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Article

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BANKING & FINANCE | RESEARCH ARTICLE

The impact of demographic factors of clients' attitudes and their intentions to use FinTech services on the banking sector in the least developed countries

Hussein Ahmed Alshari^{1,2*} and M. A. Lokhande¹

Abstract: This research aims to explore the impact of demographics (age, gender, education, and income) on clients' attitudes and their intention to use the FinTech services of banks by using the TAM model, Yemen as a case study. The data for this study were collected using a questionnaire shared among 435 respondents who are clients of five Yemeni banks that provide FinTech payment services. Structural equation modeling via PLS was used to validate the model's constructs. The results show that education and income levels have a significant negative effect on risks and a high positive effect on the perceived benefit of using FinTech to clients. Gender, income, and risks show a significant negative effect on attitude. Education, PEOU, PU, and trust all exhibit a high positive effect on the attitude of banks' clients to using FinTech services. Finally, there is a very high positive relationship of attitude with intention. As an independent study, this research contributes to clarifying the effect of demographic factors on the use of FinTech by consumers, considering that studies in this field are minimal. In addition, it contributes to highlighting important



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PUBLIC INTEREST STATEMENT

In developing countries, consumer usage of financial technology varies to varying degrees from developed countries. This is because several essential aspects play an important role, such as the demographic of customers. The level of education in the least developed countries affects the use of modern digital technology. The level of income in society also has a high impact on the advancement of digital technology. FinTech use also varies by gender and age group. Several previous studies clarified the attitudes and intentions of consumers for FinTech services in banks and FinTech companies. However, there is scarcely an independent study showing the extent to which demographic factors influence the intentions and attitudes of consumers toward FinTech services, as well as the extent to which demographic factors affect the risks and confidence of consumers. This is covered by the current study.

steps for decision makers to keep pace with financial technology developments in the least developed countries in general and in Yemen in particular.

Subjects: Finance; Business, Management and Accounting; Industry & Industrial Studies

Keywords: FinTech; payment; demographic; TAM model; trust; risks

1. Introduction

Financial technology is a recent topic in which modern technological innovations such as programs, technologies, and modern systems are mixed with financial services, and they tangibly emerged after the global financial crisis of 2008 (Wausups, 2017). This crisis has contributed to the emergence of FinTech companies as technological innovations in the field of financial services (Arner et al., 2015). Millennials and future generations are ambitious to use technology in most of the services they need and desire, starting with getting a meal to eat, obtaining transportation (taxis), making home orders of goods, booking airline tickets, and other services electronically and perhaps by mobile phone (Karsh, 2021). This approach also extends to obtaining financial services such as paying for goods or services, managing money, investing and borrowing in a safe and easy way electronically and perhaps by mobile phone (Diana & Leon, 2020). Consumers' use of financial technology varies to different degrees in developing countries, as does the availability of financial services through electronic methods and modern technologies. The adoption of technology in securing services differs from one country to another at the same level of development. There is also a difference in the use level of FinTech between developing and developed countries. This is due to the presence of many important factors that play a role there (Haddad & Hornuf, 2019). The availability of basic requirements such as smartphones and high-speed Internet is one of the important factors for obtaining FinTech services (Kalra, 2019). The extent to which financial institutions and companies adopt modern technology in providing their services is also a key factor. In addition to the factors that affect consumers' adoption of FinTech, there is an urgent need to study the individual differences between consumers in their use of FinTech. The level of education in the least developed countries affects the use of modern digital technology. Their level of education compared to developed countries is low, which affects the adoption of technology in their daily lives, including digital financial services (Habibi & Zabardast, 2020; Liu, 2020). Studies have shown that the skills gained through education determine the use of all technological services. The level of income in society also has a high impact on the advancement of digital technology. However, the least developed countries suffer from weak education systems and poor income levels. Modern digital technology has become a necessary part of finance today. Despite this, the least developed countries lag in the global digital transformation race, as recent reports have shown the widening digital technological gap between these countries and developing countries. A high proportion of younger cohorts characterize the population structure of the least developed countries. As of 2020, (39%) of the population of the least developed countries was under 15 years of age. It is also possible that a woman will need to obtain the consent of her family to own a cell phone, and in some poor families, several family members may share one mobile phone. In all developing countries, women have less access to digital technology, which prevents them from benefiting equally from digitalization. Many digital solutions reach fewer women than men (Countries, 2021). Some theories and models clarify the basic factors in adopting FinTech by consumers in their financial dealings, such as TAR theory (H. H. Ryu, 2017) and TAM model (Chuang et al., 2016; Davis, 1989). In this study, we use the TAM model to understand the attitudes and intentions of consumers in adopting FinTech. There are also other factors such as trust and risks in use, which are considered important in adopting FinTech services (Meyliana et al., 2019). These two factors were employed in the current study to gauge their impact on adopting FinTech by consumers. Other factors such as demographics (age, gender, income, and education) also directly affect this adoption. However, in previous studies, there is a paucity of investigation of such demographic factors and the extent of their impact on adopting FinTech services; this research gap is addressed in this study. The emergence of financial technology in developing countries has led to an interest in all financial services, including banks, because of their impact on

clients' desire to keep pace with modern technological developments that bring financial services within reach, making their use easier and more comfortable. This has attracted the interest of researchers who seek to investigate the effects of FinTech on financial institutions and understand the opinions of clients. This study provides an academic and practical view of consumers' attitudes and their intention to use FinTech services in Yemeni banks, measured according to the TAM model by perceived ease of use, perceived usefulness, attitude, and intention in addition to trust and risk factors; this is to achieve the purpose of this study, which is to explore the impact of demographic factors (age, gender, income, and education) on consumers' attitudes and their intention to adopt FinTech services. This study used a quantitative research methodology. The descriptive and causal modelling tests were used as methods, and the survey method involved a questionnaire for collecting data. Previous researchers have reported only a marginal effect of demographic factors. Also, studies of financial technology in the least developed countries are very few and maybe even rare. Considering these points, the researcher set out to conduct this study to identify and explore the extent of the impact of demographic factors (gender, age, education, income) on the use of FinTech in the least developed countries in general and in Yemen in particular. A questionnaire was distributed to collect data from the clients of the banks that adopt FinTech payments in Yemen to identify their attitudes and intentions. The TAM Model with its variables (PEOU, PU, attitudes, and intention) and two other variables (trust and risk) are used, which made a strong motivation to achieve this study. The results of the study reveal a significant effect of the factors; when the level of clients' education increases, the usefulness is increased, while the risks of using FinTech decrease. Also, with a higher income, the risks are reduced and benefits from the use of FinTech increase. Men and women have different attitudes towards the use of FinTech. There is a difference between their attitudes the clients' negative reason for their income. An increase in the level of education also has a large influence on increasing the clients' positive attitude towards FinTech services. This study also revealed that clients' trust and perceived usefulness of using FinTech have a high influence on their attitude towards adopting FinTech, while the risk of using FinTech has a negative influence on clients' attitude toward using FinTech. Furthermore, the research found a very strong relationship between clients' attitude and their intention of using FinTech. This study contributes to enriching literature and assisting those interested and researchers in this field, as studies focused on the extent to which customers accept FinTech services (Hu et al., 2019; Meyliana et al., 2019). Other studies focused on the extent to which customers trust these services (Fernando et al., 2018; Hu et al., 2019; Jaradat & Twaissi, 2010) and the extent to which they accept their risks (Meyliana et al., 2019; Tang et al., 2020). While this study focuses on the impact of demographic factors on the attitudes and intentions of bank customers using FinTech payment services. As well as the impact on their confidence and accept the risks of FinTech payments services. Therefore, this study is one of the very few important studies. It also contributes from a practical point of view to assist decision-makers in banks in the extent of the impact of demographic factors on the study's variables.

2. Review of literature

2.1. FinTech and theories

Through looking at previous studies, it is noticed that many researchers have theories and models to study the extent to which consumers have adopted FinTech services as the following: Theory of Reasoned Action (TRA) suggested by (Fishbein & Ajzen, 1977), has considered one of the first theories about consumer behaviour and prediction the factors affecting it. For example, consumer attitudes, prediction of their intentions, and other factors. We considered its impact on consumer behaviour (Tang et al., 2020). This theory was used to find out consumers' attitudes and intentions to adopt FinTech services, with the result that risks had a negative impact on users' intention to adopt FinTech services (H. H. Ryu, 2017; Shah et al., 2019). Technology Acceptance Model (TAM) was suggested by Davis et al., 1989), to predict the acceptance of consumers in using technology (Davis et al., 1989). The TAM model is one of the popular models used in many kinds of research because of its relationship to the extent of technology use. The current era is the era of technology and the emergence of many modern electronic programs and systems that have made

researchers more use of this model. It works on development (Davies & Venkatesh, 1995). FinTech used (TAM) to know the attitude and attention of customers to adopt FinTech services and mobile payment in particular (Hu et al., 2019; Jaradat & Twaissi, 2010; Meyliana et al., 2019). The majority of determinants of this model have perceived Usefulness (PU) as the acceptance to use of any technology depends on the benefit that the consumer gets (Davis, 1989). Perceived Ease of Use (PEOU) when it is difficult to use any technology, the acceptance of using this technology is weak or absent (Davis, 1989; Hu et al., 2019). Attitudes Towards Using (ATU) Consumer attitudes express their beliefs about accepting the use of a particular technology (Fishbein & Ajzen, 1977). Intention to use (IU) Consumers' intentions and aspirations respond to their attitudes toward acceptance of technology in a particular (Fishbein & Ajzen, 1977). According to (Hu et al., 2019; Meyliana et al., 2019), the results show that the users' trust in FinTech services has a significant impact on users' attitudes toward adoption (Fernando et al., 2018; Stewart & Jürjens, 2018). While the perceived risk hasn't influenced users' attitudes toward the adoption of FinTech services, but the study of (Fernando et al., 2018) goes the opposite which shows there is an effect of perceived risk on adopting FinTech. (Fernando et al., 2018). Opposite trust is one of the most significant perspectives identified in consumer attitude and their intentions, and recently, because of the use of technology in many areas, researchers have worked to find the impact of consumers' trust in the adoption or use of modern technology (Fernando et al., 2018; Hu et al., 2019; Jaradat & Twaissi, 2010). The Risks, Consumer behaviour and belief about risks to use of new technology lead to the generation of an intention in the consumer to hesitate or not use this technology. Thus, the risk factor has a significant role in determining consumers' intention towards using new technology or a specific (Meyliana et al., 2019; Tang et al., 2020; Chen & Li, 2017; H. H. Ryu, 2017). This study contributes to enhancing the impact of demographic factors in consumers' attitude and their intention to use FinTech services by (TAM) model. This study covers a gap because of the lack of studies on the demographic factors of the consumers' intention of FinTech services.

In Table 1 the researchers show a summary of the previous essential studies (Hazaea et al., 2021).

3.2. Conceptual framework and research hypothesis

3.2.1. Age

The Studies (EY, 2017; Frost, 2020; Gulamhuseinwala et al., 2015; Shah et al., 2019) indicate to the age group has an impact on consumers' trust in the use of technology in general and financial technology in particular. The consumers' trust in the technology, the older age category may be less than the young age category. Also, the age category influences accepting the risks of using financial technology (Meyliana et al., 2019; Tang et al., 2020). So, this study hypothesized the following:

H1a: Whenever the age increases the trust in to use of FinTech decreases.

H1b: Whenever the age increases the risks to use FinTech decreases the use of technology by older individuals decreases. The benefit of using technology becomes less, as well as for younger individuals whose ability to use technology is more (Lee et al., 2010; Porter & Donthu, 2006).

H1c: Whenever the age increases the PEOU to use FinTech decreases.

H1d: Whenever the age increases the PU to use FinTech decreases.

3.2.2. Gender

Global System for Mobile Network Association (GSMA): In 2020 the latest assessment showed that women use fewer mobile phones than men, especially in low- and middle-income countries where

Table 1. Shows the summary of the previous essential studies

No	Reference	Country/ methodology	Objective of the study	Results of the study
1	Jin et al. (2019)	Malaysia (TAM model)	<ul style="list-style-type: none"> To examine the extent of Malaysians' awareness of the use of FinTech services, and factors that affect consumer acceptance of FinTech products. To develop a conceptual framework that includes independent variables such as ease of use, perceived risk, perceived cost, comparative advantage, benefit, and mediating effect to educate consumers about the dependent variable of consumer acceptance of FinTech products and services. 	<p>The consumers' intention to adopt online product services is significantly influenced by their perceived usefulness.</p> <p>Relative advantage has a significant impact on attitude and intention to adopt mobile banking.</p> <p>The intent of consumer behavior is significantly influenced by the perceived risk.</p> <p>Perceived cost significantly affected behavioral intent to use mobile payment.</p> <p>Age has a significant impact on the individual when using a mobile phone for electronic payment.</p>
2	Fernando et al. (2018)	Indonesia TAM model	<ul style="list-style-type: none"> To investigate the influence of risk and trust in the use of FinTech in Indonesian society. 	<p>This study has developed a tool to find out the effect value of the elements of trust and risk.</p> <p>This study has validated a tool in adopting a FinTech service perspective on trust and risk in Indonesia.</p>
3	Stewart and Jürjens (2018)	Germany TAM model 209 questionnaires (EFA)analysis	<ul style="list-style-type: none"> To determine the factors that affect the expectations of both users and organizations in adopting FinTech, such as data security, value-added, user interface design, customer trust, and promotion of FinTech. 	<p>The results of this study confirm that data security, user interface design, and customer trust influence FinTech adoption.</p>
4	Kim et al. (2015)	Korea TAM model Elaboration Likelihood Model	<ul style="list-style-type: none"> To investigate the acceptance of customers in the use of FinTech services when paying electronically. To analyse the causal relationship between CFIP (Concern for Information Privacy) and Self-efficacy by adopting them as moderating variables. 	<p>Mobility had no effect on the intention to use FinTech services. This means that the mobility is not particularly attractive to the user when executing the transaction. In this study, the most important factors for acceptance were utility and ease of use which means that swift registration, ease of use, and comfortable UI/UX environment may be the most important factors in the acceptance of potential users of payment type FinTech services.</p>
5	Lim et al. (2019)	Apple Pay and Samsung Pay EPAM model 14-9 questionnaire	<ul style="list-style-type: none"> To analyze the relationships between knowledge regarding services, perceived benefit, confirmation, and perceived safety and satisfaction. To develop a research model using the Extended Post-Acceptance Model (EPAM) as a theoretical framework in the context of Fintech services. 	<p>Perceived security and thorough knowledge of the importance of mobile FinTech services have a significant impact on users' confirmation and their perceived usefulness. Perceived security does not directly affect users' satisfaction and continued intention to use significant relationships between perceived benefit, confirmation, satisfaction, and continued intent to use FinTech services.</p>

(Continued)

Table 1. (Continued)

No	Reference	Country/ methodology	Objective of the study	Results of the study
6	Humbani and Wiese (2018)	South Africa TRI model 416 questionnaire	<ul style="list-style-type: none"> To contribute to the applicability of the TRI to new contexts. To suggest various additional drivers and inhibitors that need to be considered in the adoption of mobile payment applications. 	Compatibility and convenience drive consumers' adoption of mobile payment services whereas risk, cost, and insecurity are inhibitors. The adoption of mobile payment services leads to significant socio-economic benefits regardless of Gender.
7	Mulyana et al. (2020)	Indonesia UTAUT model	<ul style="list-style-type: none"> To investigate how the adoption of customer behavior as a business media by using the UTAUT model developed by Venkatesh. 	Intent behavior is positively influenced by social influence, facilitation conditions, expected average effort, and performance expectation, and has implications for user behavior based on the UTAUT model. Implementing customer behavior in the use of FinTech for business needs to take into account performance developments.
8	H.-S. Ryu (2018)	Korea 243 questionnaire (PLS-SEM)	<ul style="list-style-type: none"> To understand why people may or may not want to use FinTech. To identify how the effect of perceived benefits and risks of continuance intention differs depending on user types (i.e., early and late adopters). 	The results show that convenience has the strongest positive effect on FinTech's viability intention, while the legal risk has the most negative effect. Differences in specific benefits and risk effects were found between early and late adopters.
9	Chuang et al. (2016)	Taiwan TAM model 440 questionnaire	<ul style="list-style-type: none"> To understand the impact of different age groups and consumer behavioral intentions on the adoption of financial technology in Malaysia To understand the intention of using FinTech services in the manufacturing industries. 	Brand and service trust, Perceived usefulness, Perceived ease of use, and behavioural intention have significantly positive effects on attitudes toward using FinTech Services.
10	Hu et al. (2019)	China TAM model 387 questionnaire	<ul style="list-style-type: none"> To investigate the factors that influence on the adoption of FinTech services through analyzing the behavioral intentions of users. To provide a view of the determinants of users' attitudes by combining the trust of FinTech Services with TAM. 	Users' trust in FinTech services has a very large impact on users' attitudes towards FinTech adoption. Perceived ease of use and perceived risk do not influence users' attitudes towards adopting FinTech services.

women have fewer mobile phones and use less Internet than men. This reflects the use and utilization of technology and expresses the degree of confidence and risks in the use of modern technology by women in general and FinTech in particular (GSMA, 2019). Thus, this study hypothesized the following:

H2a: Trust about the use of FinTech is higher for men than for women.

H2b: Risks about the use of FinTech are higher for men than for women.

H2c: PEOU to use of FinTech is higher for men than for women.

H2d: PU to use of FinTech is higher for men than for women.

3.2.3. Education level

The educational level of consumers affects the use of technology and also benefits from it. People who have a higher education have more knowledge of the use of modern technology. They affect the level of trust in the use of technology and its risks (Alafeef et al., 2011; Im et al., 2003). Thus, this study hypothesized the following:

H3a: The higher the level of education, the greater the confidence in using FinTech.

H3b: The higher the level of education, the lower the risk of using FinTech.

H3c: The higher the education level, the higher the PEOU to use FinTech.

H3d: The higher the level of education, the higher the use of FinTech.

3.2.4. Income level

The level of income is one of the significant factors in the case of modern devices that deal with high technology. People who have high income can get devices that work with modern technologies, for example, smartphones. Therefore, their use of these devices is more than others and also their benefit from technology is more than others (Gulamhuseinwala et al., 2015). So the people who get higher income will have greater confidence in the use of technology, as well as in accepting the risks of use (Teo et al., 2012). This study hypothesized the following:

H4a: Whenever the income increases the trust to use FinTech increases.

H4b: Whenever the income increases the risks to use FinTech decrease.

H3c: Whenever the income increases the PEOU to use FinTech increases.

H4d: Whenever the income increases the PU to use FinTech increases.

3.2.5. Influence of demographic factors on attitudes to use fintech

According to the study (Karsh, 2021; Shah et al., 2019), the attitudes of older people towards using modern technology will be negative. And they may need someone to help them use modern technology, and therefore their attitudes towards adopting modern technology may be weak (Gulamhuseinwala et al., 2015). As for gender, women are less likely to have technology devices such as phones, and also less use them, according to the GSMA report (The Mobile Gender Gap Report 2020). Therefore, women's attitudes toward the use of technology are twice as positive

compared to men's (Teo et al., 2012). When the level of education increases for people, they have more information about the use of modern technology and how to deal with it, and thus their attitudes towards using technology will be more knowledgeable (Teo et al., 2012). Consumers who have high income get more technology devices and whose attitudes towards using modern technology will be great (Gulamhuseinwala et al., 2015). So, this study hypothesized the following:

H5a-H5d. There is a significant association among all the demographic factors, including a—age, b—gender, c—education, d—income on attitudes to use FinTech.

3.2.6. *Influence of consumer adoption/acceptance variables on attitudes to use fintech*

The TAM model clarifies the factors influencing clients' attitudes and their intentions toward adopting technology (Davis et al., 1989). The most important of these factors explained by this model are the factors of usability and usefulness. Furthermore, many researchers indicate the influence factors of trust and risk in using technology to determine consumer attitudes and their intentions towards using modern technology in general and financial technology in particular (Fernando et al., 2018; Hu et al., 2019; Stewart & Jürjens, 2018). Thus, this study hypothesized the following:

H6a: There is a significant association among the clients' trust in attitudes.

H6b: There is a significant association among the risks of use on attitudes.

H6c: There is a significant association among PEOU on attitudes.

H6d: There is a significant association among PU on attitudes.

3.2.7. *Influence of consumer attitudes on intentions to use fintech*

Consumers' intentions depend on their attitudes toward the use of FinTech, according to TRA theory and TAM model. Depending on the attitude of the consumers, may predict their behaviour towards the use of FinTech (Davis, 1989; Fernando et al., 2018; Fishbein & Ajzen, 1977; Jaradat & Twaissi, 2010). Thus, this study hypothesized the following:

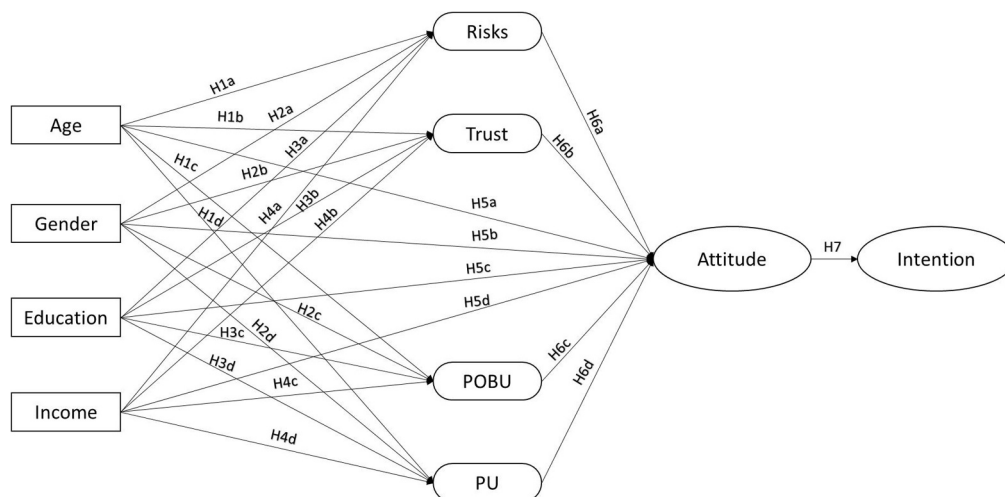
H7. There is a significant association among the attitudes and intentions to use FinTech. See, Figure [Figure 1](#).

3. Methods

3.1. *Data collection*

In this study, a quantitative, descriptive, and causal modelling test method is used. A questionnaire was used during a survey for collecting data. The questionnaire contents of a 24-item instrument quantifying respondents: trust, risks, PEOU, PU, attitudes, and intentions to use FinTech. Digital payments measure FinTech via mobile phones to clients. The questionnaire was presented to five bank clients (Alkuraimi Islamic Bank, Cooperative Agricultural Credit Bank, Yemen Kuwait Bank, Al-Amal Microfinance Bank, and Tadamon International Islamic Bank) in the Republic of Yemen. Those banks provide their services via a mobile application and using FinTech payment. The questionnaire was prepared by Google form. We identified bank clients available by numbers of mobile phones, email, and social media (e.g., WhatsApp, Facebook, etc.). The target population was 519,179 until December 2019 according to (AlSamawi et al., 2020); it was selected from the five banks' list of clients who use FinTech payments according to the Banks of Yemen database, by using a simple random sampling method. The survey was implemented during November and

Figure 1. Model of the study.



December 2021. About 500 valid questionnaires were sent while 435 were returned for this study, see, Table 2 for details.

4.2. Statistics methodology

This paper followed SEM model suggested by (Anderson & Gerbing, 1988). SEM model is an incredible multivariate strategy that is progressively present to test and evaluate multivariate causal connections (Fan et al., 2016). SEM using PLS 3.3.3 is available for examining the proposed model PLS is broadly utilized in IS research (Henseler et al., 2016; Urbach & Ahlemann, 2010) and does not make suspicions about the dissemination of factors and ensures ideal consistency precision (Urbach & Ahlemann, 2010), also exceptionally valuable when the investigation model intricate with an enormous number of construct and pointers (Nitzl & Chin, 2017; Urbach & Ahlemann, 2010). The PLS model contains two normal related models, the Measurement model and the Structural model.

4.3. Measures

The questionnaire in this study uses six variables (Trust, Risk, PEOU, PU, Attitude, and Intention) in addition to demographic variables (Age, Gender, Education, and Income). For each variable, the researcher determined the majority areas of that variable. It also identifies the indicators that were used to represent each variable from the previous research (Davis, 1989; Meyliana et al., 2019; H. H. Ryu, 2017; Shah et al., 2019; Teo et al., 2012). The survey tool and measurement scale were modified to measure attitudes and intentions to use FinTech (Fernando et al., 2018; Hu et al., 2019; Jaradat & Twaissi, 2010). A 5-point Likert-type scale from “strongly disagree” to “strongly agree” is used to measure variables rating the trust, risks, PEOU, PU, attitudes, and intentions to use FinTech. And also four questions relating to demographic information of the participants using nominal scales.

4. Analysis and results

4.1. Descriptive statistics

The client demographic information age, gender, education level, and income level are measured. The total number of respondents is 435. The male is 87.6% while 12.4% are female. This ratio is close to the ratio of the number of male and female bank accounts, and this is due to the culture of a society in which males bear more financial burdens and transactions than females. The respondents are 47.6% in 25–34 years of age, 37.2% are in 35–44 years of age, 9% are in 45–54 years of age, and only 4.1% are in 18–24 years. The respondents who carry a bachelor’s degree

Table 2. Number of client accounts in banks that use FinTech payment and sampling

Name of bank	Population	Percentage	Q-Sent	Sampling	Percentage
Alkuraimi Islamic Bank	391050	75.32	230	204	46.9
Cooperative Agricultural Credit Bank	27457	5.29	150	135	31.0
Yemen Kuwait Bank	36136	6.96	25	15	3.4
Al-Amal Microfinance Bank	47670	9.18	75	66	15.2
Tadamon International Islamic Bank	16866	3.25	20	15	3.4
Total	519179	%100	500	435	%100

Source: (AlSamawi et al.,2020)
 Q-sent: sent valid questionnaires

are (44.8%). The respondents get income From \$100 to \$300 are (40%), 22.8% of respondents get income below \$100, 8.3% of respondents get income \$1000 see, Table 3.

5.2. Measurement model

The measurement model is the Confirmatory Factor Model (CFA) which tests terms of factor loadings, reliability and validity (Anderson & Gerbing, 1988). Then it should be the value of the loading factor which should be ≥ 0.60 for each item. The items out with values should be less than 0.60 regarding reliability when Cronbach's Alpha (α) and Composite Reliability (CR) are with values ≥ 0.70 attained them (Urbach & Ahlemann, 2010). It measures validity by using convergent validity and discriminant validity. The average variance extracted (AVE) for each construct was calculated. It should be ≥ 0.50 (Fornell & Larcker, 1981). In discriminant validity, the correlation must value less than the square root of AVE for each construct. The variable should be greater than its loadings on all other latent variables (Urbach & Ahlemann, 2010). In Tables 4-6, all information related to this is included in them. All these criteria (e.g., loadings, reliability, and validity) support the measurement model TAM. Therefore, this study examines the multicollinearity issue and familiar method bias (CMB). Any research study can have a multicollinearity issue that means the variance external constructs described in the internal construct overlap with each other, and therefore do not explain any unparallelled variance in the internal variable (O'Brien, 2007). To test and measure the multicollinearity score, a variance distension factor (VIF; O'Brien, 2007). As for CMB, this study has underlined the importance of assessing the effect of CMB on statistical analysis results (Chin et al., 2012). In this study, the CMB has underlined the importance of evaluating the influence on statistical analysis results (Chin et al., 2012). Based on (Kock, 2015), the occurrence of a VIF above 3.3 shows either a multicollinearity issue or a sign that a model may be a CMB. As presented in Table 3 all VIF values are ≤ 3.3 , confirming is no multicollinearity problem and no CMB either, see, Tables 4-6.

The study compares AVE values with the square of the correlation estimates for any two constructs by supporting a precise discriminant validity test. It is noticed that Risks, Trust, PEOU, PU, and attitudes are higher than the squared correlation estimation.

5.3. Structural model

After verifying the scale of validity and reliability, the structural model evaluation has been done which includes hypothesis testing evaluation of R^2 , Q^2 predictive significance, effect size (f^2), and model fit (Memon & Rahman, 2014).

Table 3. Descriptive statistics analysis (N = 435)

Factor	Number	Percentage
Gender		
Male	381	87.6
Female	54	12.4
Age		
From 18 to 24 years	18	4.1
From 25 to 34 years	207	47.6
From 35 to 44 years	162	37.2
From 45 to 54 years	39	9.0
From 55 to 64 years	9	2.1
Education Level		
Primary School	3	0.7
Secondary School	21	4.8
Diploma After High school	24	5.5
Bachelor	195	44.8
Master	120	27.6
Ph.D.	72	16.6
Income Level		
Below \$100	99	22.8
From \$100 to \$300	174	40.0
From \$300 to \$500	51	11.7
From \$500 to \$750	45	10.3
From \$750 to \$1000	30	6.9
Above \$1000	36	8.3
Total	435	100%

5.3.1. Hypotheses testing and *f*-squared

The test of hypotheses of this article by (β -value, *t*-value, and *p*-value) and the samples have 5000 for application. The links between the constructs (β -values) in the model can be seen as that of the path coefficients in Figure [Figure 2](#). The *T* and *P* values have been used to test whether the way coefficients (β) values are measurably critical (i.e., at $p < 0.05$, $p < 0.01$, or $p < 0.001$). In [Table 7](#). Effect sizes (f^2) have been tested in this research. The specialist can test the impact size of every case in SEM by methods for Cohen's f^2 (Urbach & Ahlemann, 2010). Deciphering the estimations of impact size (f^2) by Cohen (1988): the f^2 value of >0.35 shows a huge impact, from 0.15 to 0.35 demonstrates a medium impact, between 0.02 and 0.15 shows a little impact, and under 0.02 demonstrates no impact size. In the current study outcomes of f^2 as shown by the effect sizes can be seen in [Table 7](#): two (large), five (small) and the remaining construct (no effect size) see, in [Table 7](#) also [Figure 2](#).

5.3.2. Assessing (R^2) and predictive relevance Q^2

This study has to assess (R^2) and predictive relevance Q^2 and *R*-Squared alludes to the variety in the reliant variable (DV) that free factor/s (IVs) clarity. As shown by (Fan et al., 2016) intention and attitude are variables that include the rest of the dependent variables which explains the effect of the independent variables of this present study, intention is 0.428 and attitude is 0.586 which both are more prominent than 0.10. The predictive relevance of Q^2 has been assessed using the procedure in PLS 3. The cutoff point of Q^2 is > 0 , and the purpose of the model has predictive relevance (Hair et al., 2011). All the Q^2 values are > 0 , see, [Table 8](#). The predictive

Table 4. Result of measurement model- convergent validity

Latent variable	Item No	Factor loadings	CR>0.7	AVE> 0.5
Risks	Ris_1	0.735	0.872	0.632
	Ris_2	0.716		
	Ris_3	0.866		
	Ris_4	0.852		
Trust	Tru_1	0.835	0.893	0.677
	Tru_2	0.791		
	Tru_3	0.827		
	Tru_4	0.838		
PEOU	PEOU_1	0.900	0.900	0.751
	PEOU_2	0.922		
	PEOU_3	0.770		
PU	PU_1	0.849	0.870	0.770
	PU_2	0.905		
Attitudes	Att_1	0.862	0.897	0.744
	Att_2	0.847		
	Att_3	0.878		
Intention	Int_1	0.851	0.932	0.773
	Int_2	0.887		
	Int_4	0.856		
	Int_5	0.920		

Supporting relevance of the model in relevance is to the latent endogenous variables.” Predictive relevance Q^2 : uses blindfolding to get cross-validated redundancy measures for each construct. Coming about Q^2 estimations > 0 shows that the exogenous constructs have prescient predictive relevance for the endogenous construct under consideration (Hair et al., 2011). This study has all constructs Q^2 is > 0 that support the prescient importance of the model in pertinence to the inactive endogenous factors.

5.3.3. Assessing the model fit

The final step is to calculate the model fit. In PLS, the model fit evaluate conducted using the following two criteria:

- (1) The model Goodness of Fit (GoF) By (Hair et al., 2011) indicates how well the decided model duplicates the noticed covariance framework among the marker things through the model Goodness of Fit (GoF). We have built up the file as a general proportion of the model (i.e., both the estimation model and the underlying model are in PLS). The forecast execution of the model is solitary estimating (Vinzi et al., 2010). There is no worldwide fit measure in PLS. Nonetheless, scientists propose a worldwide GoF characterized as the mathematical mean of both the normal of AVE and the normal of R^2 for endogenous (Tenenhaus et al., 2005) given utilizing the accompanying equation:

$$GoF = \sqrt{(R^2 \times AVE)} \tag{1}$$

The criteria determined for GoF are Not fit, small, medium, or large (Wetzels et al., 2009), where GoF < 0.1 is No fit, GoF between 0.1 to 0.25 is Small, and GoF between 0.25 to 0.36 is Medium, and GoF greater than 0.36 is Large.

Table 5. Result of measurement model—latent variables correlation

	Age	Attitude	Education	Gender	Income	Intention	PEOU	PU	Risks	Trust	VIF
Age	1.000										1.000
Attitude	0.104	0.863									1.902
Education	0.320	0.241	1.000								1.000
Gender	-0.008	-0.109	-0.037	1.000							1.000
Income	0.174	0.079	0.172	-0.199	1.000						1.000
Intention	0.051	0.654	0.194	-0.143	0.044	0.879					2.788
PEOU	0.029	0.428	0.095	-0.029	0.092	0.486	0.867				2.207
PU	-0.003	0.713	0.185	-0.031	0.153	0.586	0.482	0.877			1.418
Risks	-0.039	0.128	-0.176	0.052	-0.144	0.243	0.289	0.195	0.795		1.747
Trust	0.076	0.534	0.068	-0.107	0.103	0.606	0.522	0.502	0.480	0.823	1.912

Table 6. Result of measurement model—cross loadings

	Age	Attitude	Education	Gender	Income	Intention	PEOU	PU	Risks	Trust
Age	1.000	0.104	0.320	-0.008	0.174	0.051	0.029	-0.003	-0.039	0.076
Attitude1	0.083	0.862	0.178	-0.124	0.085	0.548	0.354	0.605	0.059	0.431
Attitude2	0.073	0.847	0.201	-0.043	0.054	0.568	0.342	0.599	0.159	0.478
Attitude3	0.112	0.878	0.244	-0.114	0.066	0.576	0.410	0.639	0.112	0.472
Easy_of_use1	0.013	0.418	0.071	-0.035	0.078	0.477	0.900	0.460	0.230	0.444
Easy_of_use2	0.028	0.403	0.075	-0.024	0.123	0.452	0.922	0.457	0.297	0.514
Easy_of_use3	0.042	0.270	0.113	-0.012	0.023	0.308	0.770	0.312	0.222	0.391
Education	0.320	0.241	1.000	-0.037	0.172	0.194	0.095	0.185	-0.176	0.068
Gender	-0.008	-0.109	-0.037	1.000	-0.199	-0.143	-0.029	-0.031	0.052	-0.107
Income	0.174	0.079	0.172	-0.199	1.000	0.044	0.092	0.153	-0.144	0.103
Intention1	0.001	0.582	0.163	-0.163	0.027	0.851	0.381	0.552	0.154	0.520
Intention2	0.033	0.513	0.144	-0.077	-0.025	0.887	0.414	0.479	0.302	0.505
Intention3	0.066	0.564	0.218	-0.132	0.097	0.856	0.432	0.479	0.192	0.480
Intention4	0.074	0.630	0.156	-0.125	0.050	0.920	0.477	0.544	0.215	0.613
PU3	-0.046	0.561	0.066	-0.012	0.160	0.448	0.443	0.849	0.144	0.371
PU4	0.032	0.680	0.241	-0.039	0.114	0.570	0.408	0.905	0.194	0.499
Risk1	0.030	0.037	-0.146	0.129	-0.099	0.037	0.083	0.081	0.735	0.281
Risk2	0.025	0.070	-0.056	0.070	-0.162	0.118	0.190	0.105	0.716	0.209
Risk3	-0.117	0.162	-0.182	0.005	-0.084	0.319	0.366	0.225	0.866	0.549
Risk4	-0.032	0.117	-0.157	-0.012	-0.129	0.250	0.243	0.184	0.852	0.427
Trust1	0.062	0.472	0.052	-0.127	0.095	0.520	0.496	0.402	0.356	0.835
Trust2	0.035	0.314	-0.025	-0.007	0.075	0.366	0.343	0.323	0.483	0.791
Trust3	0.110	0.428	0.077	-0.087	0.130	0.479	0.472	0.431	0.372	0.827
Trust4	0.039	0.501	0.093	-0.102	0.040	0.582	0.386	0.469	0.404	0.838

Table 7. Results of structural model (path coefficient of research hypothesis)

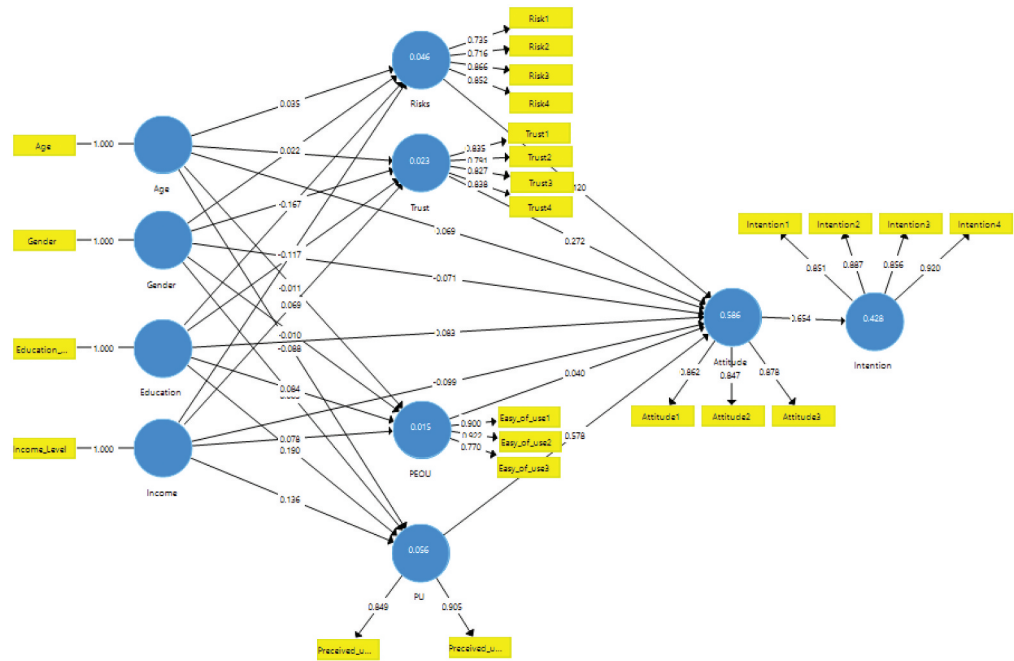
Hypo	Relationship	Std. Beta	Standard Error	T Values	P Values	Decision supported	f ²	Effect size
H1a	Age -> Trust	0.052	0.049	1.060	0.290	Not	0.002	No
H1b	Age -> Risks	0.035	0.062	0.567	0.571	Not	0.001	No
H1c	Age -> PEOU	-0.011	0.050	0.225	0.822	Not	0.000	No
H1d	Age -> PU	-0.088	0.059	1.491	0.136	Not	0.007	No
H2a	Gender -> Trust	-0.092	0.048	1.925	0.055	Not	0.008	No
H2b	Gender -> Risks	0.022	0.052	0.429	0.668	Not	0.001	No
H2c	Gender -> PEOU	-0.010	0.053	0.192	0.848	Not	0.000	No
H2d	Gender -> PU	0.003	0.042	0.068	0.945	Not	0.000	No
H3a	Education -> Trust	0.037	0.059	0.618	0.537	Not	0.001	No
H3b	Education -> Risks	-0.167	0.057	2.908	0.004*	Supported	0.026	small
H3c	Education -> PEOU	0.084	0.060	1.402	0.162	Not	0.006	No
H3d	Education -> PU	0.190	0.052	3.642	0.000***	Supported	0.034	small
H4a	Income -> Trust	0.069	0.046	1.515	0.130	Not	0.004	No
H4b	Income -> Risks	-0.117	0.056	2.112	0.035*	Supported	0.013	No
H4c	Income -> PEOU	0.078	0.062	1.260	0.208	Not	0.006	No
H4d	Income -> PU	0.136	0.056	2.437	0.015*	Supported	0.018	No
H5a	Age -> Attitude	0.069	0.035	1.955	0.051	Not	0.010	No
H5b	Gender -> Attitude	-0.071	0.032	2.239	0.026*	Supported	0.011	No
H5c	Education -> Attitude	0.083	0.032	2.613	0.009**	Supported	0.014	No
H5d	Income -> Attitude	-0.099	0.030	3.323	0.001**	Supported	0.021	small
H6a	PEOU -> Attitude	0.040	0.041	0.983	0.326	Not	0.003	No
H6b	PU -> Attitude	0.578	0.039	14.849	0.000***	Supported	0.524	large
H6c	Risks -> Attitude	-0.120	0.035	3.433	0.001**	Supported	0.024	small
H6d	Trust -> Attitude	0.272	0.043	6.397	0.000***	Supported	0.093	small
H7	Attitude -> Intention	0.654	0.034	19.507	0.000***	Supported	0.748	large

Note: Significance at: *p < 0.05, **p < 0.01 and ***p < 0.001

Regarding the result GoF in this study is calculated as follows:

$$\overline{AVE} = 0.7245, \overline{R^2} = 0.19233$$

Figure 2. PLS algorithm results.



$$GoF = \sqrt{(R^2 \times AVE)} = 0.37329$$

In the current study includes GoF = 0.373, which is > 0.36 which is represent high value. That suggests the model is highly accurate.

- (1) Normalized Root Mean Square Residual (SRMR): (SRMR) has been decided by the cutoff estimation of less or equal to 0.08 (Henseler et al., 2016). Utilizing PLS 3, the SRMR appears in this investigation with 0.070, which is not exactly the cutoff esteem decided in writing.

5. Discussions

5.1. Age

(H1a-H1d): The results for the demographic factor “Age” indicate that they are not significant at (p > 0.05). The hypotheses (H1a-H1d) are rejected, and show no significant difference between the age of clients in their trust, risks, PEOU, and PU to influence the use of FinTech. These results contradict the results of other studies such as (Hu et al., 2019; Teo et al., 2012), which show the existence of age differences in adopting FinTech. The reason may be the sample population of the

Table 8. R square & Q square

	R Square	Q Square
Attitude	0.586	0.429
Intention	0.428	0.325
PEOU	0.015	0.009
PU	0.056	0.038
Risks	0.046	0.028
Trust	0.023	0.013

R Square: above 0.67 = High, 0.67–0.33 = moderate, 0.33–0.19 = weak, below 0.19 = Unacceptable
 Q Square: should be above 0.000

two age groups between 25–34 and 35–44 represent 84.82% of the research sample. Because people over 24 years old are often in college and there is no urgent need to open bank accounts. After the age of 24, pledges and financial transactions that are used through electronic payments begin.

5.2. Gender

(H2a-H2d). The results for hypothesis testing to demographic factor “Gender” indicate no significant difference between the clients ($p > 0.05$). The results suggest rejecting the hypothesis (H2a-H2d). The mean is no significant difference between men and women of clients in their trust, risks, PEOU, and PU to influence of use FinTech. Some articles found the same result of another study e.g., (Aluri & Palakurthi, 2011). That means there is no difference between men and women in the benefit, ease of use, trust, and risks in using FinTech services, whatever some other studies found there is a different significance between males and females e.g., (Abayomi et al., 2019; Chawla & Joshi, 2018; Mkpojiogu et al., 2016; Teo et al., 2012).

5.3. Education

(H3a-H3d). The results for the demographic factor “Education” on effects (H3b) education → risks ($\beta = -0.167$, $p < 0.01$). The results indicate significant negative path coefficients signifying the influence between Education and Risks of their clients to use FinTech. This means that when the education level increases the risks decrease. Education → PU (H3d) ($\beta = 0.190$, $p < 0.001$). The results show significant positive path coefficients signifying influence among education with a high positive coefficients PU. That means increasing the education level leads to increase usefulness to use FinTech. While the result of the hypothesis of (H3a),(H3c) shows no significant difference between education with trust, PEOU of clients to use FinTech. This means that the level of education does not affect the ease of use and the trust of clients in adopting FinTech where there are similar studies that have reached the same result e.g., (Aluri & Palakurthi, 2011; Salleh & Ibrahim, 2011).

5.4. Income

(H4a-H4d). A significant negative effect is found between income with risks (H4b) as a result ($\beta = -0.117$, $p < 0.05$) that indicates the clients increase the income level, and face decrease risks to use FinTech. The result of the hypothesis (H3d) Income → PU is ($\beta = 0.136$, $p < 0.05$). That means significant positive path coefficients signifying influence among income with PU. The reason is the great income, the great purchasing power to acquire modern phones that have the ability to confidentiality and security and maintain personal financial data, the reduces the risks and increases the chance of obtaining a higher benefit from the use of FinTech. The result of path coefficients (H4a) and (H4c) is not significant at ($p > 0.05$). The hypotheses (H4a),(H4c) reject suggesting no significant difference between the income of clients with trust and PEOU to use FinTech. As for significant impact of income with PU, there are some studies that found the same result e.g., (Teo et al., 2012).

5.5. Influence of demographic factors on attitudes

(H5a-H5d). The hypotheses to explore the influence of demographic on attitudes proposed to test the direct influence of age, gender, education, and income on attitudes. The results of the hypothesis (H5b) gender → attitude ($\beta = -0.071$, $p < 0.05$), (H5d) income → attitude ($\beta = -0.099$, $p < 0.01$). There is a negative significant effect on gender and income with attitude. This clarifies that clients’ attitudes differ between men and women, as well as regarding income. Clients’ attitudes differ according to their income to use FinTech services. Some studies agree with this result e.g., (Aluri & Palakurthi, 2011; Chawla & Joshi, 2018). The hypothesis (H5c) Education → attitude ($\beta = 0.083$, $p < 0.01$). There is a positive significant effect on education with attitude. This means that the education level of clients increases the attitude of them to increase using FinTech. While the “age” as a result is ($p > 0.05$), which indicates no significant effect of age clients with attitude to use FinTech. Other studies indicate there is the same finding on education e.g., (Alafeef et al., 2011), while some studies go to different findings e.g., (Abayomi et al., 2019).

5.6. Influence of clients adoption/acceptance variables on attitudes to use fintech

(H6a- H6d). The hypotheses have proposed the influence of clients' adoption/acceptance (PEOU, PU, risk, and trust) variables to influence attitudes. The results of the hypothesis (H6b) PU → attitude ($\beta = 0.578$, $p < 0.001$), (H6d) trust → Attitude ($\beta = 0.272$, $p < 0.001$). A high positive significant effect among PU and trust with attitude. This shows that an increase in the desired benefit from the use of FinTech leads to an increase in customer attitudes towards it, as well as an increase in customers' trust and attitudes towards FinTech services, and this corresponds to the reality of customers and other studies e.g., (Hu et al., 2019; Jaradat & Twaissi, 2010). The hypothesis (H6c) risk → attitude ($\beta = -0.120$, $p < 0.01$) is a negative significant effect on risk with attitude. This means when the risks of using FinTech decrease the customers' attitudes towards that increase. And this is one of the important results this study reaches. Therefore, the result of PEOU is ($p > 0.05$) which indicates no significant effect of PEOU on clients with their attitude to use FinTech. In the current study, other studies reach a result that there is a significant relationship of trust with attitude e.g., (Hu et al., 2019; Jaradat & Twaissi, 2010). As for PU with attitude, some studies found positive significant e.g., (Jaradat & Twaissi, 2010). Other studies got a different result. However, risks affect with attitude, some studies have reached another conclusion from this study e.g., (Meyliana et al., 2019).

5.7. Influence of clients attitudes on intentions to use fintech

(H7). The hypotheses have proposed the influence of client's attitudes on intentions to use FinTech Attitude → Intention ($\beta = 0.654$, $p < 0.001$). That is a very high positive significant effect on the attitude of clients on the intention. The results suggest that intentions to use FinTech are highly measured by the attitudes of the clients to use them. This result is considered one of the significant results reached by this study, which indicates the presence of customers' intentions to adopt the uses of financial payment services.

6. Conclusions

The study investigates the role of demographic factors and their impact on customers' attitudes and intention to adopt FinTech payment services in the least developed countries, Yemen as a case study. It is found that the factors of education and income levels directly affect the adoption of FinTech services. The study shows that the level of education has a significant role in the adoption of FinTech and in absorbing its benefits. As well as education has a significant role in determining the attitudes and intentions of clients. It is clear that education has a role in consumers' understanding of reducing the risks of using FinTech and also in understanding the steps and procedures for using the services safely. The study also shows that income level has a significant role in the use of FinTech services. The low level of income in the least developed countries has a direct impact on adopting FinTech, reducing the risks of using it, and achieving the maximum benefit desired from it. People in these countries lack the purchasing power to acquire modern and safer devices that can preserve customers' financial information, so as to prevent hacking or tampering with the electronic devices to achieve the maximum desired benefit. The research also indicates that there is a strong relationship between trust and risk and their role in customer attitudes and in determining their intention of adopting FinTech services. Increasing the clients' trust strengthens their positive attitude and intention to adopt FinTech services and reduces the risks of using FinTech services in their financial obligations. The study reveals that men and women have different attitudes towards adopting FinTech services. Finally, the study shows that there is a very strong relationship between customer attitudes and their intention to adopt FinTech services, this supports the study results (Jin et al., 2019).

6.1. Limitations and future research

This study succeeded in achieving its objectives, but there are some limitations as follows:

Frist: This study was implemented in Yemen as a case study for the least developed countries. The results of this study can be generalized to the least developing countries at the same level. Future studies can implement this study in other developed countries and compare them.

Second: This study was carried out on bank customers who use FinTech payment services. Future studies can implement these variables on clients of FinTech companies who use FinTech payments services and compare the results between clients of banks and FinTech companies.

Third: The current study targeted bank customers who use FinTech payment services and identified the impact of demographic factors on their trust and the extent to which they accept the risks of these services, as well as their impact on their intentions and attitudes towards using them and continuing to use them. Future studies can target bank customers who do not use FinTech services and find out the reasons and the extent to which demographic factors affect them and their intentions and attitudes to adopt FinTech services.

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Appendix

Questionnaire

Dear, clients of banks in the Republic of Yemen,

I am pleased to put in your hands this questionnaire, which is an essential and approved measure for scientific research, and you are kindly requested to answer it appropriately. It contributes to obtaining accurate results in a way that enhances the achievement of the objectives of this study entitled “The Impact of Demographic Factors of Clients’ Attitudes and Their Intentions to Use FinTech Services on Banking Sector in the Least Developed Countries” Yemen as a case study. You must know that the answer will be used for scientific research. So I kindly ask you to answer the questions on the questionnaire.

*Important note: This study targets customers of banks with mobile payments applications such as (Al-Kuraimi Bank, CAC Bank, Yemen Kuwait Bank, Al-Amal Bank, and Al-Tadamon Bank). We apologize if you do not have an account for one of these banks.

Thank you for your kind cooperation

Researcher: Hussein Al-Shari

Items	Answer
Gender	
Male	
Female	
Age	
From 18 to 24 year	
From 25 to 34 year	
From 35 to 44 year	
From 45 to 54 year	
From 55 to 64 year	
Education Level	
Primary School	
Secondary School	
Diploma After High school	
Bachelor	
Master	
Ph.D.	
Income Level	
Below \$100	
From \$100 to \$300	
From \$300 to \$500	
From \$500 to \$750	
From \$750 to \$1000	
Above \$1000	

(Continued)

Constructs	Indicator and item.	Source
Perceived usefulness (PU)	E-Payments services by mobile can save efforts.	(Huh et al., 2009; Robertson et al., 2007)
	Overall, I would find using the I B to be advantageous.	
Perceived ease of use (PEOU)	It is easy to use E-Payments services by mobile.	(Zhao et al., 2019)
	I think the operation interface of E-Payments by mobile is clear and understandable.	
	It is easy to have the equipment to use E-Payments services by mobile.	
Attitude (ATT)	I believe using E-Payments by mobile services is a good idea.	(Chong et al., 2010)
	Using E-Payments services by mobile is a pleasant experience.	
	In my opinion, it would be desirable to use the IB	
Intention (INT)	I would use the IB for my banking needs	(AlKailani, 2016)
	I would like to use E-Payments services by mobile soon	
	I will recommend E-Payments services by mobile to my friends.	
	If I have used E-Payments services by mobile, I am willing to continue using them.	
Trust(Tur)	I believe mobile payment services are trustable.	(Chong et al., 2010)
	I believe Fintech services keep my personal information safe.	
	I believe the financial transactions and results from digital payments via mobile phone are correct.	
	Overall, I can rely on digital payments via a mobile phone to conduct my financial transactions	
Risks (Ris)	I think digital mobile payments services are not risky.	(AlKailani, 2016)
	I think the risk of using digital mobile payments is low.	
	I don't find it dangerous to deal with digital payments via mobile.	
	I do not find it dangerous to save my information on banking and finances on my mobile device	



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