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Comparative analysis of digital health insurance platform adoption among urban–rural users: A UTAUT and financial literacy integration perspective

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Abstract

Objective: The aim of this study is to compare the determinants of digital health insurance platform adoption among urban and rural users. The study incorporates a financial literacy (FL) perspective in the unified theory of acceptance and use of technology (UTAUT) model to explore the effect of FL on users' adoption intentions.

Methods: This study used a cross-sectional research design, utilising a sample of 389 urban and 323 rural users familiar with digital health insurance platform. Furthermore, this study employed partial least squares multi-group analysis (PLS-MGA) to examine the path differences between urban and rural groups.

Results: The results revealed some differences in the factors that shape the willingness of urban and rural users to adopt digital health insurance platforms. Performance expectancy (PE), effort expectancy (EE), social influence (SI), and FL positively affect the adoption intentions of rural and urban users. However, facilitating conditions only positively affect rural users' adoption intentions. Regarding the moderation effect, FL strengthens the effect of PE on adoption intentions for both urban and rural users. Interestingly, FL shows differences moderating role between urban and rural users in the relationship between EE and SI on adoption intentions.

Implication: By introducing a FL perspective, this study addresses the lack of attention to FL in Insurtech studies. It provides a theoretical basis for the government and platform operators in formulating differentiated promotion strategies to help increase the popularity of health insurance in urban and rural areas.

Keywords

Digital health insurance, insurance platform, financial literacy, unified theory of acceptance and use of technology model, urban–rural users

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Introduction

Insurtech is transforming the traditional insurance transaction model by integrating innovative insurance services with information technology.[1] Today, Insurtech has become a focal point of global business attention. Some scholars regard this transformation as a 'utopian vision', believing it has the potential to redefine the future of insurance services.[2] With the development of Industry 4.0 technology, health insurance services are no longer limited to traditional transaction models but are integrating with the healthcare sector. The digital health insurance platform is an example of cutting-edge technology which relies on advanced technologies (e.g. blockchain and big data) to not only break down the barriers between healthcare and health insurance services but also connect the application of Insurtech in the health sector.[3]

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Digital health insurance platforms are usually developed by technology companies to mainly display and provide protection services by integrating health insurance products from multiple insurance companies. Users can perform insurance comparison, risk assessment, insurance enrolment, tailor-made personalised insurance and claim application on the platforms.[4–6] Furthermore, the platforms implement data sharing with hospitals and clinics. Users can also access health management services such as medical appointments, healthcare consultation, and disease management through the platforms.[5] Compared to traditional website-based insurance, digital health insurance platforms are more focused on covering users' life-cycle protection needs, including disease prevention, health management, and medical expense claims. Currently, common digital health insurance platforms (e.g. AntSure, Tencent WeSure) are usually integrated as embedded modules in popular mobile applications such as WeChat and Alipay. For users with limited insurance knowledge, the platforms can assist in matching more suitable protection solutions based on their health status and financial capability, thereby lowering the entry barrier to insurance services. Thus, the emergence of digital health insurance platforms not only offers advantages in terms of service efficiency but also breaks down geographic and social class barriers, thus promoting universal and equal access to health insurance.[7]

However, this technology's 'utopian vision' has encountered issues during its implementation. While the inclusion outcomes of digital health insurance platforms may vary across different social contexts, their promotion in China faces significant challenges. Specifically, while digital health insurance platforms have been promoted with relative success in urban areas, their adoption rates are low in backward areas. As regions become smaller, user acceptance of digital insurance gradually declines, especially in rural areas, where the penetration rate of digital health insurance is only 2.7%,[8] lower than the level in urban areas. The *China Banking Insurance Journal* suggests that this difference is closely related to the lower insurance awareness among rural residents, who are less accepting of digital insurance than urban residents.[9] In addition, although the internet penetration in China had reached 1.07 billion people in 2023, less than 100 million users accessed insurance services via mobile devices.[10] The proportion of health insurance transactions completed online has long stagnated at between 6% and 9%.[11,12] This phenomenon suggests that while digital insurance platforms aim to attract more users to access the insurance market via mobile devices, traditional offline channels still dominate. Moreover, even though COVID-19 drove the digitisation of the insurance industry, the number of users of digital insurance platforms has been declining since 2021.[11] Therefore, exploring users' adoption intentions is essential towards ensuring the diffusion of digital insurance platforms.

Although academic research on digital insurance solution is increasing, research on digital health insurance platforms is still relatively limited. Past studies have mainly focused on constructing health insurance platform information systems and applying technologies such as blockchain in digital insurance.[13,14] While some studies have begun to focus on the use of digital insurance or insurance platforms,[15,16] research from the consumer perspective is still relatively limited. The unified theory of acceptance and use of technology (UTAUT) model has emerged as an important framework for explaining users' behaviour in adopting digital financial platforms.[17,18] However, much of the existing research focuses on technological factors, leaving the potential impact of consumer financial literacy (FL) on technology adoption relatively under-explored. Digital insurance platforms have both technological and financial features.[19] Hence, users' behavioural decisions on digital insurance platforms may be influenced by their FL.[20] In particular, differences in economic conditions, technological access, and healthcare needs between urban and rural residents in China may shape their different perceptions of digital health insurance platforms. However, past studies cannot be directly used to explain and predict the intentions of urban and rural users towards platform adoption. Hence, to fill this research gap, the authors used the UTAUT model as a basis and introduces FL as a variable to reveal the role it plays in users' adoption of digital health insurance platform.

Since the promotion of digital health insurance platforms in China, urban–rural disparities are becoming more apparent, particularly in terms of the popularity of the platforms. China's long-standing dualistic economic system divides the social structure into urban and rural areas.[21] Urban areas typically benefit from better infrastructure and public services. In contrast, rural areas with longstanding weak infrastructure limit the ability and opportunity for residents to use and engage with digital insurance services. Moreover, differences in socio-cultural backgrounds exacerbate the differences in digital technology acceptance between urban and rural users.[22] While users in urban areas are more individualistic and have unique opinions, users who have lived in rural communities for a long time are more influenced by collectivism. The latter's decisions and behaviours are easily influenced by elders, neighbours, and community leaders.[23] In addition, users' varying levels of familiarity with technology may lead to differences in opinions when adopting new technologies.[24] These differences may stem from users' different perceptions of system attributes. Particularly in the digital insurance sector, complex insurance terminology can confuse some users due to their lack of confidence in their financial knowledge and judgement.[25,26] This scenario suggests that FL not only affects users' understanding of the system but also may hinder individuals' adoption of new technologies. Therefore, it is necessary to construct models and conduct cross-group comparative analyses to reveal urban–rural differences in the formative factors of platform adoption.

Based on the above discussion, UTAUT can support the comparative analyses of urban–rural differences.[27] In addition, UTAUT has been validated in the study of user adoption behaviour in the health sector and shows high explanatory power.[28,29] However, decisions to use digital health insurance platforms are based on considerations including risk, coverage, and financial status. As a variable measuring users' financial understanding and risk decision-making ability, FL may play a role in shaping platform adoption intentions. Therefore, this study integrates FL into the UTAUT theoretical framework to explore the antecedent structure of technology adoption decisions through cross-group comparisons between urban and rural users. Then, the model's fitness was empirically examined with data from 389 urban and 323 rural users.

The theoretical contribution of this study is presented in three aspects. Firstly, it fills the gap in research on digital health insurance platforms, as previous studies have focused on payment,[30,31] loan,[32] and investment platforms,[33] with less attention paid to insurance platforms. Secondly, this study provides a comparative analysis between urban and rural users. In contrast, previous studies have primarily focused on generalised user groups, neglecting the impact of different community backgrounds on user behaviour. Next, this study introduces the key variable of FL in the UTAUT model, thus making up for the neglect of individual FL in previous Insurtech studies. For the practical implications, this study provides policy and strategy recommendations to policymakers and platform operators. It helps to facilitate the promotion of digital health insurance platforms in different regions. For users, this endeavour is centred on improving social insurance coverage, thereby enhancing the equality and inclusiveness of insurance services.

Theoretical background and hypothesis development

Unified theory of acceptance and use of technology (UTAUT)

In technology adoption research, Venkatesh et al. integrated eight theories to proposed the UTAUT model.[34] The UTAUT model has up to 70% explanatory power in predicting technology adoption behaviour.[35] This model has been widely validated in several studies, especially in the fintech sector.[13,23,24] Further studies have also shown that the UTAUT model has high applicability in cross-cultural contexts, for example, with an explanatory power of 68% in Chinese applications.[36] Therefore, this study integrated the UTAUT model and introduced FL variables to analyse the behavioural differences between urban and rural users in China.

Hypothesis development

Performance expectancy. Performance expectancy (PE) reflect an individual's evaluation of the efficiency and usefulness of a of a technology improvement.[37,38] This expectation encompasses factors such as saving time and money and is the primary driver for users to use mobile applications.[37] Several empirical studies have demonstrated the importance of PE as a predictor of the adoption of digital finance solutions.[23,38,39] Moreover, in digital insurance services, consumers tend to choose online channels to purchase life insurance, mainly due to their perception that those online channels increase efficiency and convenience.[40] This study argues that digital platforms offer significant advantages in optimising the efficiency of insurance services and enhancing their accessibility. When users agree that the technology of digital health insurance platforms can increase efficiency and provide convenience, their willingness to adopt increases. Therefore, this study develops the following hypothesis:

> H1: Performance expectancy positively affects users' intention to adopt digital health insurance platforms.

Effort expectancy. Effort expectancy (EE) reflect user's subjective assessment of the effort required to adopt a new technological solution,[37] and it encompasses perception of the difficulty faced in understanding, learning and mastering the technology.[38,39,41] Users' willingness to use an innovation decreases when they perceive a higher difficulty level. Several studies have highlighted EE positively affect users' behavioural intentions in mobile banking and online platforms.[40,42] When users have a full grasp of how technology works, they are more likely to avoid mistakes and favour the services, which they can fully control.[41] This study argues that in digital insurance, which involves technological complexity, users' intention to use digital health insurance platforms may increase when they perceive the system easy to navigate and less costly to learn. Therefore, this study proposes the following hypothesis:

> H2: Effort expectancy positively affects users' intention to adopt digital health insurance platforms.

Social influence. Social influence (SI) refers to the extent to which individuals are influenced by the environment and the opinions of those around them (e.g. family, friends, co-workers) in their technology use decisions.[41,43] SI is seen as an essential technology acceptance behaviour in the UTAUT model but is represented as subjective norms in TRA; nonetheless, both models emphasise the potential influence of others on individual behaviour.[38] In this digital age, feedback from social networks and surrounding groups can influence individuals' attitudes and choices regarding the technology acceptance process.[44] Past research suggests

that SI may be an essential motivation that drives an individual's technology adoption behaviour.[43,45] This study argues that social norms and collective identity in social networks and community cultures may facilitate users' technology adoption. Users are more inclined to try out digital health insurance platforms when they are influenced by a social group or recommended by someone close to them. Therefore, this study proposes the following hypothesis:

H3: Social influence positively affects users' intention to adopt digital health insurance platforms.

Facilitating conditions. The extent to which individuals perceive the organisational and technological infrastructure to be supportive of the systems they use is referred to as facilitating conditions (FCs).[46] These include users' perceptions of resource availability and support for technology use.[37] In mobile fintech transactions, smartphones and internet access are essential enablers that provide ease in completing financial services transactions.[43] The availability of resources such as access to smart devices, as well as customer support from fintech service institutions, provide the basis for users to use mobile applications.[43] Research suggests that high user perceptions of this technical support, including perceptions of operational resources and technological infrastructure, can positively influence their willingness to adopt mobile applications.[37,47] Technical support, such as 4G services, smartphones, secure applications, and internet access, drives mobile payment adoption.[37,48] This study argues that adequate infrastructure and reliable technical support are key factors in reducing the barriers to use technological innovations. Adequate technical support and easy access can effectively alleviate users' concerns during the use process, thus increasing their willingness to use digital health insurance platforms. Therefore, this study proposes the following hypothesis:

H4: Facilitating conditions positively affect users' intention to adopt digital health insurance platforms.

Financial literacy. FL reflects an individual's mastery of financial information and the ability and confidence to make informed decisions in different financial contexts.[49,50] Studies have shown that financially literate people are able to fully understand the advantages of cryptocurrency and are more likely to use it. In contrast, people who lack FL have less understanding of the potential value of cryptocurrencies and are, therefore, less likely to use them voluntarily.[51] In addition, financial has been verified to enhance the effect of PE on users' behavioural intentions.[51–53] The authors argue that financially literate individuals are able to identify and assess the benefits of digital health insurance platforms and use them to optimise financial management. In contrast, those with lower FL are more susceptible to information asymmetry, which may lead them to show caution or even resistance to the platforms. Therefore, this study proposes the following hypotheses:

H5: Financial literacy positively affects users' intention to adopt digital health insurance platforms.

H5a: Financial literacy positively moderates the relationship between performance expectancy and users' intention to adopt digital health insurance platforms.

Research indicates that individuals with high FL can effectively identify and utilise various available technologies and tools,[53] such as accessing financial information and savings rates through Open Banking Protocol interfaces.[54] With a better grasp of financial information and skills, they are more likely to utilise technologies to enhance their financial management.[54] The authors argue that a high level of FL helps users more accurately understand the content of product and services offered by digital health insurance platforms. It means that their perceived burden of platforms complexities is lower, which may increase their willingness to adopt the platforms. On the contrary, users with low FL may need to spend more time and cost to learn the information on the platforms, which may reduce their willingness to use the technology. Therefore, this study proposes the following hypothesis:

H5b: Financial literacy positively moderates the relationship between effort expectancy and users' intention to adopt digital health insurance platforms.

In addition, individuals with higher FL usually rely on their financial skill and knowledge to make decision independently. They are less likely to be influenced by the community or surrounding groups, and they are able to filter and analyse information to select financial products or technologies that meet their needs.[55] Individuals with herd behaviour tend to be shaped by the influence of their peers or surroundings.[56] However, FL can moderate the impact of follower behaviour on decision-making to some extent.[57] This study argues that people with higher FL are better able to assess the value and risk of digital health insurance platforms more rationally in the face of external pressures and are less likely to be swayed by external opinions. On the contrary, individuals with lower FL lack independent judgement and rely more on external opinions, and they are easily influenced by the advice from others in making decisions. Therefore, this study proposes the following hypothesis:

H5c: Financial literacy negatively moderates the relationship between social influence and users' intention to adopt digital health insurance platforms.

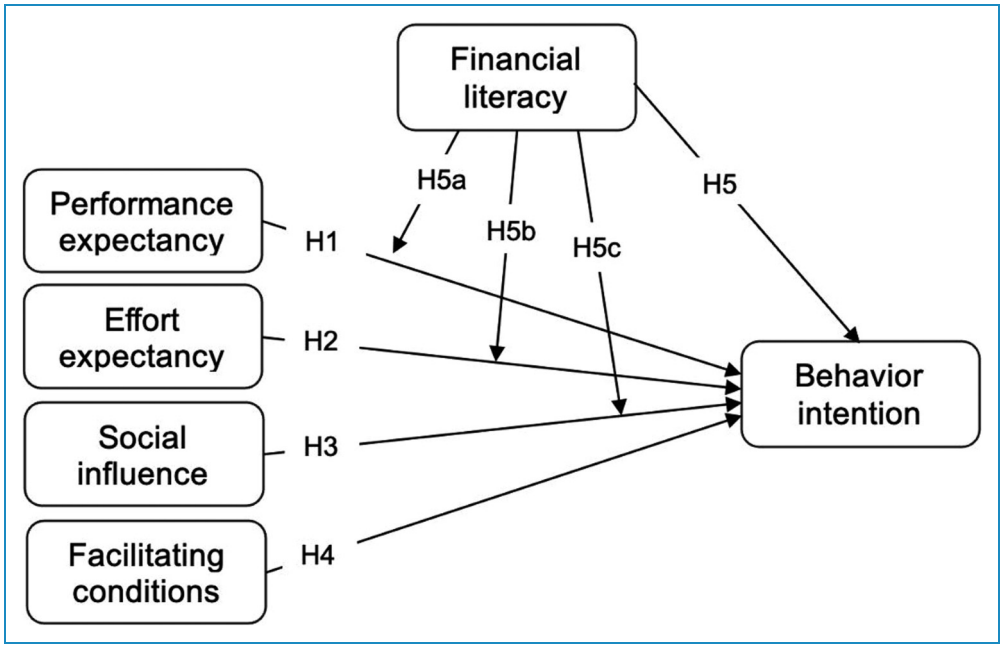


Figure 1. Research model.

This study focuses on exploring the intentions and differences in using digital health insurance platforms between rural and urban users in China. Specifically, the study examines users' perceptions of the platform's potential to improve the efficiency of the service, as well as their perceptions of the effort required to navigate the platform. In addition, this study explores impact of surrounding people's advice on user decision-making in the context of urban–rural sociocultural differences, and the role of external resource conditions in facilitating their adoption intentions. Moreover, this study introduces FL to identify its role in the user intention formation process. The research model constructed in this study is shown in Figure 1.

Methodology

Research methods and survey instrument

The study adopted a quantitative research methodology and used a cross-sectional design and structured questionnaire to collect data. As shown in Appendix A, the measurement items were appropriately adapted based on the existing literature.[24,36,58,59] Previous studies have demonstrated the validity and reliability of these measurement items in predicting users' behavioural intentions towards technology. In addition, experts in the fields of insurance and technology were invited to assess the validity of the questionnaire content, and the items were optimised based on their comments. A five-point Likert scale was used for the measurements' scale in the questionnaire. Respondents could express their level of approval with each item statement by selecting the appropriate number.[60] To validate the reliability of the instrument, a pilot study was conducted with 30 participants to assess the clarity, comprehensibility, and internal consistency of the questionnaire items.

Partial least squares structural equation modelling (PLS-SEM) was used to analyse the data. PLS-SEM is known for its applicability to small sample sizes and its ability to handle path analysis for complex models. This study used SmartPLS 4.1 to analyse the data gathered from the questionnaire distributed through the Wenjuanxing platform. Assessment of structural and measurement models is part of the overall analytical process. While the measurement model is primarily used to assess the reliability and validity of the constructs,[61] and structural model is used to validate the path relationship between the constructs.[62,63] Subsequently, multi-group analysis (MGA) was used to further test whether the path coefficients differed between urban and rural users, thus revealing potential structural heterogeneity.[64]

Data sampling and data collection process

As one of the emerging markets for Insurtech, China has a diverse and rapidly growing Insurtech ecosystem.[65] Many players, from startups to traditional insurance institutions, actively promote financial inclusion. Guangdong, which was selected as the location for this study, is one of the most populous provinces in China.[66] In addition, Guangdong is home to a cluster of Insurtech innovations,[67] with many tech companies and insurance organisations

located in Guangzhou and Shenzhen. Therefore, the users in Guangdong are more familiar with Insurtech, thus able to provide sufficient and valid sample data for this study.

This study used a purposive sampling method to engage participants who could provide the most valuable information. To help respondents understand the content of the survey, the study designed the questionnaire such that it started with a brief introduction to digital health insurance platforms and examples of widely used platforms in China (e.g. Tencent WeSure, AntSure) to guide respondents' understanding of the platforms' features in a real context. To ensure the validity of the data, the study used respondents with familiarity with digital health insurance platforms as the target sample group. The questionnaire was designed with a screening inclusion question, 'Are you familiar with the Digital Health Insurance Platform?' Questionnaires were valid only if the respondent selected 'yes,' otherwise they were invalid and excluded from the analysis. It is worth noting that, this study focuses on users' intention to adopt digital health insurance platforms. According to technology acceptance theories such as TAM and UTAUT, the formation of an individual's intention is not entirely dependent on actual usage experience but rather stems more from the user's perception and subjective evaluation of the technology.[68,69] Therefore, the sample includes two types of users: (i) users with experience in using the platform and (ii) potential users who are familiar with the platform but have no usage experience. Both types of users have the ability to make rational judgements about their intention to use the platform based on their perceptions.

Regarding the determination of the sample size, the study referred to relevant literature and methodological standards in behavioural research to ensure that the sample size was reasonable. According to Krejcie and Morgan, if the total population exceeds 100,000, the appropriate sample size would be 384.[70] In addition, Hair suggests a sample size between 100 and 500 when applying SEM,[71] and Lei and Lomax suggest that a sample size of 250 to 500 is preferable.[72] Since the population of Guangdong Province is more than 100,000,[73] the minimum sample size of this study was set at 384 to ensure the validity and reliability of the results.

During the data collection process, this study strictly followed academic ethics. Each respondent was informed of the purpose of the study before starting to complete the questionnaire to ensure their participation was informed and voluntary. In addition, respondents were assured that their personal information would be maintained at the strictest confidentiality. The survey was conducted in August 2024, and the authors shared the link to the online questionnaire with the respondents through social media and online platforms (e.g. Weibo and WeChat Moments). Respondents in the survey were categorised into rural or urban user group according to their selected residence (urban or rural) in the questionnaire. Finally, valid responses were gathered from 389 urban and 323 rural users for further comparative analyses.

Table 1. Demographic information of respondents.

Item	Urban (N = 389)	Percentage	Rural (N = 323)	Percentage
Gender				
Male	190	48.84	152	47.06
Female	199	51.16	171	52.94
Age				
18–29	103	26.48	113	34.99
30–39	82	21.08	48	14.86
40–49	66	16.97	51	15.79
50–59	67	17.22	41	12.69
60 and above	71	18.26	70	21.67
Education				
Primary school or below	41	10.54	36	11.15
Secondary school	116	29.82	108	33.44
Diploma	91	23.39	77	23.84
Undergraduate	108	27.76	90	27.86
Postgraduate	33	8.48	12	3.72
Monthly Income				
Less than 2000	72	18.51	94	29.10
2000–4000	108	27.76	86	26.63
4001–6000	88	22.62	80	24.77
6001–8000	83	21.34	46	14.24
8000 above	38	9.77	17	5.27
Do you use a digital insurance platform for health insurance-related activities?				
Yes	289	74.29	242	74.92
No	100	25.71	81	25.08

Source: Authors' own data analysis.

Table 2. Descriptive statistics of the latent variable – urban user sample.

Variables	N	Min.	Max.	Mean	Std. Deviation	Skewness
Behaviour Intention	3	1	5	3.860	1.135	−0.957
Effort Expectancy	4	1	5	3.776	1.149	−0.836
Facilitating Conditions	4	1	5	3.759	1.153	−0.773
Financial Literacy	4	1	5	3.843	1.209	−0.921
Performance Expectancy	4	1	5	3.773	1.167	−0.883
Social Influence	4	1	5	3.787	1.174	−0.786

Source: Authors' own data analysis.

Table 3. Descriptive statistics of the latent variable – rural user sample.

Variables	N	Min.	Max.	Mean	Std. Deviation	Skewness
Behaviour Intention	3	1	5	3.756	1.211	−0.872
Effort Expectancy	4	1	5	3.756	1.165	−0.800
Facilitating Conditions	4	1	5	3.759	1.153	−0.789
Financial Literacy	4	1	5	3.760	1.254	−0.899
Performance Expectancy	4	1	5	3.780	1.134	−0.753
Social Influence	4	1	5	3.722	1.137	−0.729

Source: Authors' own data analysis.

Findings and data analysis

Demographic details and descriptive analysis

Table 1 presents the demographic data of the respondents. In terms of gender distribution, there is a relative balance between rural and urban area groups. In the rural area group, 47.06% of the respondents are male and 52.94% are female; in the urban area group, 48.84% are male and 51.16% are female. Young people between 18 and 29 account for the largest age group in both urban and rural areas, with 26.48% and 34.99%, respectively. Those with high school education form the largest percentages of urban and rural respondents, with 29.82% and 33.44%, respectively. The highest number of urban users (27.76%) earn a monthly income of RMB 2000–4,000, and the highest number of rural users (29.10%) earn less than RMB 2000 monthly. About three-quarters of the urban and rural respondents reported having used digital health insurance platforms. However, about a quarter of the respondents said they had not used such platforms for health insurance-related activities.

Tables 2 and 3 show the results of the descriptive statistics on the latent variables. The distribution of the value for each of the measurements ranges from 1 to 5, indicating that the observed values are within the coverage of the scale. All variables have mean values above 3.0, indicating that most respondents rated each latent variable positively. The standard deviation of the latent variables ranges from 1.135 to 1.209 for the sample of urban users and from 1.134 to 1.254 for the sample of rural users, indicating a moderate degree of dispersion in the distribution of data for the variables.[74] This finding suggests a range of variability in respondents' answers, but the concentration is relatively high. In addition, the skewness ranges from −0.773 to −0.957 for the sample of urban users and from −0.729 to −0.899 for rural users. This finding indicates a slightly negative skewness in the data distribution, with most of the data concentrated on the right side of the mean, reflecting respondents' overall more positive attitudes towards these variables.[75]

Measurement model

The purpose of evaluating the measurement model is to ensure that the research model is valid and reliable.

Table 4. Outer loadings.

Construct	Item code	Urban	Rural
Behaviour Intention	BI1	0.854	0.764
	BI2	0.857	0.820
	BI3	0.835	0.840
Effort Expectancy	EE1	0.800	0.869
	EE2	0.779	0.823
	EE3	0.786	0.804
	EE4	0.770	0.721
Facilitating Conditions	FC1	0.795	0.815
	FC2	0.778	0.816
	FC3	0.741	0.790
	FC4	0.757	0.747
Financial Literacy	FL1	0.792	0.780
	FL2	0.815	0.791
	FL3	0.851	0.806
	FL4	0.750	0.741
Performance Expectancy	PE1	0.854	0.813
	PE2	0.833	0.846
	PE3	0.779	0.761
	PE4	0.809	0.760
Social Influence	SI1	0.823	0.793
	SI2	0.808	0.847
	SI3	0.787	0.784
	SI4	0.775	0.734

Source: Authors' own data analysis.

Outer loadings, reliability, and average variance extracted (AVE). To assess the measurement model, first, we examined the items' outer loadings. The values of outer loadings should be greater than .708 to ensure that the items have sufficient explanatory power for the constructs.[76] Next, the internal consistency reliability was tested by Cronbach's α and the composite reliability (CR) values, both with recommended threshold of .70.[77,78] Meanwhile, the items must have a high degree of commonality to effectively reflect the characteristics of the constructs; thus, the minimum average variance extracted (AVE) should be .50.[79] According to Tables 4 and 5, all indicators exceed the critical values, thus proving that the constructs of the research model have satisfactory reliability and validity.

Discriminant validity. Discriminant validity is used to assess the variability among latent variables.[80] The Fornell–Larcker criterion and the Heterogeneity-Trait-Monotrait (HTMT) are two common methods of assessment. According to the Fornell–Larcker criterion, the square root of the AVE for each construct should be greater than the maximum correlation coefficient between it and the other constructs.[81] In addition, the HTMT correlation ratio should be less than .90,[82] otherwise the discriminant validity is not sufficient.[83] In the study, the Fornell–Larcker criteria are shown in Tables 6 and 7, and the HTMT ratios for the urban and rural samples are shown in Tables 8 and 9. The results for both urban and rural samples satisfy the discriminant validity requirements. These outcomes indicate a satisfactory performance of the latent variables in this research model in terms of discriminant validity.

Collinearity indicator. Before testing the relationships between constructs, it is necessary to assess multicollinearity.[84] Multicollinearity is usually tested by the variance inflation factor (VIF); a VIF value below 5 indicates that a multicollinearity problem does not exist.[85] Table 10 shows that the VIF values of all the constructs are below 5, indicating that multicollinearity is not a problem in both urban and rural samples. In other words, the variables in the model are independent of each other and do not interfere, thus ensuring that the results have high validity and reliability.

Structural model

The assessment of the structural model was designed to test the path relationships between the latent variables and the explanatory power of the model. In this study, bootstrapping technique was applied to test the statistical significance of the path coefficients and the robustness of the model. The results are shown in Figures 2 and 3.

Coefficient of determination. The coefficient of determination (R^2) is a statistical indicator used to measure the extent to which the change in one variable can explain the change in another variable.[86] The predictive power is considered strong when the R^2 value reaches .75, moderate when the R^2 value is .5, and weak when the R^2 value is .25.[87] As Table 11 shows, the R^2 value for urban users' intention to use digital health insurance platforms is .569, indicating that the model has moderate predictive power for the urban sample. For the rural sample, the R^2 value is .587, implying that the variables explain 58.7% of the variation in

Table 5. Reliability and AVE.

	Urban			Rural		
	Cronbach's α	CR	AVE	Cronbach's α	CR	AVE
BI	0.806	0.808	0.720	0.735	0.734	0.654
EE	0.791	0.792	0.614	0.820	0.835	0.650
FC	0.769	0.773	0.590	0.803	0.810	0.628
FL	0.817	0.831	0.645	0.786	0.794	0.608
PE	0.836	0.838	0.671	0.808	0.816	0.633
SI	0.810	0.813	0.637	0.800	0.808	0.625

Source: Authors' own data analysis.
CR: composite reliability, AVE: average variance extracted.

Table 6. Fornell–Larcker criterion – urban user sample.

	BI	EE	FC	FL	PE	SI
BI	0.849					
EE	0.569	0.784				
FC	0.415	0.436	0.768			
FL	0.395	0.384	0.322	0.803		
PE	0.593	0.474	0.480	0.352	0.819	
SI	0.584	0.503	0.412	0.341	0.473	0.798

Source: Authors' own data analysis.

Table 7. Fornell–Larcker criterion – rural user sample.

	BI	EE	FC	FL	PE	SI
BI	0.809					
EE	0.557	0.806				
FC	0.599	0.468	0.793			
FL	0.425	0.413	0.379	0.780		
PE	0.504	0.497	0.416	0.326	0.796	
SI	0.565	0.513	0.514	0.431	0.436	0.791

Source: Authors' own data analysis.

behavioural intentions. The model thus has similar predictive power for urban and rural users.

Hypothesis testing. In this study, path coefficients were determined using bootstrapping to verify the significance of the research hypotheses.[88] The variables relationship is statistically significant when the *p*-value is less than .05 or the *t*-value exceeds 1.96; otherwise, it is not significant.[87] In addition, the approach can be used to verify the direct effect of variables and assess moderating effects in the path.[89] Tables 12 and 13 show the results of the validation of the research hypotheses in the structural model.

Multi-group analysis

This study used the MGA to test for significant differences in structural path coefficients between urban and rural users. Prior to performing the multi-group comparative analyses, the measurement invariance of composite models (MICOM) procedure was used to assess the comparability of measurement structures between groups.[64] The results of the MGA have statistical explanatory power only if they are assessed by the MICOM,[64] as shown in Table 14, all variables passed the tests of configurational invariance and compositional invariance. Furthermore, the tests for means and variances show that all original differences are within their confidence intervals, as shown in Table 15. Therefore, the measurement models are comparable between urban and rural users and fulfil the prerequisites for conducting MGA.[90]

MGA was conducted using both Henseler's MGA and permutation test to assess the differences in path coefficients. The results are shown in Table 16. Henseler's MGA determines whether there is a statistically significant difference between two groups by comparing the path estimates of the two groups in each sample.[90] When the *p*-value is less than .05 or greater than .95, the path is significantly different between urban and rural users. The permutation

Table 8. HTMT scores – urban user sample.

	BI	EE	FC	FL	PE	SI	FL*SI	FL*PE	FL*EE
BI									
EE	0.709								
FC	0.521	0.558							
FL	0.479	0.476	0.407						
PE	0.719	0.585	0.593	0.426					
SI	0.720	0.627	0.516	0.419	0.571				
FL*SI	0.036	0.194	0.123	0.259	0.096	0.143			
FL*PE	0.042	0.159	0.136	0.206	0.224	0.101	0.472		
FL*EE	0.037	0.153	0.158	0.325	0.157	0.206	0.558	0.418	

Source: Authors' own data analysis.

Table 9. HTMT scores – rural user sample.

	BI	EE	FC	FL	PE	SI	FL*SI	FL*PE	FL*EE
BI									
EE	0.708								
FC	0.771	0.568							
FL	0.553	0.510	0.475						
PE	0.642	0.604	0.516	0.409					
SI	0.731	0.631	0.643	0.543	0.549				
FL*SI	0.124	0.146	0.084	0.248	0.130	0.179			
FL*PE	0.024	0.165	0.272	0.148	0.125	0.122	0.426		
FL*EE	0.059	0.283	0.281	0.205	0.165	0.145	0.495	0.509	

Source: Authors' own data analysis.

test also provides a p-value for each path but with more stringent criteria. Only when the p-value is less than .05 will the path be considered significantly different between urban and rural users.[90]

Discussion

The research hypotheses have been answered based on the aforementioned analyses. This section discusses the results based on the findings, leading to the conclusion of this study.

The first hypothesis aims to explore the impact of PE on platform adoption. The result shows that PE has a significant positive effect on platform adoption among both urban ($\beta = 0.325$, $p = 0.000 < 0.001$) and rural users ($\beta = 0.171$, $p = 0.000 < 0.001$). Hypothesis one is thus supported in both the urban and rural user samples. This result is consistent with the findings of studies on technology adoption.[23,38,39] It suggests that the essential purpose of users of digital health insurance platforms is to improve the convenience and the usefulness of conducting insurance transactions via the platforms. Although a positive impact is seen

Table 10. Collinearity (VIF).

	VIF (Urban)	VIF (Rural)
BI1	1.704	1.289
BI2	1.821	1.611
BI3	1.723	1.685
EE1	1.708	2.288
EE2	1.573	1.998
EE3	1.519	1.629
EE4	1.541	1.510
FC1	1.569	1.821
FC2	1.460	1.814
FC3	1.473	1.482
FC4	1.453	1.510
FL1	1.631	1.593
FL2	1.756	1.599
FL3	1.882	1.548
FL4	1.598	1.499
PE1	2.058	1.864
PE2	1.965	1.943
PE3	1.587	1.388
PE4	1.809	1.665
SI1	1.785	1.721
SI2	1.751	1.930
SI3	1.593	1.501
SI4	1.610	1.471
FL × EE	1.000	1.000
FL × SI	1.000	1.000
FL × PE	1.000	1.000

Source: Authors' own data analysis.
VIF: variance inflation factor.

among both urban and rural users, the result of the MGA shows that the path differs significantly between urban and rural users ($\beta = 0.154$, $p = 0.002 < 0.01$), with PE having a more significant impact among urban users. This scenario may stem from urban users' higher digital literacy and acceptance of technology.[91] As a result, they have higher expectations and recognition of the platforms' functionality and benefits, resulting in a greater likelihood of using the platforms.

The second hypothesis aims to explore the impact of EE on platform adoption. The result shows that EE has a significant positive effect on platform adoption among both urban ($\beta = 0.239$, $p = 0.000 < 0.001$) and rural users ($\beta = 0.209$, $p = 0.000 < 0.001$). Hypothesis two is thus supported in both urban and rural user samples. This result is consistent with the findings of studies on technology adoption.[40,42] In addition, the result of the MGA further shows that the path coefficient is not significantly different between urban and rural users ($\beta = 0.031$, $p = 0.450 > 0.05$). It suggests that easy-to-understand navigation is effective in reducing the difficulties encountered by both urban and rural users in using digital health insurance platforms. Users can quickly fulfil their needs with less effort and time, thus raising expectations of digital platform use.

The third hypothesis aims to explore the impact of SI on platform adoption. The result shows that SI has a significant positive effect on platform adoption among both urban ($\beta = 0.287$, $p = 0.000 < 0.001$) and rural users ($\beta = 0.208$, $p = 0.000 < 0.001$). Hypothesis three is thus supported for both urban and rural user samples. This result is consistent with the findings of studies on technology adoption.[43,45] While urban and rural users are in different social environments, the result of the MGA shows no significant difference between urban and rural groups for this path coefficient ($\beta = 0.078$, $p = 0.143 > 0.05$). It suggests that when urban and rural users receive positive information about a digital health insurance platform from their social networks or feel pressure from those around them, the feedback and advice increases their willingness to use the platform.

The fourth hypothesis aims to investigate the impact of FCs on platform adoption. The result shows that FCs has a significant positive effect on platform adoption among rural users ($\beta = 0.317$, $p = 0.000 < 0.001$). Hypothesis four is thus supported for the sample of rural users. Among urban users ($\beta = 0.023$, $p = 0.607 > 0.05$), however, FCs do not significantly influence their willingness to adopt digital health insurance platforms. Therefore, hypothesis four is not supported among urban users. The result of the MGA further confirms the significant difference in paths between urban and rural users ($\beta = -0.294$, $p = 0.000 < 0.001$). This reflects the difference in the extent of reliance on external resources and technical support for the adoption of digital health insurance platforms between urban and rural users. This difference may stem from the high concentration of insurance institutions and technological resources in urban areas.[92,93] Since urban users have multiple ways to access insurance services, their perceived importance of

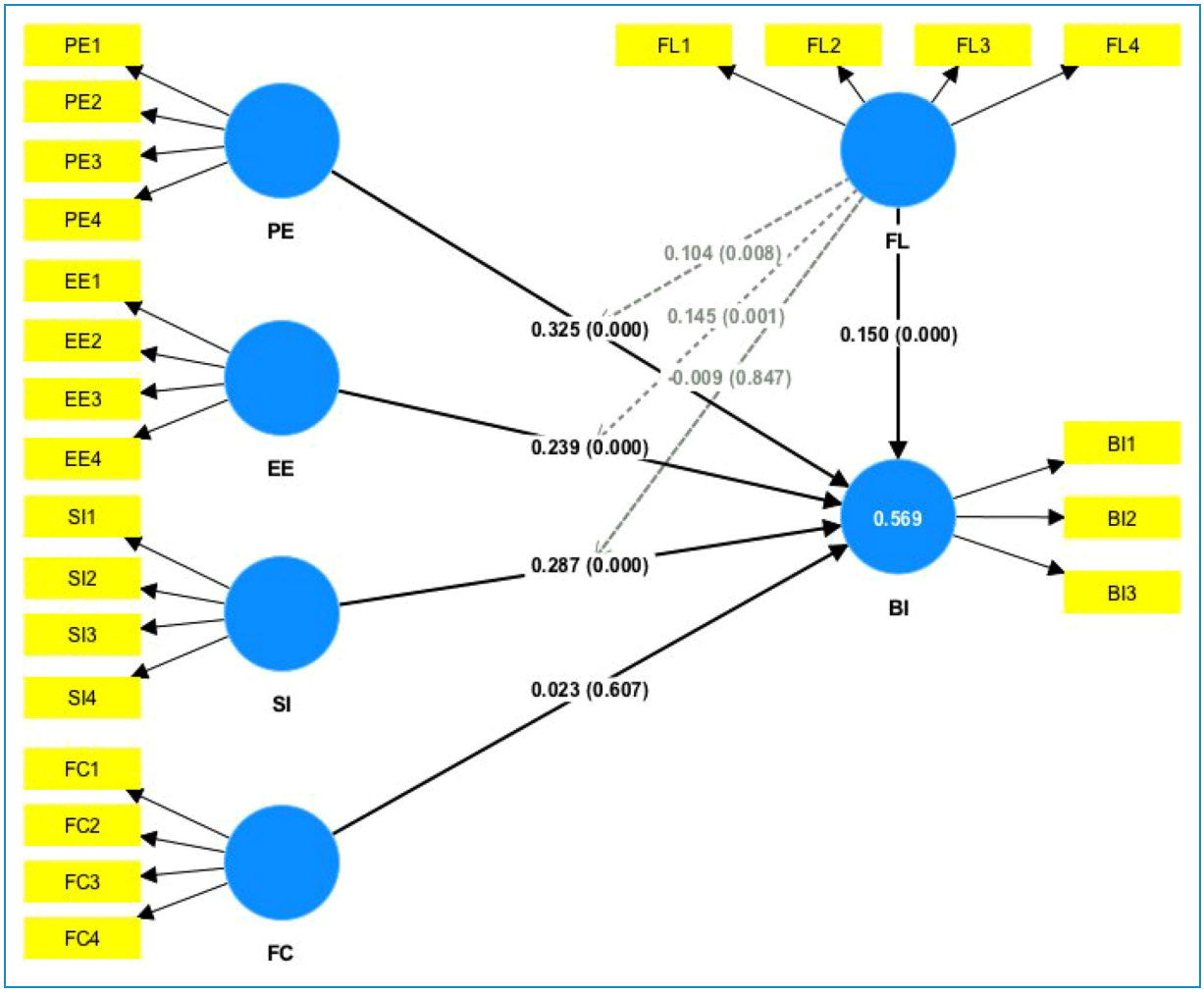


Figure 2. Structural model with findings – urban users sample.
Source: Generated by the authors using SmartPLS 4.1.

FCs may be reduced.[38,46] In contrast, rural areas have limited infrastructure and access, and digital health insurance platforms may be their primary or only way of accessing insurance services,[94] making facilitation conditions more important for rural users. Therefore, rural users rely more on external resources and technology support when adopting digital health insurance platforms.

The fifth hypothesis aims to explore the impact of FL on platform adoption. The result shows that FL has a significant positive effect on platform adoption among both urban ($\beta = 0.150$, $p = 0.000 < 0.001$) and rural users ($\beta = 0.130$, $p = 0.010 < 0.05$). Hypothesis five is thus supported for both urban and rural user samples. This result is consistent with the findings of studies on technology adoption.[51] The result of the MGA further indicates that the difference in the path coefficient between urban and rural users has no statistical significance ($\beta = 0.019$, $p = 0.395 > 0.05$). It suggests that FL increases the understanding of financial products and services among urban and rural users, thus contributing to their willingness to choose digital health insurance platforms.

The last three hypotheses were designed to examine the moderating role of FL in this study. First, FL plays a role in strengthening the relationship between PE and adoption intention among both urban ($\beta = 0.104$, $p = 0.008 < 0.01$) and rural users ($\beta = 0.103$, $p = 0.029 < 0.05$). Hypothesis 5a is thus supported for both urban and rural user samples. The moderating effect is consistent with previous findings on technology adoption.[51,52] The result of the MGA further shows that the difference in the path coefficient is not significant between urban and rural groups ($\beta = 0.001$, $p = 0.134 > 0.05$). It suggests that FL not only helps to reduce the cognitive barriers to risk tools and insurance concepts among urban and rural users but also improves their understanding and judgement of financial information such as claim benefits in insurance platforms. As FL improves,

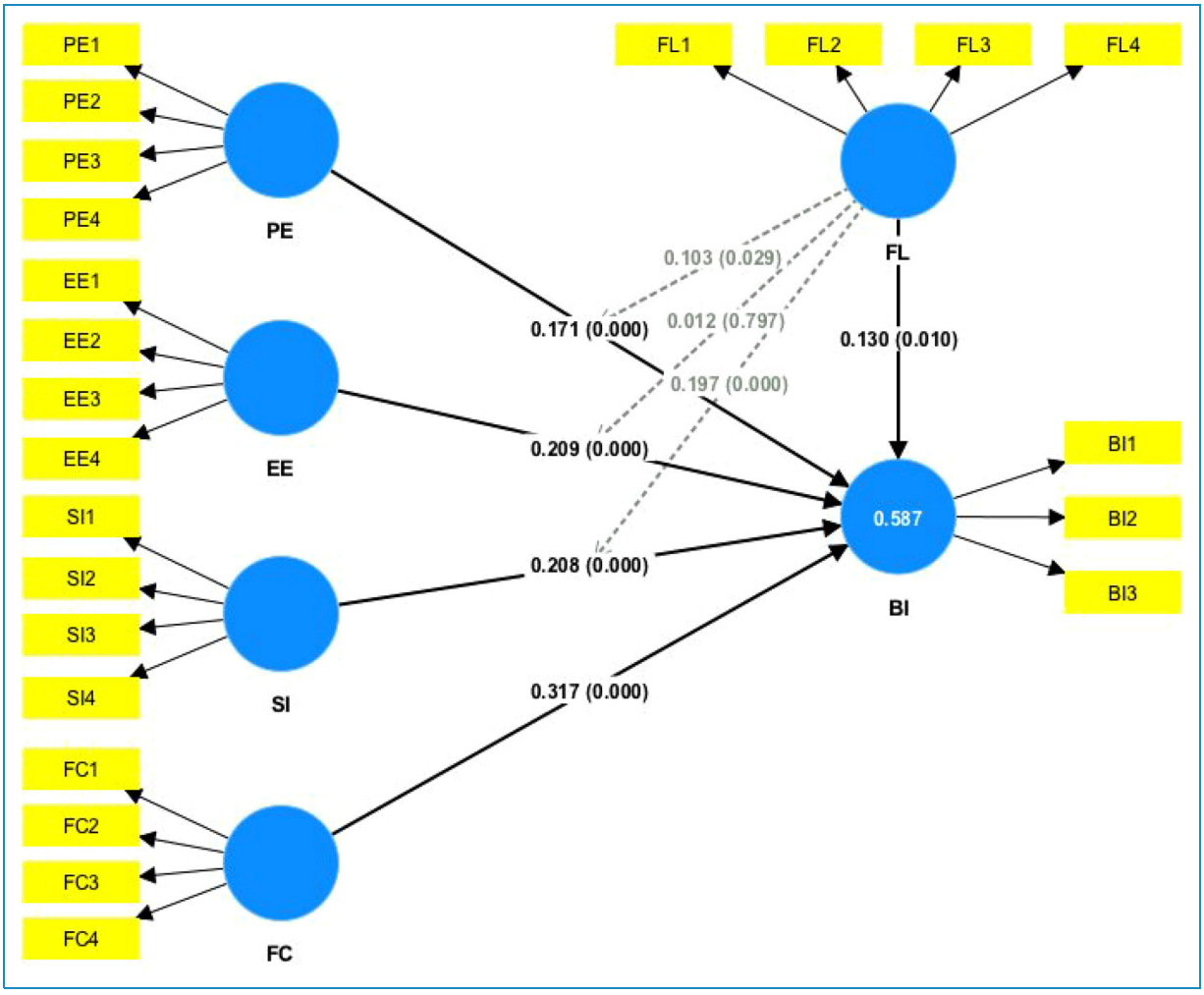


Figure 3. Structural model with findings – rural users sample.
Source: Generated by the authors using SmartPLS 4.1.

Table 11. Model fitness.

	R^2	R^2 adjusted	Explanatory power
BI (Urban Sample)	0.569	0.560	Moderate
BI (Rural Sample)	0.587	0.576	Moderate

Source: Authors' own data analysis.
R^2: coefficient of determination.

users are more likely to recognise the platforms' advantages in the areas of cost management and claims convenience. These positive perceptions are more likely to turn into actual willingness to use.

Next, FL plays a role in strengthening the relationship between EE and adoption intention among urban users ($\beta = 0.145$, $p = 0.001 < 0.005$), but it has no significant moderating effect among rural users ($\beta = 0.012$, $p = 0.797 > 0.05$). Thus, while Hypothesis 5b is supported for the urban user sample, it is rejected for the rural user sample. This difference is further validated by the MGA result on the comparison of the path coefficients ($\beta = 0.133$, $p = 0.025 < 0.05$). This result suggests that increased FL can help urban users navigate digital health insurance platforms more quickly and reduce concerns about the complexity of use and learning costs, thus enhancing the impact of effort expectation on adoption intention. However, for rural users, FL improvement is not enough to significantly alleviate their concerns about usage complexity, which may be due to the lower level of digital literacy among rural users.[95]

Finally, FL does not moderate the relationship between SI and adoption intention among urban users ($\beta = -0.009$, $p = 0.847 > 0.05$). However, it plays a strengthening role among rural users ($\beta = 0.197$, $p = 0.000 < 0.001$), contrary to the weakening effect hypothesised. Therefore, hypothesis 5c is not supported in both urban and rural user samples. Moreover, the result of the MGA shows that the path coefficient is significantly different between the urban and rural

Table 12. Structural model assessment.

	Urban			Rural		
	Original Sample, β	*t* statistics	*p*-values	Original Sample, β	*t* statistics	*p*-values
EE→BI	0.239	5.330	0.000	0.209	4.422	0.000
FC→BI	0.023	0.515	0.607	0.317	6.377	0.000
FL→BI	0.150	3.756	0.000	0.130	2.579	0.010
PE→BI	0.325	7.193	0.000	0.171	3.768	0.000
SI→BI	0.287	6.235	0.000	0.208	4.031	0.000
FL × SI→BI	−0.009	0.193	0.847	0.197	3.759	0.000
FL × PE→BI	0.104	2.655	0.008	0.103	2.188	0.029
FL × EE→BI	0.145	3.222	0.001	0.012	0.257	0.797

Source: Authors' own data analysis.

Table 13. Hypothesis testing.

Hypothesis	Path	Urban	Rural
H1	PE→BI	Sig.	Sig.
H2	EE→BI	Sig.	Sig.
H3	SI→BI	Sig.	Sig.
H4	FC→BI	N.S.	Sig.
H5	FL→BI	Sig.	Sig.
H5a	FL × PE→BI	Sig.	Sig.
H5b	FL × EE→BI	Sig.	N.S.
H5c	FL × SI→BI	N.S.	N.S.

Source: Authors' own data analysis.
Sig.: supported; N.S.: not supported.

Table 14. Results of invariance measurement testing using permutation (Step1 and Step 2).

	Configurational invariance (Step 1)	Compositional invariance (Step 2)		Partial measurement invariance
		Original correlation	5.00%	
BI	Yes	1.000	0.999	Yes
EE	Yes	0.999	0.998	Yes
FC	Yes	0.997	0.996	Yes
FL	Yes	1.000	0.996	Yes
PE	Yes	0.999	0.998	Yes
SI	Yes	0.999	0.998	Yes

Source: Authors' own data analysis.
The original correlation thresholds in step 2 should be higher than the values in the 5.00% column.

groups (β[?][?]$= -0.206$, $p = 0.001 < 0.01$). The result suggests that financially literate rural users are able to assimilate the positive messages from SIs, reduce cognitive barriers, and identify risks,[96] thus enhancing the effect of SI on willingness to use. Among urban users who have relatively high FL, the marginal effects of further improvement their FL is limited. Even increased FL is insufficient to alter their reliance on SI significantly.

Conclusion

Based on the comparative analysis conducted on urban and rural groups, this study confirms some differences between urban and rural groups in the antecedents of willingness to adopt digital health platforms and the extent to which its play a role. This study found that there are significant differences between urban and rural groups in the path of direct effect of FCs and PE on users' intentions. Moreover, the study also found that the paths of SI and EE on users' intention under the moderating effect of FL also shows significant differences between urban and rural users. Therefore, different intervention strategies should be used to enhance the adaptability of the platform to different groups.

Table 15. Results of invariance measurement testing using permutation (Step 3).

	Equal mean assessment (Step 3a)		Equal variance assessment (Step 3b)		
	Original differences	Confidence interval	Original differences	Confidence interval	Full measurement invariance
BI	0.103	[−0.154, 0.147]	−0.025	[−0.190, 0.196]	Yes/Yes
EE	0.028	[−0.154, 0.139]	−0.094	[−0.169, 0.177]	Yes/Yes
FC	−0.000	[−0.154, 0.153]	−0.070	[−0.165, 0.162]	Yes/Yes
FL	0.096	[−0.149, 0.147]	−0.013	[−0.183, 0.174]	Yes/Yes
PE	−0.012	[−0.152, 0.154]	0.113	[−0.190, 0.177]	Yes/Yes
SI	0.077	[−0.145, 0.152]	0.082	[−0.165, 0.170]	Yes/Yes

Source: Authors' own data analysis.
The original differences values in step 3a and step 3b should be in the range of the confidence interval.

Table 16. PLS-MGA test.

Relationship	Path coefficient differences, β	*p*-value Henseler's MGA	*p*-value permutation test
EE → BI	0.031	0.435	0.450
FC → BI	−0.294	1.000	0.000***
FL → BI	0.019	0.409	0.395
PE → BI	0.154	0.001	0.002*
SI → BI	0.078	0.135	0.143
FL × SI → BI	−0.206	0.998	0.001**
FL × PE → BI	0.001	0.866	0.134
FL × EE → BI	0.133	0.021	0.025*

Source: Authors' own data analysis.
MGA: multi-group analysis.
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

The results indicate that urban users' behavioural intention to use digital health insurance platforms is influenced by PE, EE, SI, and FL. However, FCs do not have a significant effect on their adoption behaviour towards the platforms. The study also finds that among urban users, FL strengthens the relationship between EE and adoption intention, as well as the relationship between PE and adoption intention. In light of these results, platform operators should prioritise optimising the platforms' core functionality and enhancing the simplicity of navigation to meet urban users' need for efficiency and ease of use. At the same time, social acceptance should be expanded by diversifying the information diffusion channels. In addition, incorporating financial education campaigns into the promotion of the digital health insurance platform to popularise its features and advantages will help to increase users' willingness to adopt the platforms.[97]

The results for rural users show that PE, EE, SI, FCs, and FL influence their behavioural intentions to adopt digital health insurance platforms. These results are consistent with UTAUT's results on the direct variable relationships. In addition, the study finds that for rural users, FL helps to strengthen the relationship between PE and adoption intention, as well as the relationship between SI and adoption intention. Based on these results, this study suggests prioritising the development of infrastructure and technical support environments in rural areas to improve the accessibility of digital health insurance platforms among rural populations. In addition, the study recommends that users' positive evaluations and experiences with the platforms be disseminated through community events, social networks, and opinion leaders to increase rural users' positive perception of the platforms.[98] Furthermore, FL and technology training can be considered as a response to the actual needs of rural users in order to increase their understanding of the functions and potential value of the platforms,[99] thus increasing their willingness to adopt the technology.

Theoretical contributions

This study provides important contributions to academic theory in three ways. Firstly, despite the rapid growth of research on fintech platforms in recent years, most studies have focused on payment platforms,[30,31] lending platforms,[32] and investment platforms.[33] Studies focusing on insurance platforms, especially those analysing user behaviour, are still limited. This study, in exploring users' intention to adopt digital health insurance platforms, not only

fills a theoretical gap in insurance platform research but also deepens the understanding of users' behaviour in adopting insurance technologies.

Second, this study adopts an urban–rural comparative analysis perspective to reveal the significant differences in digital health insurance platform adoption between urban and rural users. While previous studies have only focused on a generalised user group, this study is grounded in the differences in technology acceptance across different social background groups. The findings suggest that while urban users are most concerned with the platforms' technical performance enhancement and convenience, rural users are most reliant on externally provided infrastructure and technical support. This comparative analysis not only enriches the applicability of UTAUT theory in different socio-economic contexts but also provides an essential reference for understanding the impact of China's specific economic and social environment on Insurtech adoption behaviour.

Finally, by integrating FL into the UTAUT model, this study provides insights into the interaction between FL and technology adoption. Existing studies have been mainly based on TAM and UTAUT theories, emphasising the technical aspects while neglecting the role of individual financial knowledge.[100,101] This study fills this gap by emphasising the dual financial and technological attributes of digital health insurance platforms and revealing the differential impacts of FL among urban and rural users.[19,102] From an innovation perspective, this study not only provides a new theoretical framework for understanding the convergence of technological and financial elements but also offers a theoretical basis for policy formulation and dissemination of practices.

Practical implications

The Chinese government is concerned about the different adoption rates of digital health insurance platforms between rural and urban regions. In particular, the lower adoption rates in rural areas are a priority issue that needs to be addressed urgently.[8,11] However, existing policies have not been effective in addressing the barriers to rural users' access to commercial health insurance. By analysing the different factors influencing rural and urban users' adoption of digital health insurance platforms, this study provides a more effective policy guidance framework for the government. The results show that the key factors for increasing the adoption of digital health insurance platforms by rural users are improved infrastructure and technical support in rural areas. This study thus provides targeted strategic support for the government to promote the diffusion of digital health insurance.

Urban and rural users have different needs in regard to digital health insurance platforms. Existing marketing strategies do not adequately consider these user differences and fail to exploit the potential user value and market opportunities fully.[9] This study provides platform operators with a multidimensional frame of reference based on users' needs in different regions. Platform operators can use the findings to increase user acceptance of the platforms through differentiated design and targeted marketing strategies. For example, while the focus in urban areas can be on improving technical performance and optimising user experience, the focus in rural areas should be on improving technical advisory services and offering concise and easy-to-understand user navigation.

In addition, this study observes that users in rural areas face greater challenges in accessing insurance services, mainly due to a lack of physical insurance outlets and limited access to information.[94] This study highlights the possibility of addressing this issue by enhancing the accessibility of rural insurance services through digital health insurance platforms. Unlike urban users who focus on technological performance enhancement and convenience, rural users' platform use depends more on the external technical support provided. Therefore, this study contributes to narrowing the gap between rural and urban insurance accessibility towards achieving equality and inclusiveness in insurance services.

Limitations and future research

This study has identified the key factors that influence urban and rural users' adoption of digital health insurance platforms, while also recognising some research limitations and future research directions.

Firstly, health insurance literacy as a highly relevant potential variable to the research topic deserves further exploration in this area. The use of digital health insurance platforms involves not only users' understanding and judgement of technical and financial information but may also relies on users' basic knowledge of healthcare such as medical insurance policies and disease risk assessment. Most of the existing health insurance literacy measurement tools have been developed based on the healthcare mechanisms and contexts of Western countries.[103,104] The applicability of these measurement scales in China may be limited due to differences in health insurance policies across countries. Future research can develop more locally adaptable health insurance literacy measurement tools based on Chinese healthcare policies and urban–rural users' characteristics for application to research in the field of digital health insurance platform in China.

Secondly, although this study has explored the differences in the use of digital health insurance platforms between urban and rural users from several perspectives, there is room for further expansion. For example, cultural values (e.g. collectivism vs. individualism), which are important contextual variables that shape individuals' perceptions and behaviours, may potentially play a role in users' acceptance and use of the platforms. There are

differences between urban and rural residents in China in terms of social structure,[21] information access, and value orientation, and the intervention of cultural factors can provide a more comprehensive understanding of the drivers of user behaviour. Future research can introduce cultural dimensions on the basis of the existing framework to enrich the relevant theoretical exploration and empirical analyses.

Finally, this study design to use a purposive sampling method on a sample from Guangdong Province, one of the most developed provinces in China.[105] While users in this province are more knowledgeable about Insurtech to facilitate data collection, the results may not be applicable to less developed regions. Therefore, the study suggests using a national stratified sampling method in future research. The sample can be reasonably stratified according to the regional population size to improve the generalisability of the results. Moreover, the cross-sectional approach used in this study could not capture the dynamics of changes in user behavioural intentions over time.[106] Future studies should combine adopt a longitudinal design to observe the effects of policy changes on user intentions and behaviours in order to gain a more comprehensive understanding of changes in user behaviour.

In summary, this research opens the gate to exploring how digital innovation can bridge the healthcare coverage gap, thus providing a promising avenue for improving global insurance accessibility in the future. This is not only a response to the reality of China's needs but also an effort towards the global goal of digital health inclusion. This study calls for the development of the digital health insurance platform in order to pay more attention to the needs and situations of disadvantaged groups, especially in developing countries where the urban–rural divide is still significant. While the disadvantaged groups often lack healthcare coverage and deserve to benefit from digital technology, they are the most likely to be excluded because of technical and knowledge barriers. This study focuses on driving the accessibility and adoption of digital health insurance platforms, a necessary action towards achieving the sustainable development goals of good health and well-being and reducing inequalities.

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Ethical considerations

The research institutional review board of Universiti Utara Malaysia have approved this study (Approval Number: UUM/COB/P-40). This study has been performed in accordance with the Declaration of Helsinki. Written informed consent for participation was obtained from respondents who participated in the survey. No data was collected from anyone under 18 years old.

Author contributions

The authors declare that they contributed equally to the preparation of this manuscript and that all authors have reviewed and approved the final version of the manuscript for submission.

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Appendix A

Measurement Items	Sources
Performance expectancy	Venkatesh and Zhang[36]
PE1: I would find the digital health insurance platform useful in my insurance management.	
PE2: Using the digital health insurance platform enables me to manage my insurance affairs more quickly.	
PE3: Using the digital health insurance platform increases my efficiency.	
PE4: If I use the digital health insurance platform, I would increase my chances of enjoying a more cost-effective health insurance.	
Effort expectancy	Venkatesh and Zhang[36]
EE1: My interaction with the digital health insurance platform would be clear and understandable.	
EE2: It would be easy for me to become skilful at using the digital health insurance platform.	
EE3: I would find the digital health insurance platform easy to use.	
EE4: Learning to operate the digital health insurance platform is easy for me.	
Social influence	Venkatesh and Zhang[36]
SI1: People who influence my behaviour think that I should use the digital health insurance platform.	
SI2: People who are important to me think that I should use the digital health insurance platform.	
SI3: The head of Resident Committee has been helpful in the use of the digital health insurance platform.	
SI4: In general, the community has supported the use of the digital health insurance platform.	
Facilitating conditions	Venkatesh et al.[58]
FC1: I have the necessary resources to use digital health insurance platform.	
FC2: I have the necessary knowledge to use digital health insurance platform.	
FC3: The digital health insurance platform is compatible with other technologies I use.	
FC4: I can get help from others when I have difficulties using the digital health insurance platform.	
Financial literacy	Mutlu and Özer[59]
FL1: I know what inflation and interest rates changes mean.	
FL2: I make a price comparison when buying a product or service.	
FL3: I pay attention to the price/performance ratio when buying a product or service.	
FL4: I have knowledge about financial products.	
Intention to adopt digital health insurance platforms	Slade et al.[24]
BI1: I intend to use the digital health insurance platform in the future.	
BI2: I will always try to use the digital health insurance platform in my daily life.	
BI3: I plan to use the digital health insurance platform frequently.	