



Educational Disparities in Virtual Healthcare App Acceptance: A Multi-Group TAM Analysis Among Existing Users in West Bengal, India

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Abstract Background: Education may play a role in digital health adoption. Yet, how exactly it influences the Technology Acceptance Model (TAM) among existing users of virtual healthcare consultation apps is not clear in India. This paper explores whether different levels of education change the effects of main TAM variables on the acceptance of virtual healthcare apps by the people of West Bengal, India. The study focuses on existing users of virtual healthcare consultation apps. **Methods:** This quantitative cross-sectional study collected data from 341 individuals from three education groups through online-only recruitment. The study used a 19-item questionnaire adapted from validated TAM, technology acceptance and telehealth studies on virtual healthcare app usage and purposive stratified sampling was used to ensure group representation. After assessing reliability, validity and measurement invariance, multi-group structural equation modelling in IBM AMOS 20.0 was used to test five moderation hypotheses. **Results:** The measurement model across the three education groups produced the results of reliability and validity within acceptable limits. Configural and metric invariance were both supported. However, the structural weights model demonstrated a significant chi-square difference which pointed to path coefficients varied across the groups. Education significantly moderated the influence of attitude on behavioural intention ($\Delta\chi^2 = 18.063$, $df = 2$, $p < 0.001$) and the influence of behavioural intention on actual use ($\Delta\chi^2 = 15.789$, $df = 2$, $p < 0.001$). The effects of trust on attitude, perceived usefulness on attitude and perceived ease of use on attitude were not significantly moderated by education. **Conclusion:** Education level significantly moderated two of the five TAM pathways examined: The relationship between attitude and behavioural intention and the relationship between behavioural intention and actual use. The relationships from trust, perceived usefulness and perceived ease of use to attitude were not significantly moderated by education. Therefore, in digital health research, education factor evaluation when considering TAM pathways across user groups should not be overlooked.

Key Words Technology Acceptance Model, Digital Health Adoption, Virtual Healthcare Consultation Apps, Education, Multi-Group SEM, West Bengal

INTRODUCTION

The COVID-19 pandemic significantly changed healthcare delivery across the world. Digital health technologies were adopted at an unmatched speed and virtual care became the key element of modern medical services [1]. In the United States, telemedicine utilization increased from 154% of baseline levels in early 2020 to over 766% of baseline by mid-2020 across different studies [2,3]. Weekly telemedicine consultations in the U.S. increased from approximately 13,000 before the pandemic to 1.7 million at

the peak in April 2020 [4]. The growth of virtual consultations was consistent across the United Kingdom, Canada and New Zealand [5]. Usage increased in the United States alone from 1.84% in 2020 to 4.81% in 2023, which is consistent with the global trend at large [6].

However, this growth was not equally distributed across all groups. In general, older adults, racial minorities and people with lower education levels regularly encountered even more difficulties in terms of access [7]. Education determines the level of digital literacy, health information

processing skills and technology confidence of an individual. Hence, people with higher education are more likely to adopt digital health services [8,9]. In low- and middle- income countries, there is a large gap in education levels and digital skills, which makes it difficult for people to access and use digital health services. This raises the concern that digital health services may only benefit to the privileged groups, rather than being a universal right for everyone [10,11].

India shows this challenge prominently. Insufficient patient education levels, limited knowledge about digital technologies and a traditional mindset against change are among the major barriers in the adoption of digital health in the country, yet digital health benefits remain unequally distributed across educational groups in India [12]. In this context West Bengal is a pertinent research setting, offering a meaningful opportunity to examine how education shapes the acceptance of virtual healthcare.

The Technology Acceptance Model was developed by Davis in 1989 as a theoretical framework of understanding technology adoption decisions. This model has been widely validated over the years [13]. The model proposes perceived usefulness and perceived ease of use influence one's attitude towards a technology first, which in turn leads to behavioural intention and actual use. Trust is another factor in the Indian healthcare scenario. Studies in the Indian context have reported that patients express concerns about data privacy, unauthorized sharing of medical records and the authenticity of doctors providing online consultations [14]. Trust is therefore included as an additional predictor of Attitude in this study. Trust reduces perceived risk and uncertainty in healthcare settings, which leads to more favourable attitudes toward using virtual healthcare platforms. So, trust is being considered as a broader idea in this research. Even though the Technology Acceptance Model (TAM) is a very powerful tool for explaining adoption behaviour, it is still not clear how education level affects its main relationships. Learning that perceived usefulness generally predicts adoption of the technology only raises the question whether this is the case equally for the users with different levels of education.

This gap actually leads to tangible effects. For example, health initiatives that are made without considering people's education levels may benefit more educated users while neglecting the less educated, they might even increase existing health inequalities. This study addresses this issue by investigating if the level of education influences five major relationships in the adoption of virtual healthcare apps by the people of West Bengal, India. Theoretically, this study extends the literature of the Technology Acceptance Model while practically it offers education-driven approaches to bridge the digital health gap. It should be noted that this study examines existing users of virtual healthcare consultation apps rather than initial adoption. All participants had used a virtual healthcare app at least once, so the study investigates attitudes, intentions and continued use among existing users. The paper continues with a

literature review and then the following sections: Methodology, results, discussion and recommendations.

LITERATURE REVIEW

Technology Acceptance Model: Foundation and Healthcare Applications

Technology Acceptance Model (TAM) developed by Davis in 1989 is one of the most popular models to predict and understand the technology adoption behaviour of individuals [13,15-17]. The Technology Acceptance Model (TAM) identifies two main beliefs that determine whether a person will accept a technology or not. Perceived Usefulness (PU) is the belief that using a certain technology will make one's job better. Perceived Ease of Use (PEOU) is a term which denotes the level of a person's perception that using a technology would entail the least amount of effort [18-20]. These beliefs determine the opinions about the technology, which then influence behavioural intention and finally, actual usage [13,21]. A comprehensive review of a total of 134 research papers which were published across 72 journals in 30 countries, showed that a massive 83 percent of the researchers changed the original TAM to suit the healthcare context, with telemedicine coming out as the most explored target area 26 percent and nurses being the most frequently recognized subject group 17 percent, followed by physicians and patients with 13 percent each [22]. In spite of such a wide range of uses, most TAM healthcare research have considered their samples as a whole, giving average effects and not checking if the model's predictive relationships work the same for users with different education levels. This assumption of homogeneity restricts the theoretical accuracy and practical benefit of TAM-based results in the healthcare setting of developing countries.

How TAM Works: Evidence from Research

Research regularly indicates that it is the usefulness of a technology that is most influential in a person's decision to adopt it, not the ease of using that technology. King and He [23] found that perceived usefulness was the most influential factor in technology use intention, showing an average correlation of 0.589, on the other hand, perceived ease of use had a less direct effect with an average correlation of 0.429. This means that the main effect of ease of use is to increase the perception of usefulness of technology, rather than to directly induce the intention. Telemedicine research revealed that doctors were mainly concerned whether using the technology enabled them to deliver better healthcare, with less focus on how user-friendly it was [19]. These differences indicate that TAM relationships could differ between user groups, however, the reasons for this variation have not been sufficiently studied yet.

Understanding Moderation in Technology Research

Baron and Kenny [24] pointed out a major difference in research. Moderators tell us when or for whom a relationship is effective, mediators, on the other hand, tell us how or why

it is effective. A moderator regulates the power or the course of a link between the other two variables. For example, education can be a moderator if the strong positive relationship between ease of use and adoption of a product exists for the lower-educated users. First, the general users revealed the most significant impact of perceived ease of use on their behavioural intentions, then students and lastly professionals. This is indicative of the fact that the TAM relationships are different in a systematic way across the user types [23]. Despite this finding, TAM literature still mostly considers education as a background variable and does not usually test whether it changes the way in which TAM relationships work in healthcare settings [25]. That poses a significant question for health management researchers. If user type influences the relationships in TAM, then the level of education, which mainly dictates one's digital and health literacy, could also be a very important moderating factor in the adoption of healthcare technologies.

How Education Affects Technology Adoption: Theory and Evidence

Education affects how technology is adopted in a few different ways. First, it helps people develop their digital skills so they know how to use online platforms, fix technical problems and judge the quality of information, which in turn makes it easier for them to adopt new technologies [26]. Second, education boosts health literacy by providing the intellectual skills necessary for individuals to determine if a healthcare technology can truly enhance their treatment [27]. Third, education is a great initiator of critical-thinking skills that assist individuals in determining whether a particular technology is reliable and desirable for them to adopt [28]. Fourth, education develops technology self-efficacy, which refers to a person's belief in his/her own capability to learn and utilize new technologies, thus having a direct positive impact on the intention to adopt [29]. Collectively, these mechanisms suggest that education may moderate all five TAM pathways: Digital skills and self-efficacy may strengthen Perceived Ease of Use to Attitude; health literacy and critical thinking may enhance Perceived Usefulness to Attitude and Trust to Attitude and resource access associated with education may facilitate the conversion of Attitude to Behavioural Intention and Behavioural Intention to Actual Use to. Across studies, education is almost always the top sociodemographic factor that can predict digital health literacy. Actually, 76.2 percent of studies have shown that people with a higher level of education tend to have better digital health skills [30]. Among the four mechanisms, digital literacy and technology self-efficacy stand out with the most solid empirical evidence of a relationship with adoption outcomes. This implies that skill-based obstacles probably have a greater impact than attitude-based ones for the less educated users. These are the consequences of designing interventions. Awareness-raising interventions will be useless if people do not have the necessary skills to apply their knowledge. One clear evidence that education

influences healthcare technology adoption came from research conducted in India by Sriram and Pichaandy [31], who studied 171 healthcare professionals working in ESIC hospitals located in Tamil Nadu. Bachelor's degree holders consistently scored significantly higher than master's degree holders across all TAM constructs including perceived usefulness, perceived ease of use and behavioural intention. The researchers attributed this to recency of digital training rather than credential level, suggesting that the direction of education's moderating effect depends on when and how technology skills were acquired. Individuals with a Bachelor's degree scored higher than Master's degree holders on all the TAM constructs such as perceived usefulness, ease of use and behavioural intention, the reason is not their credential level but more recent digital training of these bachelor degree holders. This suggests the timing and method of acquiring technologically related skills play an essential role in determining the impact of education on the level of technology adoption [31].

The Indian and West Bengal Context

Education influences technology adoption. India's health sector is a good place to study this relationship because the level of education of the people in India is very diverse. India is 77% literate at the national level. Literacy rates vary between 64 percent and 94 percent across states. Besides, there are significant literacy gaps between urban and rural areas [32]. West Bengal shows the diversity clearly, with total literacy being 76.26 percent. The female literacy rate is lower at 70.54 percent as opposed to 81.69 percent male literacy level and the urban-rural difference is 84.78 percent against 72.13 percent [33]. The state has higher educated urban populations in Kolkata and rural districts have lower literacy rates, creating natural variation for research. In 2021, India initiated the Ayushman Bharat Digital Mission, which as of June 2023 had enrolled more than 400 million individuals and connected 273 million health records, indicating a major move towards digitally Integrated healthcare [34]. Research in India has found that TAM is applicable to telemedicine adoption and the research conducted in Odisha has shown that TAM has a capability of accurately forecasting the behaviour of physicians towards telemedicine service adoption [35].

Research Gap and Study Contribution

Even with the considerable amount of evidence, no research has systematically looked at whether education alters the workings of TAM relationships in Indian virtual healthcare settings. A systematic review by Rahimi *et al.* [22] of 134 TAM healthcare studies published across 72 journals in 30 countries found that 76 percent of studies modified TAM by adding new variables but none examined education as a moderator of the complete set of TAM relationships. King and He [23] conducted a meta-analysis of TAM studies and examined user type as a moderator but did not focus on education specifically. Sriram and Pichaandy [31] analysed

TAM construct scores across education groups in Indian healthcare settings but did not test whether the TAM pathways themselves differ among education levels. This study addresses three significant gaps. Firstly, it uses the Technology Acceptance Model (TAM) to test the moderation role of education on five main TAM relationships at one time, which leads to a better understanding of when and for which individuals the TAM model is suitable [36]. Secondly, through the diverse population of West Bengal during the Indian government's major digital health initiative, it provides evidence while also addressing the lack of research on TAM in India. Thirdly, it employs multi-group structural equation modelling instead of relying on simple group comparisons, thus permitting the accurate measurement of the Influence of education on the moderation of each TAM relationship [37]. In fact, the results will serve as the basis for developing the intervention. If ease of use is the main factor for users with lower education level, then Intervention programmes will have to focus on simple interfaces and hands-on training. If highly educated users value usefulness more, programmes should highlight clinical benefits and functionalities. This customized strategy ensures that digital health programs are effective for people with all levels of education, therefore supporting health equity. This is also in line with the World Health Organization's frameworks for equitable digital health [38].

Objectives of The Study

- To examine whether education level moderates the relationship between trust and attitude toward use of virtual healthcare platforms
- To examine whether education level moderates the relationship between perceived usefulness and attitude toward use of virtual healthcare platforms
- To examine whether education level moderates the relationship between perceived ease of use and attitude toward use of virtual healthcare platforms
- To examine whether education level moderates the relationship between attitude toward use and behavioural intention to use virtual healthcare platforms
- To examine whether education level moderates the relationship between behavioural intention and actual use of virtual healthcare platforms

Hypothesis

- **H₀₁:** Education level does not significantly moderate the relationship between trust and attitude toward use of virtual healthcare platforms
- **H₀₂:** Education level does not significantly moderate the relationship between perceived usefulness and attitude toward use of virtual healthcare platforms
- **H₀₃:** Education level does not significantly moderate the relationship between perceived ease of use and attitude toward use of virtual healthcare platforms

- **H₀₄:** Education level does not significantly moderate the relationship between attitude toward use and behavioural intention to use virtual healthcare platforms
- **H₀₅:** Education level does not significantly moderate the relationship between behavioural intention and actual use of virtual healthcare platforms

Proposed Model

Most studies on healthcare app adoption use the basic TAM model, which may not fully apply in regions like West Bengal where education levels vary widely. Therefore, we added Trust as a third factor, alongside Perceived Usefulness and Perceived Ease of Use, to better explain why people accept or reject virtual healthcare apps. Figure 1 shows how these three factors shape Attitude, which then drives Behavioural Intention and finally Actual Use. We also tested whether education level changes these relationships, since a highly educated user and a less educated user may respond to the same app very differently.

METHODS

Study Design and Sampling

A quantitative cross-sectional approach was taken for the study design. Data were collected from January 2026 to March 2026. Participants were residents of various districts of West Bengal, India, including both urban and rural areas. Participants were recruited through purposive stratified sampling using online channels including social media platforms like WhatsApp, Facebook. The questionnaire link was shared with potential participants who met the eligibility criteria and they were asked to complete the survey if they had previously used a virtual healthcare consultation app at least once. The sample size was calculated by using Cochran [39] formula for an unknown population 384. A total of 400 responses were collected and 341 were finalized for analysis and rest were excluded for incomplete response. Although this falls marginally below Cochran's cut-off of 384, it is still adequate for the purposes of structural equation modelling, as it is well beyond minimum sample size levels determined by the amount of indicator variables in the model [40,41]. Simulation studies indicate that sample sizes as small as 50 can yield reliable SEM results when indicators show at least moderate reliability, which supports the adequacy of the Middle Education (n = 92) and Lower Education (n = 97) groups in this study [42]. The eligibility criteria for respondents were being at least 18 years old, having a smartphone, using a virtual healthcare consultation app at least once and giving informed electronic consent. Therefore, the study examines existing users rather than initial adoption. To ensure sufficient representation of each education level, purposive stratified sampling based on the three education groups was done. Respondents were divided into three categories such as Higher Education (postgraduate or professional degrees, n = 152), Middle Education (undergraduate degree holders, n = 92) and Lower Education (higher secondary education or diploma holders, n = 97). The three education groups contain 152, 92 and 97 participants,

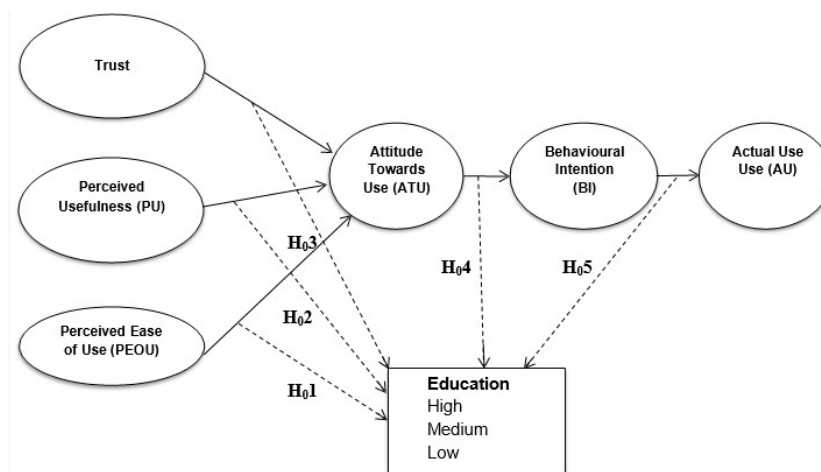


Figure 1: Our Proposed Model

respectively. The smaller groups ($n = 92$ and $n = 97$) exceed the minimum threshold of 50 participants recommended for stable parameter estimates in multi-group SEM when reliability is adequate. The high factor loadings, composite reliability values and average variance extracted values reported in Table 1 further support the adequacy of these group sizes for the multi-group analysis.

Questionnaire Design

The survey was based on 19 questions related to six different areas, namely Trust, Perceived Usefulness, Perceived Ease of Use, Attitude toward Use, Behavioural Intention and Actual Use. All of the items were taken from previously validated scales in TAM, technology acceptance and telehealth studies and adapted for virtual healthcare app usage, as summarized in Table 1 [13]. Trust was conceptualized as users' confidence in the telemedicine platform and the healthcare providers using it. The construct was measured with four items adapted from validated TAM-related scales. Trust was included as an expanded concept since it is a well-recognized factor in the India digital health environment [14]. All items were rated on a Seven-point Likert scale with the options ranging from 1 (Strongly Disagree) to 7 (Strongly Agree) [43]. The questionnaire was administered in both English and Bengali to facilitate respondent comprehension.

Data Analysis

Data analysis was done by using IBM SPSS 21.0 for descriptive statistics and IBM AMOS 20.0 for confirmatory factor analysis and structural equation modelling. Reliability was measured by both Cronbach's alpha and composite reliability. Values equal to or higher than 0.70 were deemed as satisfactory, as per the usual SEM criteria [44,45]. Convergent validity was established since average variance extracted was greater than 0.50 [46]. Discriminant validity was tested using the Fornell, Larcker criterion which demands that the square root of the AVE of a construct is

greater than its correlations with all the other constructs [46]. Common method bias was assessed using Harman's single factor test. Model fit was determined using χ^2/df (<3.0), CFI, TLI, IFI, RFI and NFI (>0.90) and RMSEA (<0.08) [47,48]. Effect sizes for the structural paths were estimated using Cohen's f^2 based on the coefficient of determination (R^2) for each endogenous construct obtained from the AMOS structural model. For each predictor, f^2 was calculated as:

$$f^2 = \frac{R^2_{\text{Included}} - R^2_{\text{Excluded}}}{1 - R^2_{\text{Included}}}$$

where, R^2_{Included} is the R^2 value of the dependent construct with the predictor included in the model and R^2_{Excluded} is the R^2 value when that predictor is omitted. Following Cohen [49], f^2 values of 0.02, 0.15 and 0.35 were interpreted as small, medium and large effects, respectively. All R^2 and path estimates were obtained from the covariance-based SEM in IBM AMOS 20.0 [49]. Moderation by education level was investigated via multigroup structural equation models by contrasting unconstrained, measurement weights constrained and structural weights constrained nested models.

Data Availability Statement

The dataset utilized for analysis in this study cannot be shared publicly for ethical reasons and to ensure the confidentiality of the participants. However, data may be obtained from the corresponding author upon a reasonable request (Table 2-3).

Nearly all skewness and kurtosis values fell within the normal range of ± 2.0 for skewness and ± 7.0 for kurtosis. Two items in the middle-education group ($BI1 = 7.072$ and $BI2 = 7.487$) showed kurtosis values slightly above the ± 7.0 threshold. It is acceptable as the sample size is sufficiently large to absorb very small variations in the data [50,51], these minor deviations do not affect the results (Table 4).

Table 1: Rotated Factor Loadings (PCA), CFA Loadings, AVE, $\sqrt{\text{AVE}}$, Composite Reliability (CR) and Cronbach's Alpha for All Constructs with VIF and Tolerance Across Higher, Middle and Lower-Educational Group

		Rotated factor loading (PCA)	AVE	CR	Tolerance	VIF	Cronbach Alpha	Loading	T	PU	PEOU	ATU	BI	AU
Higher Educated (KM -0.804; Bartlett's Test of Sphericity ≤ 0.001)	T1	0.909	0.73	0.887	0.921	1.086	0.96	0.736	0.854					
	T2	0.95						0.88						
	T3	0.882						0.795						
	T4	0.941						0.986						
	PU1	0.946	0.974	0.991	0.918	1.09	0.996	0.994	0.260**	0.987				
	PU2	0.94						0.975						
	PU3	0.946						0.993						
	PEOU1	0.982	0.976	0.991	0.962	1.039	0.996	0.985	0.148	0.160*	0.988			
	PEOU2	0.983						0.985						
	PEOU3	0.983						0.995						
	ATU1	0.926	0.961	0.986	-	-	0.994	0.958	0.330**	0.268**	0.262**	0.98		
	ATU2	0.938						0.994						
	ATU3	0.938						0.99						
	BI1	0.886	0.985	0.995	-	-	0.998	0.995	0.340**	0.505**	0.243**	0.489**	0.992	
	BI2	0.891						0.994						
	BI3	0.882						0.989						
Middle Educated (KMO 0.800; Bartlett's Test of Sphericity ≤ 0.001)	AU1	0.924	0.988	0.995	-	-	0.998	0.986	0.316**	0.439**	0.105	0.415**	0.541**	0.994
	AU2	0.924						0.998						
	AU3	0.923						0.998						
	T1	0.977	0.969	0.991	0.908	1.101	0.996	0.983	0.984					
	T2	0.977						0.977						
	T3	0.976						0.984						
	T4	0.982						0.994						
	PU1	0.989	0.984	0.994	0.998	1.002	0.997	0.989	-0.046	0.992				
	PU2	0.992						0.989						
	PU3	0.991						0.998						
	PEOU1	0.973	0.985	0.995	0.909	1.1	0.997	0.998	0.301**	-0.029	0.992			
	PEOU2	0.969						0.981						
	PEOU3	0.975						0.999						
	ATU1	0.945	0.969	0.989	-	-	0.995	0.977	0.278**	0.138	0.321**	0.984		
	ATU2	0.944						0.991						
	ATU3	0.948						0.986						
Lower Educated (KMO 0.799; Bartlett's Test of Sphericity ≤ 0.001)	BI1	0.946	0.949	0.981	-	-	0.99	0.968	0.101	0.166	0.15	0.415**	0.974	
	BI2	0.953						0.987						
	BI3	0.954						0.968						
	AU1	0.983	0.955	0.984	-	-	0.992	0.996	-0.02	-0.068	-0.002	0.141	0.317**	0.977
	AU2	0.983						0.994						
	AU3	0.968						0.942						

Table 1: Continued

Lower Educated (KMO = 0.622; Bartlett's Test of Sphericity ≤ 0.001)	T	Rotated factor loading (PCA)		AVE	CR	Tolerance	VIF	Cronbach Alpha	Loading				T	PU	PEOU	ATU	BI	AU
		T1	T2						T1	T2	T3	T4						
	T	0.981	0.978	0.976	0.993	0.878	1.139	0.997	0.996	0.991	0.984	0.982	0.858					
		0.977																
		0.976																
		0.976																
	PU	0.968	0.968	0.978	0.992	0.901	1.11	0.996	0.984	0.987	0.996		0.313**	0.989				
		0.967																
		0.982																
		0.982																
	PEOU	0.982	0.982	0.989	0.996	0.973	1.028	0.998	0.989	0.997	0.998		-0.163	-0.023	0.994			
		0.982																
		0.961																
		0.969																
	ATU	0.968	0.968	0.969	0.989	-	-	0.995	0.967	0.989	0.989		0.193	0.329**	0.025	0.984		
		0.963																
		0.969																
		0.97																
	BI	0.958	0.958	0.958	0.985	-	-	0.993	0.97	0.968	0.999		0.12	0.029	0.289**	0.296**	0.979	
		0.994																
		0.996																
		0.996																
	AU	0.984	0.984	0.984	0.994	-	-	0.997	0.99	0.995	0.991		0.059	-0.063	-0.06	0.03	0.047	0.992

Table 2: Demographical Profile

Item	Frequency	Percentage
Level of Education	Higher Educational Group	152
	Middle Educational Group	92
	Lower Educational Group	97
Area of Living	Urban	165
	Rural	176
Gender	Male	181
	Female	160

Table 3: Descriptive Statistics by Education Group

Higher Educated		Factor	N	Mean	St. deviation	Skewness	Kurtosis
Higher Educated	T1	T	152	3.405	0.362	0.592	3.414
	T2		152	3.388	0.345	0.070	1.869
	T3		152	3.394	0.354	0.671	4.043
	T4		152	3.382	0.332	0.165	2.372
	PU1	PU	152	3.533	1.029	-0.590	0.407
	PU2		152	3.540	1.010	-0.542	0.428
	PU3		152	3.520	1.030	-0.554	0.374
	PEOU1	PEOU	152	3.609	0.664	-0.010	3.424
	PEOU2		152	3.610	0.654	-0.069	3.691
	PEOU3		152	3.621	0.664	-0.054	3.448
	ATU1	ATU	152	3.687	1.108	-0.577	-0.329
	ATU2		152	3.712	1.109	-0.596	-0.296
	ATU3		152	3.705	1.123	-0.569	-0.393
	BI1	BI	152	3.511	1.124	0.199	1.144
	BI2		152	3.511	1.113	0.207	1.281
	BI3		152	3.516	1.109	0.205	1.320
	AU1	AU	152	3.475	2.098	0.445	-1.324
	AU2		152	3.454	2.095	0.460	-1.325
	AU3		152	3.460	2.078	0.467	-1.303
Middle Educated	T1	T	92	3.3147	0.77376	1.397	6.069
	T2		92	3.3212	0.77701	1.361	5.876
	T3		92	3.2929	0.72398	1.233	6.800
	T4		92	3.3092	0.75988	1.390	6.531
	PU1	PU	92	3.3122	0.98092	-0.458	0.509
	PU2		92	3.3339	0.99597	-0.449	0.430
	PU3		92	3.3274	0.99618	-0.430	0.416
	PEOU1	PEOU	92	3.5037	0.85815	-1.329	1.777
	PEOU2		92	3.5211	0.87137	-1.278	1.688
	PEOU3		92	3.5048	.85616	-1.355	1.800
	ATU1	ATU	92	3.8517	1.09265	0.030	0.930
	ATU2		92	3.8735	1.07873	0.027	1.040
	ATU3		92	3.8659	1.09113	0.000	0.949
	BI1	BI	92	3.5459	0.59370	-1.881	7.072
	BI2		92	3.5383	0.58030	-2.130	7.487
	BI3		92	3.5404	0.53173	-1.790	6.365
	AU1	AU	92	4.0198	1.56774	0.109	-0.387
	AU2		92	3.9970	1.56874	0.147	-0.384
	AU3		92	4.0622	1.61834	0.180	-0.542
Lower Educated	T1	T	97	3.5229	0.63391	0.432	2.938
	T2		97	3.5210	0.63526	0.433	2.897
	T3		97	3.5347	0.63530	0.391	2.862
	T4		97	3.5360	0.63263	0.383	2.949
	PU1	PU	97	3.5290	0.87161	-0.921	1.489
	PU2		97	3.5230	0.88547	-0.819	1.274
	PU3		97	3.5098	0.87202	-0.862	1.402
	PEOU1	PEOU	97	3.4665	0.87423	-0.689	1.124
	PEOU2		97	3.4702	0.87082	-0.703	1.186
	PEOU3		97	3.4729	0.87084	-0.719	1.174
	ATU1	ATU	97	3.6653	1.31389	-0.136	0.266
	ATU2		97	3.6941	1.33197	-0.162	0.140
	ATU3		97	3.6976	1.33512	-0.167	0.111
	BI1	BI	97	3.3113	0.58272	-1.357	4.991
	BI2		97	3.2887	0.57552	-1.663	4.618
	BI3		97	3.3031	0.55798	-1.736	5.367
	AU1	AU	97	3.0764	1.05740	0.516	0.775
	AU2		97	3.0640	1.06402	0.507	0.783
	AU3		97	3.0755	1.05437	0.527	0.811

Table 4: Constructs and Measurement Items Used in the Study

Construct	Item Code	Measurement Item
Trust [52,63,56]	T1	I trust that virtual consultation platforms in healthcare keep my personal health information secure.
	T2	I believe that the doctors available on virtual consultation platforms in healthcare are reliable and qualified.
	T3	I feel confident that my conversations with doctors during virtual consultations remain private and confidential.
	T4	I believe the medical advice received through virtual consultation platforms in healthcare is trustworthy.
Perceived Usefulness (PU) [56,55]	PU1	Using virtual consultation platforms helps me save time when managing healthcare consultations.
	PU2	Virtual consultation platforms in healthcare improve my access to healthcare services.
	PU3	Overall, virtual consultation platforms in healthcare meet my healthcare consultation needs.
Perceived Ease of Use (PEOU) [57,60,61]	PEOU1	I find it easy to schedule appointments through virtual consultation platforms in healthcare.
	PEOU2	Learning to use virtual consultation platforms in healthcare is simple for me.
	PEOU3	Interacting with virtual consultation platforms in healthcare is clear and understandable.
Attitude Toward Use (ATU) [62,64]	ATU1	Using virtual consultation platforms in healthcare for medical consultations is a good idea.
	ATU2	I have a positive attitude toward using virtual consultation platforms in healthcare.
	ATU3	I think using virtual consultation platforms in healthcare makes healthcare consultation more convenient.
Behavioural Intention (BI) [65,68]	BI1	I intend to use virtual consultation platforms in healthcare for future doctor consultations.
	BI2	I will recommend virtual consultation platforms in healthcare to others.
	BI3	I am willing to use virtual consultation platforms in healthcare whenever I need medical advice.
Actual Use (AU) [69,71]	AU1	I regularly consult doctors through virtual consultation platforms in healthcare.
	AU2	I have used virtual consultation platforms in healthcare multiple times in recent months.
	AU3	My most recent doctor consultation was through a virtual consultation platform in healthcare.

Table 5: Total Variance explained (Extraction Method: Principal Component Analysis)

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	Percentage of Variance	Cumulative (%)	Total	Percentage of Variance	Cumulative (%)
1	6.479	34.101	34.101	3.911	20.582	20.582
2	3.566	18.767	52.868	3.013	15.860	36.442
3	2.940	15.476	68.343	2.998	15.778	52.220
4	2.374	12.493	80.836	2.997	15.776	67.996
5	1.995	10.499	91.335	2.965	15.607	83.603
6	1.429	7.521	98.856	2.898	15.253	98.856

RESULTS

Measurement Model-Validity and Reliability

Although the scales were adapted from validated instruments, exploratory PCA was conducted to verify the factor structure in the present context and CFA was then used to assess model fit. Both analyses were performed on the same sample due to sample size constraints. An exploratory factor was performed to figure out the basic dimensions in the model. Following the Varimax rotation, a six-component pattern matrix was generated [72]. These six factors combined account for 98.856% of total variance according to Table 5. These values were carefully checked in the raw data and calculation procedures and no errors were found. The sampling adequacy was checked by Kaiser-Meyer-Olkin (KMO) test which reveals values of 0.804, 0.800 and 0.622 respectively for higher, middle and lower-education groups shown in Table 1. All values exceed the minimum acceptable level of 0.6, which indicates that the data are fit for factor analysis and Bartlett's test of sphericity was significant for each of three educational groups ($p < 0.001$), indicating factor analysis was appropriate [73]. Cronbach's alpha was calculated for all the constructs across the three educational groups and all the figures were above the threshold of 0.70 [44,45] which is considered acceptable, indicating high reliability. Some constructs showed very high reliability (close to 0.99), which may reflect closely related item wording. Inter-item correlations were examined and were high but below 1.00, suggesting items were consistent without being identical. All items were retained to

maintain construct coverage. Table 1 displays the outcomes of the evaluation of the measurement model for the three different education groups. Column 1 presents the KMO and Bartlett's values of all three educational groups, column 2 is showing the name of the constructs, column 3 represents the items in each construct, column 4 shows the rotated factor loading (PCA). Column 5, 6 and 9 present, respectively the Average Variance Extracted (AVE), Composite Reliability (CR) and Cronbach's alpha. Column 7 and 8 are showing tolerance and VIF values. The last six columns (Columns 11 to 16) present the correlation between constructs and the square roots of AVE of each construct, highlighted in bold. Trust, perceived usefulness and perceived ease of use were checked for redundancy and multicollinearity. The tolerance values for each predictor were computed to determine the proportion of its variation that is not shared with other predictors. VIF values in the higher-education group were between 1.039 and 1.090, the middle-education group between 1.002 and 1.101 and the lower-education group between 1.028 and 1.139, as indicated in Table 1. Tolerance, which is the inverse of VIF, was also checked.

Multicollinearity is serious when tolerance values fall below 0.1 and VIF values exceed 10 [74]. Tolerance values ranged from 0.918 to 0.962 for the higher-education group, 0.908 to 0.998 for the middle-education group and 0.878 to 0.973 for the lower-education group. All VIF values were well below 10 and all tolerance values were well above 0.1, indicating that multicollinearity was not a problem in this study [74].

Convergent Validity

Factor loadings and Average Variance Extracted (AVE) were used to assess convergent validity. In order to establish convergent validity, the loading of each factor should be greater than 0.50 [72]. Fornell and Larcker [46] suggested that a construct's AVE should reach at least 0.50. This means the construct should account for more than half of the variance in its indicators. The reliability was checked through various methods such as Cronbach's alpha, composite reliability, factor loadings and AVE. Cronbach's alpha and composite reliability are two metrics that must both reach the 0.70 minimum threshold level, indicating a reliability level that is accepted [44,45] shown in Table 1. Every three education level groups have passed these thresholds for the constructs, which means that their convergent validity and reliability are at a satisfactory level.

Discriminant Validity

Discriminant validity was evaluated with the Fornell and Larcker [46] criterion. Standardized factor loadings of 0.70 or greater support convergent validity [46]. Indicators should have lower cross-loadings on the other constructs than their own loadings on the respective constructs. In Table 1, the outer loadings for each construct are above the threshold of 0.70 across the three education groups. Besides this, each indicator's loading on its own construct is higher than its cross-loadings on other constructs, further supporting the discriminant validity for these groups.

F and R-Square and Common Method Variance

The first component by Harman's single factor test accounted for 34.101% variance which is below the 50 percent threshold shown in Table 6 [73]. This suggests that common method bias is unlikely to be severe; however, because Harman's test alone cannot rule out common method bias, this possibility cannot be completely excluded. Thus, the common method bias is not a concern in this study. Table 7 shows the R-squared values for the endogenous latent variables in the structural model. The use of the R²

value for the attitude toward use (ATU) construct was 0.182 (18.2 percent) for the higher-education group, 0.163 (16.3 percent) for the middle-education group and 0.120 (12.0 percent) for the lower-education group. For the behavioural intention (BI) construct, the R² value was 0.239 (23.9 percent) for the higher-education group, 0.172 (17.2 percent) for the middle-education group and 0.088 (8.8 percent) for the lower-education group. For the actual use (AU) construct, the R² value was 0.293 (29.3 percent) for the higher-education group, 0.101 (10.1 percent) for the middle-education group and 0.002 (0.2 percent) for the lower-education group. Notably, for the lower-education group, the R² for actual use was only 0.002, indicating that the model explains approximately 0.2% of the variance in actual use. This reflects extremely weak explanatory performance for this subgroup. The values of effect size (f^2) for each predictor construct are presented in Table 8. For the higher-education group, Trust had an f^2 value of 0.075, whereas the value for Perceived Usefulness (PU) was 0.032 and for perceived ease of use (PEOU) was 0.045. The middle-education group had the following f^2 values: 0.045 for Trust, 0.029 for PU and 0.075 for PEOU. Meanwhile, the lower-education group had the f^2 values as follows: 0.013 for Trust, 0.090 for PU and 0.003 for PEOU.

Measurement Invariance

To test measurement invariance, first configural and metric invariance models were used. Configural invariance testing helps us find out if people from various education levels interpret the factor structure in the same way. Specifically, it examines if the pattern of indicators that correspond to the latent constructs is the same in all groups [76]. The unconstrained configural invariance model appeared to be a good fit for the three education groups, as shown by the values RFI = 0.934, TLI = 0.961, CFI = 0.967, IFI = 0.967, NFI = 0.944 and RMSEA = 0.062, all of which are listed in Table 9. We next evaluated metric invariance by imposing equality constraints on factor loadings across groups. The model with constrained measurement weights

Table 6: The Test of Harman's Single Factor

Criterion	Acceptability
Harman's Single Factor Test	34.101% variance proportion

Table 7: R Square of ATU, BI, AU of All Three Educational Groups

	Value of R ² for High	Value of R ² for Middle	Value of R ² for Low
ATU	0.182	0.163	0.120
BI	0.239	0.172	0.088
AU	0.293	0.101	0.002

Table 8: F Square of T, PU, PEOU of All Three Educational Groups

	f^2 of High	f^2 of Middle	f^2 of Low
T	0.075	0.045	0.013
PU	0.032	0.029	0.090
PEOU	0.045	0.075	0.003

Table 9: Multigroup SEM Model Fit: Unconstrained, Measurement Weights and Structural Weights Models

Model	χ^2	df	χ^2/df	CFI	TLI	RFI	NFI	IFI	RMSEA
Unconstrained	1014.812	438	2.317	0.967	0.961	0.934	0.944	0.967	0.062
Measurement weights	1052.032	464	2.267	0.966	0.963	0.935	0.942	0.966	0.061
Structural weights	1055.856	448	2.357	0.965	0.960	0.933	0.941	0.965	0.063

Table 10: Measurement and Structural Invariance Tests Across Education Groups

Model	DF	CMIN	P	NFI Delta-1	IFI Delta-2	RFI rho-1	TLI rho2
Measurement weights	26	37.220	0.071	0.002	0.002	-0.001	-0.001
Structural weights	10	41.044	<0.001	0.002	0.002	0.001	0.001

still demonstrated satisfactory fit, having RFI = 0.935, CFI = 0.966, IFI = 0.966, TLI = 0.963, NFI = 0.942, RMSEA = 0.061 and CMIN/df = 2.267, as presented in Table 9. The unconstrained model, by contrast, showed a CMIN/df of 2.317. The constrained and unconstrained models showed no significant differences, the p-value was 0.071, implying that factor loadings across educational groups are not significantly different. Therefore, metric invariance is confirmed, which supports the cross-group comparisons carried out in this study.

The measurement-weights model did not differ significantly from the unconstrained model, $\Delta\chi^2(26) = 37.220$, $p = 0.071$. The change in CFI was 0.001 and the change in RMSEA was 0.001, providing additional support for metric invariance across the education groups (Table 10).

Structural Model

The conceptual framework was formulated after extensive research of the prior literature. The model was tested to find out whether the relationship hypotheses outlined in the theoretical framework were supported by the data. The model fit assessment was done based on conventional indices such as RMSEA, CFI, TLI, IFI, RFI and NFI [47]. The model fit index chi-square (CMIN) was 1055.856 with 448 degrees of freedom; thus, the CMIN/df ratio was 2.357, a value fitting within the acceptable range of below 3.0 [47]. TLI, CFI, IFI, RFI, NFI and RMSEA values were 0.960, 0.965, 0.965, 0.933, 0.941 and 0.062, respectively, all consistent with the commonly recommended thresholds [48]. These findings verify that the structural model has an acceptable fit with the data.

Structural Invariances

Structural invariance across the three education groups was tested by comparing the unconstrained and the structural weights constrained models. The comparison checks if the relationships between the latent constructs differ significantly among the three groups of higher, middle and lower education. Although both models showed acceptable overall fit, constraining all structural paths to be equal across the education groups significantly worsened model fit, $\Delta\chi^2(10) = 41.044$, $p < 0.001$. Therefore, full structural invariance was not supported, indicating that at least some path coefficients differed across the education groups. In addition to the overall structural-weight invariance test, we examined individual path differences across education groups. The paths from Trust to Attitude, Perceived Usefulness (PU) to Attitude and Perceived Ease of Use (PEOU) to Attitude did not differ significantly across the education groups. In contrast, the paths from Attitude Toward Use (ATU) to Behavioural Intention (BI) and from BI to Actual Use (AU) differed significantly across education groups. These individual path comparisons represent the central statistical evidence for moderation by education level, rather than the overall structural-weight chi-square test alone.

Table 11: Test for Multigroup Analysis and Hypothesis

Relation	Higher -Education B (unstandardized coefficient) {p-value}	Middle-Education B (unstandardized coefficient) {p-value}	Lower-Education B (unstandardized coefficient) {p-value}	Delta chi square	Delta df	p-value	Result of the hypothesis
Path for Level of Education				41.044	10	0.000	
Trust to attitude toward use.	0.781 {0.002}	0.293 {0.042}	0.206 {0.331}	3.421	2	0.181	Not rejected
Perceived usefulness to attitude toward use	0.190 {0.020}	0.171 {0.109}	0.446 {0.003}	2.528	2	0.283	Not rejected
Perceived ease of use to attitude toward use	0.327 {0.009}	0.336 {0.008}	0.079 {0.585}	2.206	2	0.332	Not rejected
Attitude toward use and behavioral intention	0.493 {<0.001}	0.203 {<0.001}	0.129 {0.002}	18.063	2	<0.001	Rejected
Behavioral intention to actual use.	1.023 {<0.001}	0.941 {0.002}	0.090 {0.640}	15.789	2	<0.001	Rejected

Multigroup Comparison

Multi-group structural equation modelling was used to test the moderating effect of education level. Two models were compared, one was a constrained model in which regression weights were kept equal across all three education groups and another was an unconstrained model in which regression weights were allowed to vary freely across groups. The constrained model was employed to determine if imposing equality restrictions on paths would lead to a significant deterioration in model fit. Chi-square difference tests ($\Delta\chi^2$) were computed to evaluate differences between the constrained and unconstrained models [78]. The five model paths were all analysed for interaction effects among the three education groups. The results of these path-level tests are given in Table 11. We conducted five separate tests on each path coefficient by freezing one path at a time and allowing the rest of the paths to change freely. The Overall comparisons of parameters were done to identify if the changes between the three groups were statistically significant. We used chi-square difference tests to determine the importance of the individual constraints. The outcomes of these path-level analyses, along with the interaction effects that came from different education groups, are displayed in Table 11.

DISCUSSION

The aim of this research was to study whether education level could change the effect of virtual healthcare app acceptance of the people of West Bengal, India. For the purpose, the Technology Acceptance Model along with Trust was used as the model. The overall model demonstrated acceptable fit in this sample, indicating that the TAM framework, extended with Trust, is applicable to the studied group of smartphone-using, prior virtual-healthcare users in the Indian digital healthcare context. The Trust to Attitude relationship did not differ significantly across the education groups. In fact, the coefficient was the highest in the higher-education group and progressively lower in the middle and lower groups. However, the chi-square difference test of this path was not statistically significant (H_0 is not rejected), which suggests that this variation cannot be considered as a confirmed moderation. Such pattern supports the finding that trust is a constant factor in affecting both attitude and intention. However, the extent of its influence is subject to the nature of the outcome variable being analysed [79]. This pattern suggests that users with a higher level of education seem to be more cautious in their evaluation of trust before they develop a favourable attitude. On the other hand, less-educated users are more dependent on the advice of their peers or their immediate needs. The coefficients for Perceived Usefulness revealed a reverse trend as they indicated the greatest effect for the lower-education group whereas the lowest for the higher-educated users. Again, this variation failed to attain statistical significance (H_0 is not rejected), so it cannot be interpreted as confirmed moderation. Recent evidence holds that the

influence of an individual's perception of health technology usefulness on their acceptance of the said technology is not similar for all user groups rather it changes to a large extent depending on the user's context and the type of technology [80]. The observed pattern showed that lower-educated users are more driven by the immediate utility of the health problem-solving aspects, though this needs to be checked further by research. The coefficients of Perceived Ease of Use in higher and middle-education groups were even higher than the lower group. Despite this, the difference was also not statistically significant (H₃ is not rejected). This pattern is consistent with the theory that mainly digitally experienced users will notice the importance of ease of use. However, as the result was not statistically significant, this is still just an exploratory observation and not a confirmed finding. Attitude toward Use was a strong predictor of Behavioural Intention in all the groups and the multigroup comparison revealed that education is a statistical moderator in this relationship, thus H₄ was rejected. This finding aligns with the evidence that attitude positively affects behavioural intention towards teleconsultation use [81] and even further shows that education plays a major role in strengthening this relationship. The results indicate that the association between Attitude toward Use and Behavioural Intention was stronger in the higher-education group ($B = 0.493$) than in the middle-education group ($B = 0.203$) and lower-education group ($B = 0.129$). The multigroup comparison confirmed that this relationship differed significantly across education groups (Delta chi-square = 18.063, $df = 2$, $p < 0.001$). Given the cross-sectional design, these findings indicate an education-related difference in the attitude-intention relationship rather than a causal effect of education. Behavioural Intention predicted Actual Use only for the education groups of higher and middle levels and this moderation was statistically confirmed as well (H₅ rejected). For lower-educated users, intention seemed not to lead to actual use, suggesting that real-life structural barriers such as limited internet access, lower digital literacy, device constraints or affordability issues may prevent adoption even when willingness exists. The marked difference in the strength of this relationship between the middle- and lower-education groups may also reflect measurement or model-specification limitations. This pattern is consistent with prior evidence that gaps between internet access and actual use are often driven by differences in digital skills and literacy, which can limit users' ability to benefit from online services even when connectivity is available. While these factors were not directly measured in the present model, they offer plausible explanations for the weak intention-use relationship observed among lower-education users and should be examined explicitly in future research. It is also important to note that all respondents in this study had already used a virtual healthcare consultation app at least once. Therefore, the very weak relationship between Behavioural Intention and Actual Use in the lower-education group should be interpreted as reflecting differences in the

frequency or intensity of continued use, rather than whether individuals adopt virtual healthcare in the first place. Within this sample of existing users, lower-education users with strong intentions may still use the apps less often or less consistently, possibly due to contextual constraints or competing priorities. The findings of this study should not be generalized to all residents of West Bengal or to the wider Indian population. The sample was purposively recruited online and consisted exclusively of adults who owned smartphones and had prior experience using virtual healthcare consultation apps. As a result, the study primarily reflects the acceptance patterns of digitally connected, relatively tech-savvy users and may not capture the barriers faced by individuals without internet access, smartphones or previous exposure to teleconsultation. Consequently, the reported relationships between education, attitudes, intentions and use are most applicable to similar online, smartphone-using populations rather than to the general population. Taken together, the individual path comparisons show that education level primarily affects the later stages of the TAM model. Specifically, the ATU to BI and BI to AU paths differed significantly across education groups, whereas the Trust to Attitude, PU to Attitude and PEOU to Attitude paths did not. This indicates that the basic belief-attitude relationships are similar across education groups, while the attitude-intention and intention-use relationships vary by education level. Therefore, interventions aimed at increasing the actual use of virtual healthcare applications should focus on helping users translate favourable attitudes into intentions and intentions into use, particularly among lower-education users. These recommendations are offered as practical implications based on the observed patterns, rather than as interventions directly tested in this study.

CONCLUSIONS

Education level is a potential moderating factor in the acceptance of virtual healthcare apps by West Bengal residents, as this study shows. The study used the Technology Acceptance Model extended with Trust as a variable. Besides, multi-group structural equation modelling was used on three education levels. As a result, the findings were not only statistically valid but also of immediate practical importance. It was found that the level of education plays a major role in the way the Technology Acceptance Model (TAM) framework impacts user behaviour. Education had a significant impact on the attitude to intention and intention to use paths. Earlier paths like trust, perceived usefulness and perceived ease of use, which varied by group, were not statistically significant. It looks like education mostly impacts the conversion of willingness into actual behaviour stage, rather than the stage at which people form the first beliefs about the technology. The major practical discovery here is that, in the lower-education group, the path from Behavioural Intention to Actual Use was not statistically significant, indicating that intention did not reliably predict actual use in this subgroup. This clearly

reflects the most obvious real-world obstacles like limited internet access, low digital literacy, device constraints and affordability concerns. In practice, the findings imply that developers of healthcare apps and public health policymakers in India cannot use one single approach for everyone. For lower-educated populations, it makes sense to focus on boosting the perceived functionality and value of apps, as well as removing access barriers through simplified interfaces, subsidised connectivity and local digital literacy programs. For higher-educated users focus should primarily be guided towards creating their trust in the platform by basing it on clear and transparent privacy policies as well as on health care credentials that have been thoroughly verified. Conceptually, this research paper adds to the Technology Acceptance Model by pointing out education as a boundary condition that specifies the time and the person for whom the TAM routes work in digital health environments. This extends the research on how digital health is adopted in developing countries by pointing out that applying one uniform TAM in a singular way might not adequately reflect the behaviour of educationally diverse groups.

Future Recommendations

Many possible future directions could significantly extend this work. First, future researches should add other Indian states as well, particularly those which differ in the level of digital infrastructure and healthcare services. This would indicate if the education-related trends identified here can also be seen in the rest of India. Second, a longitudinal study is more suitable to reveal the change in virtual healthcare app adoption over time as cross-sectional studies only represent the single moment of the behaviour while attitudes and usage may change with the improvement of digital literacy and access. Third, Future research should consider several factors such as income, gender and digital access besides education. In India, these factors often overlap and may provide a fuller understanding of adoption behaviour than education alone. Fourth, qualitative methods like interviews or focus group discussions with less-educated users may uncover the real barriers that hinder intention from turning into actual use. Survey data alone remains insufficient to capture fully lived experiences or contextual hurdles. Fifth, further research could target rural populations, as the disparities in digital access and health literacy are usually much higher there. Exploring the adoption behaviour of rural India is crucial for planning digitally-enabled public health interventions that work effectively. Finally, as virtual healthcare platforms incorporate features like AI consultations and support for regional languages, it is expected that future studies will re-examine the TAM model and see whether other factors may be required to understand adoption by various user groups.

Limitations

There are some limitations to this research. Firstly, the study was only conducted in West Bengal, India and was based on

cross-section data. As a result, the findings may not be generalizable to other areas and causality cannot be established. The sample was collected using purposive stratified sampling and it cannot be claimed that it perfectly represents the larger population of virtual healthcare app users. Participants were recruited online, which may have resulted in a sample that is more digitally connected and tech-savvy than the broader population of virtual healthcare users. Actual Use was measured using self-reported Likert-scale items rather than objective usage data (for example, number of consultations or app logs), which limits the precision of the behavioral measure. Finally, the three education groups differed in sample size, which may have affected the precision of the multigroup comparisons. Using a self-reported Likert scale can lead to some social desirability bias, however, common method bias was not a serious issue. Further research can be conducted by applying longitudinal methods, incorporating more areas of study or making a comparison between urban and rural environments. The eligibility criteria required smartphone ownership and prior use of a virtual healthcare app. Consequently, individuals with the lowest digital access or literacy have been excluded. Therefore, the findings may not fully represent barriers faced by people who have never used virtual healthcare because of limited digital access or skills. In addition, education is closely linked with age, income, occupation, digital literacy and access to technology, which were not measured or controlled in this study. Therefore, the observed differences between education groups may reflect these unmeasured factors as well as education itself. In particular, the very weak intention-use relationship observed among lower-education users may be influenced by measurement or model-specification limitations, in addition to unmeasured contextual factors.

Ethical Statement

The purpose of the study was explained to participants before the online survey. Participation was voluntary and electronic informed consent was obtained before respondents completed the questionnaire. Participants were assured of anonymity and confidentiality and no incentives were offered. Data were collected from January to March 2026. Formal approval from an Institutional Ethics Committee was not required because the study was a non-invasive, questionnaire-based survey involving minimal risk to participants.

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