial system.

Technology Acceptance Models (TAM)

Technological expansion and advancement partly explain the increase in Fintech-focused studies in recent years, along with the growth of the sector. Specially, those studies related to the identification of factors that influence the intention to use Fintech services as financing alternatives.

One of the main applications is the 'Technology Acceptance Model' (TAM), developed by Davis (1989), which has often been used as a base model to identify the factors that are key to accessing alternative sources of financing (Sumak, Hericko, & Pusnik, 2011).

This model provides insight into the attitudes of economic agents towards technology, although it is not the only one, nor is it free of criticism. Its unquestionable influence on social psychology and, by extension, on the analysis of behaviour patterns of those who seek financial resources, makes its inclusion and description necessary, although in our case we will do so in a synthetic way.

The TAM Model is based on a theory that draws from disciplines such as social psychology, data science and ICTs, and makes it possible to determine the degree of acceptance of modern technologies by a society. Through analysis, this model is based on the premise that it can be inferred whether a society is more inclined to incorporate novelties, or it has a conservative attitude (Heijden, 2003).

According to this theory, a person's use of a system can be identified by two variables: "Perceived ease of use" (degree to which a user has faith in the belief that he/she will not make extra effort while using the technology) and "Perceived usefulness" (degree to which a user has faith in the belief that the use of technology will improve his/her work performance, productivity) (Venkatesh & Bala, 2008).

The model has undergone several updates, although the most important ones are those known as TAM2 and TAM3, dating from 2008, which included new items and factors to be considered.

The review of the specialised literature on the concept "Intention to use" of financial technology services, shows the advances in the identification and explanation of the influence of the determining factors in the access to alternative financing sources of the investment demand required by SMEs, micro-enterprises, or family businesses, etc,. In addition, it provides information and transparency in the restricted financial world of developing economies and, in particular, in the limited Peruvian financial system.

Among the theoretical references related to the identification of influential variables in the intention to use Fintech services appear Van et al. (2019), who were interested in identifying the factors affecting the intention to use Fintech services in Vietnam. For this task, they used the modified TAM model, and they added the determinants of Risk Perception, Brand Image, and User Innovation to the base model. The conclusion of this study was that User Innovation had the greatest influence.

Similarly, Hu, Ding, Li, Li, Chen, and Yang (2019) investigated the intention to use Fintech services by users of two China banks (Hefei Science and the Technology Rural Commercial Bank). They used the TAM base model and added new determinants, such as User Innovation, Government Support, Risk Perception, Trust, Attitude and Brand Image to improve the effectiveness of the base model. They found that Perceived Risk and Perceived Ease of Use did not influence the intention to use the Fintech service, while Brand Image, Government Support, Trust, and User Innovation did significantly.

On the other hand, Jin, Seong and Khin (2018) sought to identify the intention to use Fintech products and services in Malaysia. For this task, they used the TAM model and added factors such as competitive advantage (perceived level of service innovation in relation to past services), Risk Perception and Cost Perception, to identify the factors that influence this intention to use. The study showed that all five determinants influenced the intention to use Fintech.

In the Peruvian case, Chávez, Miranda, Quispe and Robles (2019) studied the factors that affect the intention to use mobile payment technology in retail businesses in Metropolitan Lima using the TAM model, and they concluded that perceived control, perceived usefulness, and perceived ease of use influenced intention to use. They also showed that perceived usefulness is influenced by perceived risk, user innovation and support services, while perceived ease of use is influenced by user innovation and support services.

In other areas of knowledge, many models related to information systems include the Satisfaction variable (Al-Azawei & Lundqvist, 2015, Al-Azawei, Joo, So, & Kim, 2018), a variable that is not included in the Technology Acceptance Model. In order to assess the factors that explain user satisfaction in DLS (Distance Learning Systems), the variable "Satisfaction", defined as "a measure of the pleasant feeling when customers' expectations are met at desired levels with the services provided", was included in the extended TAM model. The results of the studies that included this variable have been important.

Therefore, the irruption of Fintech in the world has been aimed to promote the development of an alternative financial ecosystem and making themselves known to operators or entrepreneurs who create innovative initiatives in the sector. A notable feature of the sector is vertical specialisation: each Fintech is dedicated only to a specific service, which responds to a specific and digital financial need. As we will show throughout this study, the line between service and technology is increasingly blurred.

Moreover, Fintech companies include RegTech startups that help financial competitors obey with regulation by relying on new technologies to reduce time and costs. The structure of this financial system shows that the majority of Fintech, 52%, have a B2B (Business to Business) business model, compared to 34% that focus their efforts only on the final consumer, and therefore have a B2C (Business to Customer) model.

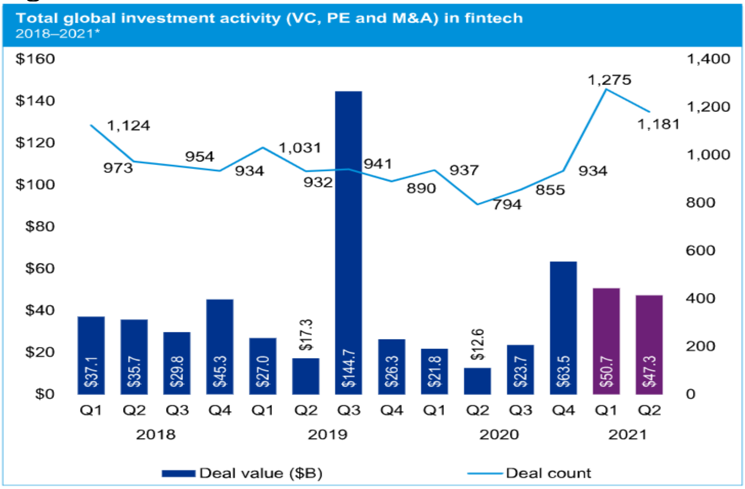
Compared to other innovation waves in banking throughout its history, the current wave removes many barriers to entry and allows for the fast development of new business models, making it a more disruptive movement than previous ones.

As a result, a new competitive environment is developing that significantly affects the financial sector. Due to this changing environment, it is crucial for the sector and for all agents involved to identify the determining factors of the intention to use Fintech by small and medium-sized enterprises, microenterprises, fast-growing companies, family businesses, etc. The objective of this initiative is to facilitate equitable access to sources of equity finance for small businesses, with a view to supporting their investment in capital equipment and working capital.

Empirical Perspective

The Fintech industry is booming, as shown in the "The pulse of Fintech" report by KPMG (2021) (Figure 1). During 2021, interest and investment in fintech grew significantly in many regions of the world, expanding its reach much further than its initial definition. This expansion, combined with the growing development of several fintech sub-sectors, is expected to lead an increased investment in less developed jurisdictions, and growing corporate interest, to keep investment at a high level as the years progress.

Figure 1: Total investment through Fintech



Source: Own elaboration based on data from Pulse of Fintech H2’21

In this environment, Fintech are increasingly focusing on data value propositions to attract investment. In recent years, there has been a growing trend among financial companies in the Asia-Pacific region to reinvent themselves as data organisations to attract more investment funds. For this purpose, they present themselves as data providers offering payments, loans, insurance, or other related activities, rather than simply financial companies.

Moreover, investors are increasing their interest in jurisdictions considered underdeveloped in terms of financial services, and more arrangements are underway in regions such as Africa, Southeast Asia, Latin America, and the Middle East. Data confirms this trend, with large investments in Latin America in 2021. For example, Brazil-based Nuben el Bank raised US$1.1 billion, Argentina-based Uala raised US$350 million, and Mexico-based Kueski raised US$202 million.

Dapp (2017) wrote that, in the medium to long term, success and failure in the financial sector will not only be measured by new products, but by the type of technologies and analytical methods used. This author points out that the secret lies in evaluating customer transactions to predict future wishes through probability calculations and modern algorithms. He also concludes that the new entrants, Fintech companies, in the financial sector are not reinventing the banking business. However, it is important to know how to make good use of modern methods of data analysis and data sets to individualise financial services digitally and get the most out of customers with a high level of Internet knowledge.

In Latin America, MSMEs are a fundamental part of national economies (they represent 99% of the companies in the region, employ 67% of people in Latin America and the Caribbean, and generate 30% of GDP). However, according to IDB, a notorious problem for the nearly 27.5 million MSMEs in the region is the existing financing gap, which makes it impossible to improve the productivity and growth of this business segment.

Thus, for example, according to Peru's National Institute of Statistics and Informatics (INEI), in December 2018 there were more than two million enterprises nationwide, of which 94.9% were microenterprises. Metropolitan Lima area (the country's capital) concentrates 46.2 % of all existing companies. MSMEs represent around 99% of all enterprises and they have had a growth rate of 6.2% between 2014-2018 (INEI, 2019).

In this context, Peruvian business activity has a financing type that continues to be a limiting factor for its growth, productivity, technological incorporation, and innovation. As shown in Table 1, only 46.3% of small enterprises have access to the regulated financial system, they usually obtain their resources outside the conventional financial system, but at a higher cost.

Table 1: Percentage of enterprises with access to finance (Peru)

Companies	Number of companies registered with SUNAT	Number of companies registered in the Financial System - December 2017	% Participation in the Financial System
Microenterprise	1’836848	83839	4,6%
Small	60702	28116	46,3%
Medium	2304	1269	62,4%
MSMEs	1’899584	113224	6,04%

Source: Adapted from Produce (2017)

This situation would explain the frequent reinvestment of their profits, as well as the low investment in equipment or technology (Adex, 2020) by SMEs. The requirements to access alternative credit may vary depending on productivity, location, and size of the enterprise, as well as the types of financial products requested (León, 2017).

In 2019, only 20% of SMEs received credit and of this percentage, 51% was financed by microfinance Institutions, while 47% was financed by commercial banks; These data indicate that, in Peru, commercial banks only offer credit to around 10% of SMEs (Lima Chamber of Commerce, 2020).

In addition to the above described, there are the consequences of COVID-19 pandemic on Peruvian business activity. One of the business activities most affected by this situation has been services, and within this sector, the most affected has been tourism, where some 70,000 companies went bankrupt, resulting in the loss of around 650,000 jobs (INEI, 2020).

Microcredit is the most widespread financial product in the informal sector or in activities with low level of bank access since it allows generating resources to open up new employment and commercial possibilities to create their own businesses.

This type of financial product has served as the basis for the progress made in financial inclusion. Arner, Buckley, Zetzsche and Veidt (2020). In fact, in the Peruvian case, Ames (2018) showed that there was a positive correlation between the development and growth of Fintech financing and MSME payments and transfers.

The object of study in the present research is small enterprises in the service sector. This choice is mainly due to the importance of the sector in the national economy: In 2016, it contributed to 49.9% of total employment (1,684,902 workers) and 28.5% of national GDP. It should be noted that in Peru, 86.4% of all service enterprises are small (including micro enterprises), while medium-sized and large enterprises represent 4.1% and 9.5%, respectively.

In summary, it can be seen that there is a significant financing gap for SMEs in Latin American economies, particularly in Peru, which is a problem for the development of national economies. In this area, Fintech, due to their greater use of technology, can provide financial services in an efficient, agile, and reliable manner, and they represent an opportunity for SMEs to access financing and overcome the limitations of access to investment funds, and thus achieve their growth and development objectives.

Methodology

This paper considers the business environment as a particular corporate system, in which the demands of investment resources constitute one of its key elements. The objective is to "model" the use or adoption of technological platforms for access to financial resources by Fintech, based on analysis of the determinants that influence the intention to use these new technologies in business activity.

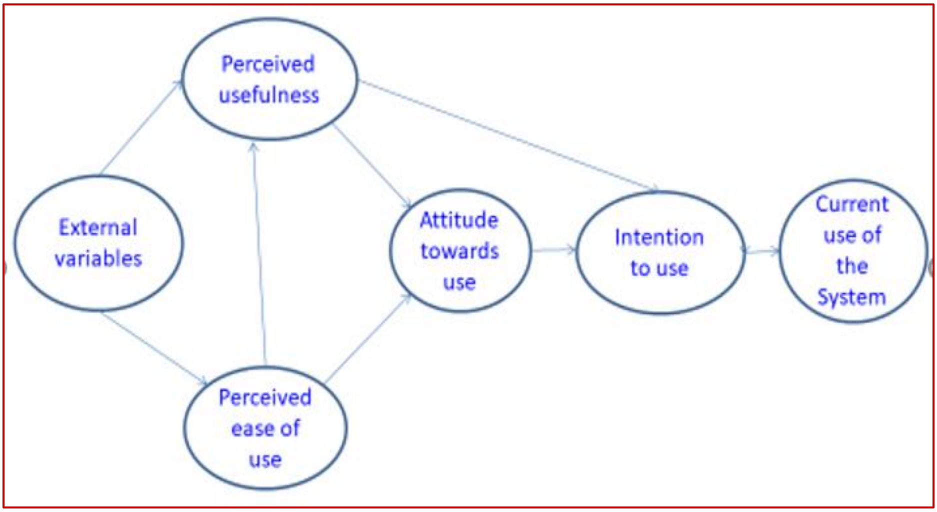
As mentioned above, the main theoretical model on the "Intention to Use" of technological services is the Technological Acceptance Model (TAM), which was developed by Davis (1989), and it is based on the reasoned action theory (Fishbein & Ajzen, 1975).

Since its development, the (TAM) model has been adapted to a large number of different technologies and it has proven to be very useful in a research and innovation context. Therefore, two main determinants influencing the intention to use technology were initially proposed: Perceived Usefulness and Perceived Ease of Use.

The latent variable "Perception of usefulness" refers to the perception that a person has about the improvement in work efficiency and effectiveness due to the technology use. It is evident that an elevated perception of usefulness is associated with a greater probability of technology acceptance. On the other hand, "Perceived ease of use" refers to the degree to which a person believes that the technology will be easy to use. The higher the perceived ease of use, the more likely the technology incorporation will be (Davis, 1989).

The analysis of these two constructs, shows that the relationships between them are direct but not with the "Intention to use". In particular, the "Faculty of use" establishes an indirect relationship with the latent variable "Intention to use" (Figure 2), through the construct "Attitude towards use"; which refers to the favourable or unfavourable feeling towards the technology use. That is, the degree to which an economic agent is willing to incorporate and to use technology in his or her business and work activity.

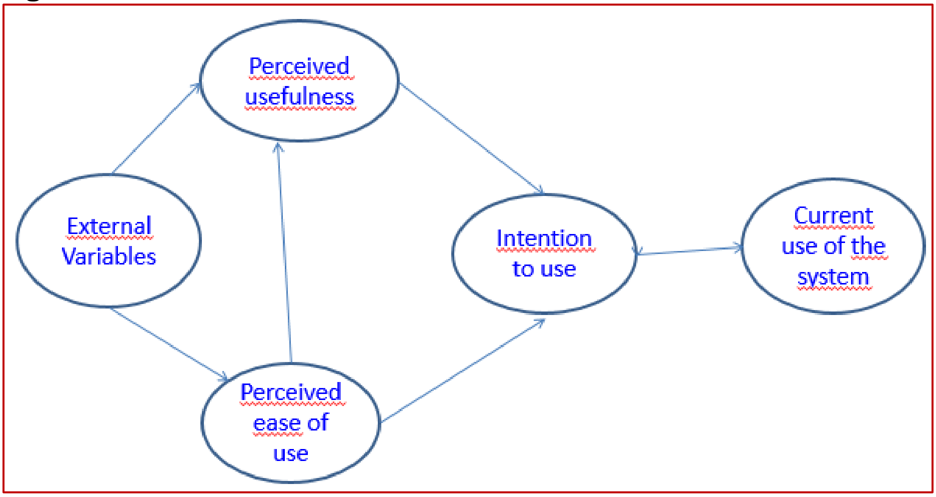
Figure 2: Basic Technology Acceptance Model (TAM)



Source: Own elaboration. Adapted from Davis (1989)

However, research by Venkatesh and Davis (1996) showed that the "perceived usefulness" and "perceived ease of use" factors are direct determinants of "intention to use" (see figure 3), unlike the basic model that includes the construct "attitude towards use" as a mediating factor.

Figure 3: Modified intention-to-use model with direct latent variables.



Source: Own elaboration. Adapted from Venkatesh and Davis (1996)

In summary, it is a fact that individuals are always making decisions about the acceptance, adoption, and use of computing and information technologies. Research that has studied the determinants of such a decision has found that “perceived ease of use” is a determinant of “intention to use.” Similarly, “perceived usefulness” has also been found to be a key determinant of “intention to use” (Venkatesh and Davis, 1996).

Empirical Research on Intention to Use Financial Technology Services

The TAM model has been adapted in its development to a multitude of different technologies and it has proven to be very useful in studies on factors influencing the intention to use Fintech services. Moreover, it was observed that the TAM model was one of the most widely used as base models to find the key latent variables that explain the intention to use and/or acceptance of technology. Thus, following Van et al. (2019), a modified TAM model was used in which factors such as Risk Perception, Brand Image, and User Innovation, among others, were considered.

The study by Van et al. concluded that "User Innovation" had the greatest influence. However, reviewing other previous empirical studies, we also identified other factors that have a greater recurrence and that have been shown to influence the intention to use Fintech services: “Perceived Usefulness, Perceived Ease of Use, Brand Image, User Innovation and Risk Perception” (Usma Córdoba, 2021).

Moreover, many empirical studies have found that this factor (“perceived usefulness”) has a significant and positive impact on intention to use (Martín-Sánchez, 2014; Sánchez et al. 2007; Miranda et al. 2015, Rial et al. 2014).

Methodological procedure

This paper assumes a quantitative approach. For data collection, we used a survey addressed to owners or representatives of small service enterprises in Metropolitan Lima.

For this purpose, a study strategy was developed for small businesses in the service sector that have used or heard about alternative sources of finance such as Fintech. According to 2019 data from Peru's INEI, there are 24,134 small enterprises operating in the service sector in Metropolitan Lima. However, there is deficient information on how many of these small businesses have heard of or used Fintech as an alternative financing source therefore, a non-probability sampling model was employed.

The questionnaire was designed and pilot-tested with five small enterprises, validated by experts and sent to representatives of the 100 small service enterprises selected in the initial sample. The survey was conducted virtually, between June and August 2021; 67 completed questionnaires were obtained, leaving 55 valid questionnaires after filtering and cleaning.

To determine the sample size, the multiple of 5 rules established by De la Garza-García et al. (cited by Rositas, 2014) was applied, which indicates that the number of observable items or variables should be multiplied by 5 to obtain the appropriate sample size. Since there were 20 items considered in the initial matrix, a total of 100 small businesses were selected, with the idea of finding differences in their behaviour in relation to their intention to use these platforms.

As it was a non-probabilistic sample, the results obtained can be considered as findings and not conclusions that can be generalised to the population of small enterprises in the whole of Metropolitan Lima. However, this sampling is useful for studies such as ours that require a careful and controlled choice of cases with certain characteristics, rather than a representativeness of elements of a population (Hernandez et al., 2014).

The measurement instruments used in this research are based on Van et al. (2019) studies, who referenced many other authors. The Perceived Usefulness factor (PUF) was adapted from Huh et al. (2009), Lim et al. (2018) and Hu et al. (2019); Ease of Use (FU) from Hu et al. (2019); Perceived Risk (PR) from Marakarkandy et al. (2017) and Hu et al. (2019); Brand Image (MI) by Ruparelia et al. (2010) and Hu et al. (2019); Government Support by Hu et al. (2019); and finally, Intention to Use (IU) by Marakarkandy et al. (2017). The observed variables and the factors that were identified and deemed relevant for this study are detailed in Annex 1.

The questionnaire consists of closed questions, measured on scales. The questionnaire used is detailed in Dolores and Vasquez (2022). The scale used is a

Likert-type scale consisting of 5 levels with 1 = Strongly Disagree and 5 = Strongly Agree.

The internal consistency of the collected quantitative data was assessed using Cronbach's alpha coefficient and the complex reliability (CR) criterion. Then, the confirmatory factor model was used for the estimation and examination of the measurement model, and the structural equation model was used for the causal model. These methods are widely used in the fields of economics, business, psychology, and behavioural sciences, etc...

Analysis Of Empirical Evidence

In the analysis of the internal reliability of the data, we use the Cronbach's Alpha coefficient, which estimates the reliability based on the average of the correlations between the items or variables. According to Leech et al. (2005), Cronbach's Alpha coefficient should be higher than 0.7 in exploratory research to guarantee sufficient reliability or greater consistency of items among themselves.

The reliability analysis results are shown in Table 2, where Cronbach's Alpha coefficients show values higher than 0.7 for all the scales considered. Moreover, "Perceived usefulness" and "Intention to use" factors have much higher values: 0.853 and 0.819, respectively. The exception is the latent variable "Brand image" which has a value of (-0.005). However, what is surprising about this result is that this factor has been the subject of important research, such as Hu et al. (2019) and Van et al. (2019).

Table 2: Results of reliability analysis

Factor	**Alfa de Cronbach**	**Número de elements**
Perceived usefulness	0,853	5
Perceived Ease of Use	0,794	3
Brand Image	-0,005	3
Perceived Risk	0,764	3
Government Support	0,737	3
Intention to Use	0,819	3

Source: own elaboration

This prompted the need for a more detailed review of the items or elements associated with this factor, which revealed that the first item (I1 = "I consider that I prefer to use the sources of financing from more familiar companies") does not adequately measure the factor in question.

In other words, the "brand image" factor is not manifested through this item, therefore, it was removed from the set of items associated with this factor. Then, the corresponding Cronbach's alpha was recalculated and an acceptable value of 0.698 (= 0.7) was obtained. One possible explanation for that fact is the feasible predisposition in the responses to this item by company representatives, because it did not seem relevant to them to use familiar sources of finance, since their preferences are more inclined towards alternative sources such as Fintech. It could also be due to the fact that the item wording may not have been the most appropriate and it could have been worded in a different way with a more positive connotation.

Analysis of the Measurement Model (CFA)

Before building the structural model to determine the main factors influencing the use of Fintech by small service companies in Metropolitan Lima, a measurement model was built initially considering all factors and observable items included in the sample. For this purpose, the multivariate model of confirmatory factor analysis was applied using the AMOS v.26 program of the SPSS statistical package.

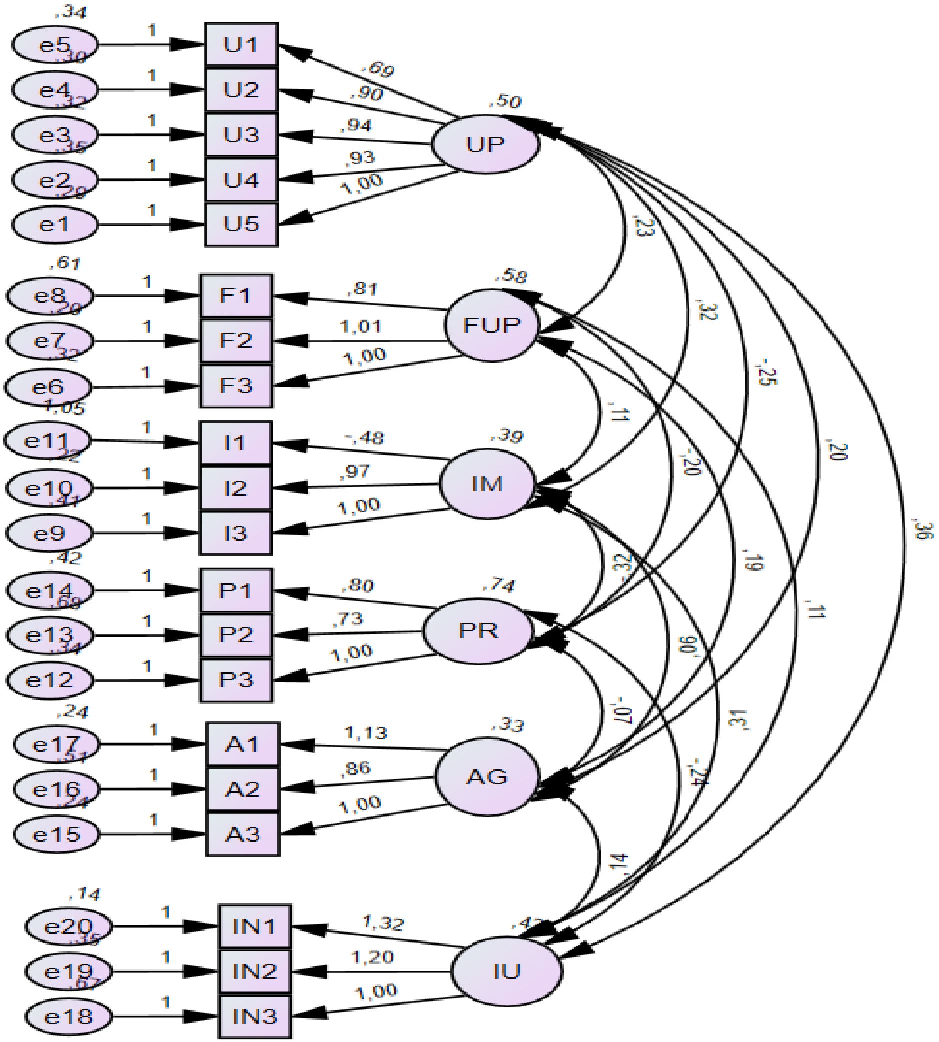
The initial measurement model, which serves as the basis for the structural equation model, includes the covariances and correlations between the factors UP (Perceived Usefulness), FUP (Perceived Ease of Use), IM (Brand Image), PR (Perception of Risk) and AG (Government Support). These factors form interdependent relationships with the aim of explaining possible influences on the behaviour of the interest factor, such as the "Intention to Use" (IU)) of Fintech financial services.

The purpose of the confirmatory factor analysis is to statistically evaluate the ability of the proposed factor model to validate the hypothesis that the latent factors are adequately revealed through the indicators associated with each one of them [Hair et al., 1998].

In the first application of CFA, we used the maximum likelihood method to validate the proposed model, initially considering all items and factors identified in theory and empirical evidence. The representation of the variance-covariance diagram of the initially proposed measurement model is shown in figure 4.

At this point, we consider that a fit indices set is the most appropriate way to check the fit goodness of the model. This set should include absolute criteria (the Chi-square test corrected by freedom degrees ($\chi2/gl$) and the Standardised Root Mean Square Residual index, SRMR), parsimonious (the Root Mean Square Residual of Approximation, RMSEA, with its confidence interval (CI), and the PCLOSE index), comparative (partial adjustments) (the Comparative Goodness of Fit Index, CFI).

Figure 4: Relationship diagram of the initial measurement model



Source: Own elaboration

Moreover, following Cheng et al. (2016) and Steppan et al. (2014) acceptable fit values are: χ2/gl ≤ 5, SRMR > 0.08, RMSEA ≤ 0.08, GFI ≥ 0.90, AGFI ≥ 0.90, TLI ≥. 90, CFI ≥ .90; and as a very good fit: χ2/gl between 1 and 3, RMSEA ≤ 0.05, GFI ≥ .95, AGFI ≥ .95, TLI ≥ .95, CFI > 0.95 and, a result will be significant if its p-value ≤ 0.05.

Based on these criteria, the validation results of the initial model fitted by confirmatory analysis were not satisfactory, although the absolute χ2/gl index is significant since it takes a 1.448 value and falls within the recommended range (1-3). However, the remaining relevant adjustment criteria were not significant, because they are above or below their corresponding thresholds (CFI = 0.87 < 0.95; SRMR = 0.11 > 0.08; RMSEA = 0.091 > 0.06) (see annex 2).

Regarding validity in convergence and discrimination terms, the reliability index denoted by 'CR', shows, in all cases, values greater than 0.7, which is the recommended value to validate the convergence of a factor (Table 3).

Similarly, it is observed that the diagonal values of the six factors are higher than the vertical and horizontal values of the factorial matrix (factorial correlations). However, in discriminant validity terms, it is observed that AVE index is lower than MSV index (in contrast to what is recommended) in the latent variables 'Perceived Usefulness' and 'Brand Image' types, so therefore, it is not possible to guarantee that both factors show different concepts.

Table 3: Initial model fit indices

	CR	AVE	MSV	MaxR(H)	UP	FUP	IM	PR	AG	IU
UP	0,858	0,549	0,605	0,864	0,741					
FUP	0,812	0,595	0,185	0,848	0,430*	0,771				
IM	0,705	0,545	0,603	0,709	0,774**	0,295	0,738			
PR	0,766	0,526	0,362	0,796	-0,414*	0,299*	-0,602**	0,726		-0,434*
AG	0,756	0,513	0,252	0,783	0,502*	0,425*	0,223	-0,147	0,716	
IU	0,830	0,624	0,605	0,888	0,778	0,220	0,776	---	0,376	0,790

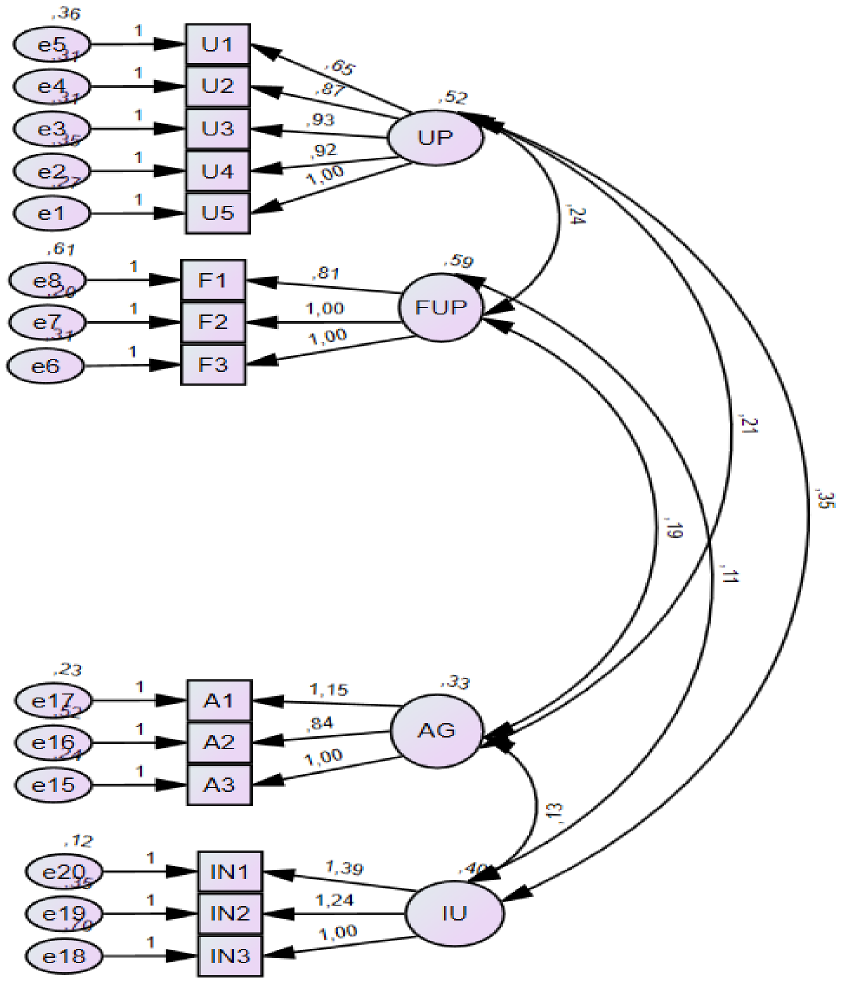
Source: Own elaboration

In summary, these results show that the indicators through which the factors are displayed present problems for measuring the theoretical concepts considered in the initial model. Therefore, it will be advisable to conduct a re-specification of the model considered the results obtained.

In this re-specification process, statistical criteria (modification and factorial saturation indices for each indicator) and theoretical criteria (conceptual coherence indicator-factor) were considered in order to maintain the conceptual value of the model (Pérez et al., 2013). After several confirmatory analyses in which we have carried out several specifications, starting with the initial model (Batista-Foguet et al., 2004) in which the low regression weights of the indicators were taken into account: U1, F1, P2 and A2, and a second model in which it is recommended to remove the "Brand Image" and "Risk Perception" factors because they did not pass the validation test. This would explain the unsatisfactory fits initially found.

The final model is shown in Figure 5, where the "Brand Image" (MI) and "Perceived Risk" (PR) factors have been removed because they did not meet the convergent and discriminant validity requirements.

Figure 5: Final measurement model



Source: Own elaboration

The estimates of the model coefficients are based on the following assumptions:

H0: The estimated covariance-variance matrix matches with the population variance matrix.

H1: The estimated variance-covariance matrix does not match with the population variance-covariance matrix.

While it is "desirable" to accept H0 (p-value ≥ 0.05 the best solution), in general, the chi-square test will be significant (CMIN = $\chi 2$ = 51.632 which is greater than the theoretical table value), which would indicate that the null hypothesis should be rejected (which we do not want) (table 4).

Table 4: Fit Indices of the final model

Measure	Estimated	Target	Interpretation
CMIN	51.632	--	--
DF	39.000	--	--
CMIN/DF	1.324	between 1 and 3	Excellent
CFI	0.953	> 0.95	Excellent
SRMR	0.079	< 0,08	Excellent
RMSEA	0.077	< 0.06	Acceptable
Pclose	0.219	> 0.05	Excellent

Source: Own elaboration

But, according to (Long, 1983, p.75; Marsh, Balla and McDonald, 1988; p.392) the chi-square is an insufficient statistic to make the decision to discard the model, since it is a very sensitive test to deviations from multivariate normality and sample size (n = 57).

Due to the obvious limitations of the chi-squared statistic, a set of alternative fit indices based on less restrictive assumptions are examined. The selected alternative measures are based on a Monte Carlo simulation by Hu & Bentler, 1998 and Marsh, Balla & McDonald, 1988.

Thus, we observe that the absolute SRMR (Standardised Root Mean Square Residual) takes a 0.079 < 0.08 value, which would indicate a good fit. Another indicator, the parsimony, represented by RMSEA (Root Mean Square of Error Approximation) has the 0.077 value, which is in the acceptable 0.06 - 0.08 range (Browne and Cudeck, 1993).

Similarly, we have the comparative or incremental indices, which compare the estimated model with a reference model (model in which all the observable variables would be uncorrelated), such as CFI (Comparative Fit Index). This last index has a 0.953 value, which is above the threshold of 0.95, indicating the good performance of the specified confirmatory factor model.

From the combination of these goodness-of-fit indices, at least one for each type: the absolute, parsimony and comparative variables, allows us to draw a preliminary conclusion of the latent variables UP, FUP, AG. The conclusion is that these variables are relevant and influential in the intention to use Fintech by small service companies in Metropolitan Lima (MSMEs) as a financing source of the investments required for their proper functioning.

Before verifying the causality hypotheses through the Structural Equations model, a convergent and discriminant validity analysis was carried out for each of the constructs, based on the CFA model, in order to determine that each construct measures what it is intended to measure (convergent validity) and that it is different from the other constructs (discriminant validity).

In other words, the reliability of the observed items was assessed in conjunction with the reliability of the constructs (see Table 5). This analysis was conducted on the basis of the Composite Reliability (CR), the Average Variance Extracted (AVE), the Maximum Shared Variance Squared (MSV), and the Mean Shared Variance Squared (Bohrnstedt, 1976).

Table 5: Validity indicators of the final measurement model.

	CR	AVE	MSV	MaxR(H)	UP	FUP	AG	IU
UP	0.861	0.608	0.526	0.866	0.780			
FUP	0.836	0.720	0.115	0.863	0.339†	0.848		
AG	0.769	0.625	0.229	0.770	0.478*	0.314	0.791	
IU	0.827	0.622	0.526	0.901	0.725	0.149	0.383	0.788

Source: Own elaboration

The reliability of the items used in the convergent validity model indicates the amount of variance due to the underlying variables, rather than measurement errors. Since a reliability greater than 0.5 is considered evidence of confidence or precision (Chau, 1997), we found that the average variances extracted (AVE) exceed the recommended threshold of 0.5 (Fornell, 1981) for all latent variables considered. This result indicates that a considerable proportion of the information contained in the indicators or variables of the model is due to the constructs of interest.

Similarly, convergent validity also assesses the degree to which items that have the same concept are correlated. Thus, a high correlation would indicate that the measurement scale is measuring the desired concept. As we can observe, the large majority of the items on the measurement scale have factor loadings greater than 0.7; although, according to Fornell and Larcker, 1981 and Hair et al., 1998, correlations with values greater than 0.5 may also be acceptable, as in the case of the constructs under study.

An indicator or test is said to be reliable if it yields internally consistent results. Consistency can be measured by the "Composite Reliability Analysis" (CR) (Fornell and Larcker, 1981). Table 5 shows that the CR values are above the recommended threshold (0.6) for all concept variables (Bagozzi and Yi, 1988).

Regarding discriminant validity, the most commonly used index is the "Maximum Shared Variance Squared" (MSV), which allows us to verify that the indicators associated with a latent construct are not related to other constructs, with which they should not be related (Hair et al., 2010). According to Fornell and Larcker (1981), the discriminant validity can also be analysed by using the 'average variance extracted' (AVE) but comparing it with the 'maximum shared variance' (MSV) so that MSV < AVE can be verified. We note in table 5 that the MSV index of each one of the constructs is lower than the corresponding AVE value, indeed, all of them exceed the 0.5 value.

In summary, based on the results of the final measurement model, we can affirm that both, the convergent and discriminant validity conditions are met, which would indicate that the constructs that make up the model reliably measure the concepts they claim to represent.

Since the final measurement model does not include risk perception as a factor influencing intention to use, it is not possible to assess the H1 initially proposed: "H1: Risk perception has a negative influence on the intention to use Fintech among small service companies".

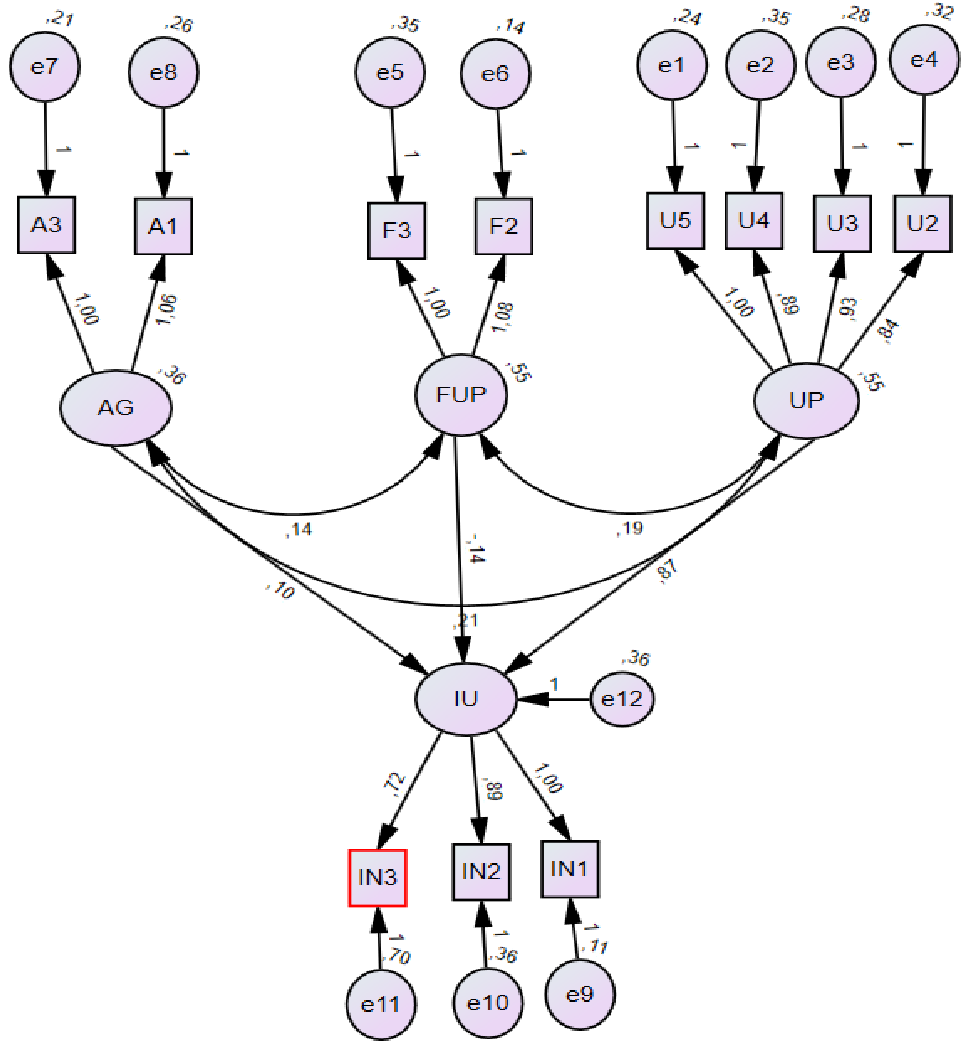
Analysis of the structural model

Once it has been verified that the constructs of the model are reliably measured and the conditions of convergent validity of the items and discriminant validity of the constructs are verified, the structural model is built. In this way, the "causality" coefficients can be estimated, and the factors considered to have a significant influence on the intention to use Fintech validated.

The structural model establishes the relationships between endogenous and exogenous latent factors and all other relationships that are not part of the measurement model. Our main interest is to obtain the weights of the relationships in the structural model. With them we could, for example, compare the strength of causal relationships or compare direct and indirect influences between variables.

Figure 6 shows the relationships between the exogenous and endogenous constructs, as well as the estimated parameters and the fit indices of the structural model.

Figure 6: Structural Model



Source: Own elaboration

To determine to what extent the estimated covariance matrix of the structural model adequately reproduces the relationships existing in the covariance matrix of the empirical data, we analysed the quality of fit using a set of indices and factor parameters. Table 6 shows the relevant indices for the analysis of the validity and reliability of the structural model used.

Table 6: Structural model fit indices.

Measure	Estimate	Target	Interpretation
CMIN	51.632	--	--
DF	39.000	--	--
CEMIN/DF	1.324	between 1 and 3	Excellent
CFI	0.953	> 0.95	Excellent
SRMR	0.979	< 0.08	Excellent
RMSEA	0.077	< 0.06	Acceptable
PCLOSE	0.219	> 0.05	Excellent

Source: Own elaboration

The first test to determine the goodness of fit of the model is the chi-square test, in particular the test corrected for freedom degrees. This indicator must be less than or equal to 3 ($\chi 2/df \leq 3$) (Kline, 2004) for reasonable model fit. Table 6 shows that the $\chi 2= 51.632$ with 39 freedom degrees (df) and $\chi 2/df = 1.324$, which is less than 3, indicating a good model fit.

This result is corroborated by the remaining absolute, parsimonious, and comparative indices. The Comparative Fit Index (CFI), which represents the discrepancy of the proposed model relative to the independent model, has an estimated value of 0.953 > 0.95 indicating a good model fit (Bentler and Bonett, 1980).

Similarly, the SRMR index, which has the value of 0.079 < 0.08, indicates that the estimated model adequately reproduces the observed data (particularly good fit). On the other hand, the RMSEA index has a value of 0.07, which is slightly above the recommended threshold of 0.06, although there are authors (Steiger, 2007) who consider that the recommended threshold is 0.07, therefore we could consider that the discrepancy level between the model and the data in the population is small. However, the RMSEA also tends to worsen when sample size and freedom degrees are taken into account, especially when working with samples smaller than N < 250 (Kenny and Mccoach, 2003).

The estimated coefficients between the latent variables show that "Perceived usefulness" have a strong direct and positive relationship with "Intention to use" (0.87), therefore, it is possible that the estimated value is significantly different from zero. While the "Perceived ease of use" and "Government support" factors show a weak relationship (0.14 and 0.10), respectively, with the UI factor (see Figure 6).

With these estimated results in the structural model, it is only possible to partially accept H2 as initially proposed. H2: Perceived Usefulness, Perceived Ease of Use, Brand Image, Perceived Risk, and Government Support significantly influence Fintech usage intention among small service companies. It is evident that Brand Image and Risk Perception were not included in the final measurement model.

Finally, the correlations between the constructs (represented by bidirectional arrows) are relatively low, among these, the correlation between GA and UP, in other words, between the construct representing government support and the perceived usefulness associated to Fintech, with a 0.21 value. By contrast, the lowest correlation is between AG and FUP, i.e., between the construct representing government support and ease of use technologies, with a 0.14 value.

Limitations and Comments

An important limitation in the development of this research has been the impossibility of personally conducting the quantitative fieldwork, especially since the study subjects were small service companies in Metropolitan Lima, and also due to the pandemic situation generated by COVID-19.

Therefore, data collection was carried out virtually. One of the consequences of this feature was that only 67% of all the companies selected completed the survey. This is a fairly significant value that allowed us to continue the research in exploratory terms. Therefore, the results cannot be generalised to the whole service sector in the Metropolitan Lima city.

However, it is a crucial step forward in the study of the financial gap in developing countries and, in particular, in the identification of the concepts that determine the use of Fintech in economies with an elevated level of informality, as in Metropolitan Lima.

Another limitation of this study is related to the application range of the SEM causal model, which in our case is limited to the Metropolitan Lima area. Therefore, the results are not universal, and it will be necessary to conduct similar studies in other countries or regions to validate and generalise the results obtained.

Conclusions

One of the conclusions of this study is that the intention to use alternative financing systems such as Fintech is a fact that has come to stay and spread among SMEs, family businesses and self-employed.

Fintech is disruptive as an alternative source to access working capital and investment financing through peer-to-business platforms because it makes capital resources available to MSMEs in short or truly brief time, unlike the traditional or analogue financing system.

The causal model initially proposed, based on theory and evidence, which sought to explain the "Intention to use" Fintech as alternatives to access business credit was not full satisfactory. Because it seems that the most relevant factor for MSMEs to apply for credit in alternative capital markets is the "Perceived Usefulness", which implies that all other factors have a non-significant effect on the decision to use Fintech.

Companies that have difficulty accessing the traditional capital market evaluate the usefulness of Fintech financing to cover their capital needs above any other factors. This factor is the determining factor for the companies surveyed to decide the use of Fintech to improve productivity, efficiency, and growth.

Regarding the 'Government support' construct, although there is a positive assessment of respondents towards it, its influence on the "UI" is exceedingly small. However, the promotion of Fintech services by the government is important for companies that are not aware of the characteristics of this alternative system of access to investment resources in working and operating capital.

On the other hand, we found that the Fintech ecosystem in Peru, and in particular in Metropolitan Lima, is relatively new for Peruvian entrepreneurs, and more than half of MSMEs have not used any type of Fintech.

We also found that it will be difficult for Fintech to compete with traditional banks in certain market segments and with certain types of products and services. The low barriers to entry provided by software-based technology and the significant difference in costs and resources between traditional institutions and Fintech start-up will make it difficult for many of them to succeed.

Finally, the results obtained in this research are considered findings and not conclusions that can be generalised to the population of small enterprises throughout Metropolitan Lima. However, this sampling is useful for studies such as ours that require a careful and controlled choice of cases with certain characteristics, rather than a representativeness of elements of a population.

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