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Exploring the Mediating Effect of Conscious Health Habits Among Factors Influencing Health App Adoption Users in India

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Abstract - **Purpose: This study explores the mediating role of conscious health habits in influencing the adoption of health apps among users in India.**

Design/methodology/approach: This research study focuses on a diverse sample of users in India, utilizing a comprehensive survey-based methodology to explore the intricate relationship between the usage of health applications and the formation of conscious health habits. After a rigorous screening process, a total of 185 respondents' data was taken to test the relationship between variables. PLS-SEM 4.0 was employed to validate the research hypothesis.

Findings: It is found that health benefits, convenience, and social factors influence health app adoption. Moreover, conscious health habits – such as regular exercise, mindful eating, and proactive health monitoring mediate the app users towards technological adoption.

Research Limitations/Implications: With growing concerns over lifestyle diseases and the demand for personalized healthcare, understanding factors that drive health app adoption is crucial. The implications of this study highlight the importance of integrating behavioral health interventions in app design to boost engagement. For future research, there is potential to explore longitudinal impacts of health app usage on sustained lifestyle changes. However, the study brings a gap among diverse demographic and geographic groups, changing preferences to assess broader applicability.

Originality/Value: This study provides valuable insights into the managerial perspectives that influence future decision-making processes within app development companies, focusing on strategic considerations rather than the technical functionalities of the applications.

Keywords: **Health App, Convenience, Conscious Health Habits, Healthcare Apps, Adoption of Mhealth Apps in India**

I. INTRODUCTION

Health apps (HA) represent a ground-breaking convergence of mobile technology and healthcare. With the ever-increasing use of smartphones, tablets, and wearable devices, Health apps (HA) have emerged as powerful tools that are transforming the healthcare landscape (Nakamura & O'Donnell, 2025). These applications are at the forefront of healthcare innovation, revolutionizing how healthcare services are delivered, accessed, and managed (Gadge et al., 2024). Smartphone adoption among patients is increasing and driving the healthcare market and investors to take advantage of the opportunity to the next phase (Xu et al., 2024; Padhye & Shrivastav, 2024). Health apps (HA) have created a data flow from patients' vital signs, lifestyles, and prior medical histories to healthcare experts that could enable the creation of a personalized medicine model (Javanmard & Manteghinejad, 2021). By continuously recording a variety of individual health issues, from chronic ailments to fitness, users can become a real-time "walking data generator" (Elsotouhy et al., 2022; Matt et al., 2019).

Over 165,000 Health apps (HA) are available, with only 5,000 downloads for 40% of them. Additionally, 300 Health app (HA) clinical trials are in progress, and 53% of them focus on the older population (Banupriya & Tholhappiyan, 2015). Fitness and diet applications are the most popular downloads, as measured by customers downloading an app more than 10 million times (Zakerabasali et al., 2021; Sarkar & Dey, 2023). In India, there is a lot of potential for using mobile health as an alternative delivery mode (Dey et al., 2023). Indians use their smartphones daily for almost three hours. Every area of our lives (health and wellness) can be impacted by mobile technology (Hayat et al., 2024).

Adoption of Health apps (HA) technology can aid in enhancing accessibility, lowering healthcare expenditures, and boosting the productivity of the healthcare staff in India (Armstrong & Tanaka, 2025). However, several obstacles are restricting Health apps (HA)'s influence in the Indian healthcare industry (Modhugu, 2023). Lack of awareness, poor infrastructure, and low expectations are a few reasons affecting the growth (PWC, 2018). To tackle these issues, the Indian government launched the National Digital Health Mission (NDHM) in 2020 intending to establish a nationwide digital health ecosystem that facilitates the incorporation of mHealth solutions into the larger healthcare system (Mishra et al., 2024; Kim, 2023; Kim, 2019; Man et al., 2024).

A. Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT is a thorough framework designed to comprehend the variables affecting the acceptance and use of technology across diverse fields. It combines and expands a number of earlier frameworks for the acceptance of technology (Kedia et al., 2024). Key factors that influence how people accept new technology include performance expectations (perceived benefits), effort expectations (perceived ease of use), social influence (subjective norms), and enabling conditions (support and infrastructure), according to UTAUT (Venkatesh & Zhang, 2010). These factors influence an individual's intention to use technology, which, in turn, affects their actual technology usage. Widely used and tested, UTAUT has proven valuable in exploring technology adoption behaviors and guiding strategies for successful implementation (Hoque & Sorwar, 2017).

B. Health Information Technology Acceptance Model (HITAM)

A specialized UTAUT application created especially for the healthcare industry is the Health Information Technology Acceptance Model (HITAM). It seeks to comprehend how healthcare professionals use and adopt health information technology (Elsotouhy et al., 2022). HITAM includes elements including work relevance (the technology's perceived relevance to certain healthcare tasks), social influence, performance expectancy, effort expectancy, and job relevance (Pang et al., 2024; Shree et al., 2024). By evaluating these elements, HITAM offers insightful data on the adoption and usage of health IT systems in healthcare settings, enabling researchers and practitioners to pinpoint issues and design interventions to support successful technology adoption and use in the sector (Matt et al., 2019; Del Rocio Medrano-Ureña et al., 2020).

II. Literature Review

A. Dimensions of Health app variables:

According to research by Bhuyan et al., (2016), Utilising Health apps (HA) on their smartphones or tablets, US consumers search for health information. A nationwide survey was conducted to examine predictors of 1) Health (HA) applications, 2) the efficiency of mobile health apps in achieving behavioural health goals, 3) usefulness in making decisions about medical treatment, and 4) getting a second opinion or asking a doctor additional question. The survey used weighted multivariate logistic regression models. The study's findings were encouraging. The multivariate models demonstrated that respondents used Health apps (HA) less frequently if they had higher salaries, were older, or lived in rural regions and more frequently if they had higher levels of education, health insurance, and confidence. Research determining which models are most effective will be critically focused on the interaction between new models of care and patients' engagement as attempts to improve the quality and efficiency of care in the US accelerate (Gordon et al., 2015). Mishra, (2018) comprehended the differences between males and females as well as across different age groups, five key criteria are taken into consideration: PU (potential usefulness), PEOU (perceived ease of use), positive attitude, usage intention, and trust. The data unequivocally demonstrated that women are embracing technology at a quicker rate than men. Generation X users, particularly women, embrace mobile health app technology, and the z-test is used to determine whether there is a significant difference between groups (Bhardwaj, 2022).

Wyatt et al., (2021) notes that using Health apps (HA) led to improvements in both short-term and long-term measurements. The study by Navaz et al., (2021) indicates how Health app (HAA) users might become more motivated, self-reliant, and involved in self-regulating their health behavior. The ability of Health apps (HA) technologies, such as apps, to enhance the delivery of healthcare services is investigated in the systematic review and meta-analysis by (Free et al., 2013). It covers a wide range of themes, including patient satisfaction, and provides a complete assessment of the body of literature. Anderson et al., (2016) investigates how patients see telemedicine's effectiveness, including Health app adoption (HAA). It studies elements that affect patient satisfaction, including practicality, privacy, and user experience. Huckvale et al., (2015) focus mainly on apps for managing asthma, but it also offers insights into the usability and patient satisfaction elements of Health app adoption (HAA). Additionally, it evaluates the features and capabilities of various apps and talks about how they might affect patient happiness. In their research Gagnon et al., (2016), Gagnon wants to better understand the factors that influence how medical professionals use mobile health (m-health) applications. Several criteria were considered, including privacy and security concerns, perceived value and usability, design and technical challenges, cost, time, familiarity with the technology, and interactions with other people (co-workers, patients, and management). The findings give healthcare professionals a complete understanding of the benefits and limitations associated with using mobile health. According to Zhang et al., 2023, people must form healthy habits to live longer, work more productively, and have better social interactions. It is found that health motivation predicts health behaviour, and that health motivation is influenced by perceived self-efficacy, perceived rewards, and perceived vulnerability.

$H_0$1: The adoption of health applications (HAA) by users and health benefits are not significantly correlated.

$H_0$2: The adoption of health applications (HAA) by consumers is not significantly correlated with convenience aspects.

$H_0$3: The adoption of health applications (HAA) by users is not significantly correlated with social characteristics.

B. Conscious health habits and app adoption

Conscious health habits such as physical fitness, monitoring and tracking health daily, and following nutritional diet charts have significantly influenced users to use health apps regularly. Health and well-being are becoming increasingly important to consumers, which is fuelling demand for nutrient-dense menu options in various dining areas (Ferreira-Barbosa et al., 2023). Health-conscious consumers can find a wealth of information and inspiration from mobile apps, websites, and social media platforms (Vaghefi & Tulu, 2019). In his paper, Bharadwaj, (2022) studies in the past ten years have seen an increase in consumer awareness regarding purchasing and using food and health-related items because lifestyle disorders are becoming more common. If acquiring and using new products is simple and convenient, consumers are more likely to adopt them, which increases customer loyalty. However, Medrano Urena et al., (2020) discussed a key factor in assessing a person's functional ability should be their level of physical fitness. We talk about the necessity to look into how self-efficacy mediates the impact of physical activity on the quality of life and well-being in the adult population of healthy individuals. Perhaps Zheng et al., (2023) yielded early results about the associations between adolescents' physical fitness and their subjective well-being, motivation, and enjoyment (Gani et al., 2023).

$H_0$4: The association between health benefits and users' adoption of health apps (HAA) is not mediated by conscious health habits (CHH).

$H_0$5: The association between convenience characteristics and users' adoption of health applications (HAA) is not mediated by conscious health habits (CHH).

$H_0$6: The association between social factors and users' adoption of health applications (HAA) is not mediated by conscious health habits (CHH).

III. METHODOLOGY

Based on the above hypothesis, the conceptual framework was drawn in Fig. 1. The study aims to examine how conscious health habits mediate health benefits, convenience, social factors and adoption of health apps among users. By using the writings of numerous researchers on the subject, a methodical questionnaire was created. The questionnaire was distributed to 254 respondents throughout India using easy sampling, and 213 of them completed it. To improve the dependability of the data, in-person interactions with employees were employed, even though some online data collection techniques were also employed. The data from 185 responders was taken for testing after it had been cleaned and filtered. 71% of the total replies were further examined after the samples were rigorously cleaned according to HAA users. A 5-point Likert scale, which is used to give a more personal emotional indication of the research variables from the population's point of view, was used to measure each item on the questionnaire (Taherdoost, 2021, Malhothra, 2006).

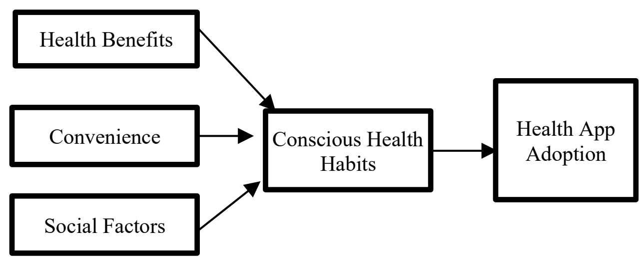

Fig. 1 Conceptual framework

Source: By author

A. Research Objectives

The study used common variables from UTAUT and HITAM models and based on that the following objectives are determined.

1. To identify the need and purpose for Health apps (HAA) apps among the users in India.
2. To assess the effects of health benefits, convenience, and social factors on the adoption of Health apps (HA) among users.
3. To analyse how Conscious Health Habits (CHH) mediates the relationship between app factors and its adoption among users.

B. Scale of Measurement

The study's foundation consists of three independent variables—social influences, user convenience, and health benefits—and one dependent variable, health app adoption (HAA). Users' adoption of health apps is gauged by three questionnaire items (Vaghefi & Tulu, 2019). Conversely, four measures evaluate conscious health practices, while three items measure convenience, social factors, and health advantages (Venkatesh & Zhang, 2010). The four conscious health habit items have all been pre-validated, and a pilot research has been carried out after consulting with subject matter experts.

IV. RESULTS

A. Demographic profile

TABLE I RESPONDENTS DEMOGRAPHICS

Demographics	Categories	Frequency	Per cent
Age	Below 20 years	13	7
	20-30 Years	83	44.9
	30-40 Years	59	31.9
	40-50 Years	20	10.8
	Above 50 Years	10	5.4
Gender	Male	92	49.7
	Female	93	50.3
Annual Income	Below 3 lakhs	61	33
	3 - 5 lakhs	45	24.3
	5-7 lakhs	24	13
	7-9 lakhs	16	8.6
	9-11 lakhs	11	5.9
	Above 11 lakhs	28	15.1
	Total	**185**	**100**

Source: SPSS

Table I highlights the demographic characteristics of respondents. The majority of respondents (44.9%) are in the 20 – 30 age range, with the 30 – 40 age range accounting for 31.9% of the sample. This suggests that young adults make up the majority of the population questioned. Only 7% of the population falls below 20 years, and 10.8% is between the ages of 40 – 50, and the smallest percentage is above 50 years, which makes up just 5.4%. Although there is a minor preponderance of females (50.3%) over males (49.7%), the gender distribution is almost balanced. A fair degree of gender inclusion in the survey sample is suggested by this nearly equal representation. A sizable percentage of respondents (33%) make less than 3 lakhs per year, according to the yearly income distribution, meaning that over half of the sample is in a lower-income category. The next largest group (24.3%) makes between 3 and 5 lakhs. Fewer people are in the upper-income groups (7-9 lakhs, 9-11 lakhs, and over 11 lakhs), which make up 8.6%, 5.9%, and 15.1% of the sample, respectively. This implies that those in the lower to middle-income group make up the majority of the sample.

B. Reliability Analysis

PLS-SEM is currently regarded as more reliable since it generates results that are largely consistent with reality. In this regard, the inner and outer models can be analysed using the Smart PLS. The data are interpreted and analysed within the framework of Smart PLS version 4.0. Verifying the validity and reliability of the outer model is the first step because these two are essential for measuring the outer model. PLS is put through several tests to evaluate its validity and dependability. For instance, the inner model's reliability is evaluated using Cronbach's Alpha, the convergent reliability of the model is evaluated using the Average Variance Extracted, and the discriminant reliability is evaluated using the Fornell and Larcker criterion.

According to Hulland, a value of 0.7 or greater is considered acceptable and desirable for Cronbach's Alpha, which gauges the internal consistency of the variable under study. Reliability data, constructs of health benefits, convenience, social influences, conscious health behaviours, and adoption of health applications (HAA) were run for Cronbach's alpha after frequency analysis. Since all of the results in Table II are greater than 0.8, they are all considered acceptable. The specifics are shown below

TABLE II CONFIRMATORY FACTOR ANALYSIS AND RELIABILITY

Constructs	Items	Factor loading	CR	AVE	Cronbach's α
	HB1	0.809			
Health Benefits (HB)	HB2	0.901	0.904	0.759	0.84
	HB3	0.875			
	CONV1	0.854			
Convenience (Conv)	CONV2	0.903	0.916	0.785	0.864
	CONV3	0.869			
	SF1	0.816			
Social factors (SF)	SF2	0.838	0.906	0.763	0.845
	SF3	0.824			
	CHH1	0.807			
Conscious health habits (CHH)	CHH2	0.816	0.928	0.764	0.897
	CHH3	0.845			
	CHH4	0.833			
Health app adoption (HAA)	HAA1	0.817			
	HAA2	0.851	0.905	0.76	0.842
	HAA3	0.839			

Similar to Cronbach's Alpha, composite reliability is also used to evaluate the inner model's dependability. A number greater than 0.6 is regarded as ideal. Moderate reliability is indicated by a composite reliability value between 0.6 and 0.7, while high reliability is indicated by a value of 0.9. All values above the suggested cutoff point of 0.7, as indicated in Table II, demonstrate their acceptability and dependability. Because they are over 0.9, which denotes great reliability, and above the suggested value of 0.07, Table II shows that all values are acceptable and trustworthy. The degree of correlation between variables within the same construct is reflected in the average variance extracted (AVE) for the variables being studied. Convergent validity is generally regarded as acceptable when the AVE value is 0.05 or more. Convergent validity results show that all values fall below the 0.05 threshold, indicating that they all meet the acceptable threshold. The measurements show dependable convergent validity, as indicated by the AVE values, which range from 0.759 to 0.784.

C. Discriminant Validity – Fornell-Larcker Criterion

Fornell and Larcker state that the square root of the average variance in each underlying variable can be used to determine the discriminant validity of that variable. Research indicates that the Fornell and Larcker approach is the most authentic and dependable method for evaluating discriminant validity. If a variable's square root exceeds its AVE value and it also has a greater correlation value, discriminate validity is established.

TABLE III DISCRIMINANT VALIDITY - FORNELL-LARCKER CRITERION

Variables	CHH	Conv	HAA	HB	SF
CHH	**0.871**				
Conv	0.639	**0.872**			
HAA	0.511	0.792	**0.874**		
HB	0.412	0.553	0.610	**0.875**	
SF	0.412	0.598	0.626	0.718	**0.886**

Using the Fornell-Larcker criterion, the results in Table III assess the constructs' discriminant validity. When the square root of the average variance extracted (AVE) for each construct (shown diagonally in the table) is higher than the correlations between that construct and others (shown off-diagonally), discriminant validity has been demonstrated. In this instance, each construct has a larger link with its own indicators than with other constructs, as seen by the square roots of the AVE for CHH (0.871), Conv (0.872), HAA (0.874), HB (0.875), and SF (0.886) exceeding their respective correlations with other variables. For instance, the square root of the AVE for both CHH (0.871) and Conv (0.872) is higher than the correlation between CHH and Conv, which is 0.639. Similarly, the square root of the AVE for SF (0.886) and HAA (0.874) is greater than the correlation between SF and HAA (0.626). These results demonstrate strong discriminant validity, demonstrating the differences between the components. The conclusion that the measurement model has adequate discriminant validity is thus supported by the fact that the Fornell-Larcker criterion is satisfied. Convenience, Health App Adoption, Health Benefits, Social elements, and Conscious Health Habits are the elements that the table shows the cross-loadings of various things on. Cross-loading assesses each item's degree of correlation with its corresponding factor. High loadings indicate that the item is a strong indication of the relevant factor; these loadings are often above 0.7.

D. Hypothesis testing and Structural Model Fit

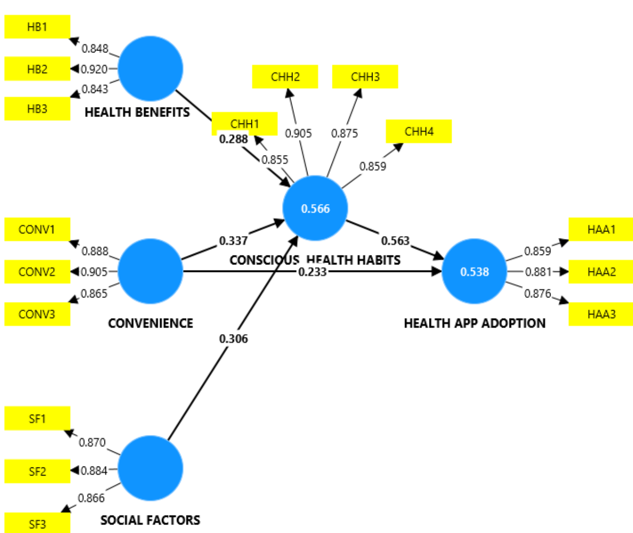

Fig. 2 PLS Measurement Model

TABLE IV HYPOTHESIS TESTING RESULTS

Variables	Beta	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Analysis
HB -> HAA	0.190	0.052	3.672	0.000	Accepted
Conv -> HAA	0.162	0.043	3.796	0.000	Accepted
SF -> HAA	0.172	0.054	3.176	0.002	Accepted
HB -> CHH -> HAA	0.190	0.052	3.672	0.000	Accepted
Conv -> CHH-> HAA	0.162	0.043	3.796	0.000	Accepted
SF -> CHH -> HAA	0.172	0.054	3.176	0.002	Accepted

The acceptance of the entire hypothesis is demonstrated by Table IV, which illustrates the direct links between PLS's Health Benefits (HB), Convenience (Conv), Social Factors (SF), and Health App Adoption (HAA). Health App Adoption (HAA) is significantly and favourably impacted by Health Benefits (HB). This suggests that the chance of using health applications rises in tandem with the perceived health benefits. This link is somewhat strong, as indicated by the beta value of 0.190. Since β=0.190, t=3.672, and $P<0.05$, H1 is acceptable. Health App Adoption (HAA) is strongly and favourably influenced by Convenience (Conv). This implies that the likelihood of a health app being adopted increases with its ease of use and convenience. This association is somewhat strong, as indicated by the beta value of 0.162. Since β=0.162, t=3.796, and $P<0.05$, H2 is acceptable. Health App Adoption (HAA) is significantly and favourably impacted by Social Factors (SF). This implies that social factors, such friend recommendations or societal standards, have a beneficial impact on the uptake of health applications. This association is somewhat strong, as indicated by the beta value of 0.172. Since β=0.172, t=3.176, and $P<0.05$, H3 is acceptable. The value of each measurement item is explained in Fig. 2.

Some techniques for measuring mediation include the distribution of product approach, the sobel test (Preacher, 2010), and casual steps. Furthermore, many researchers like bootstrapping over other mediation strategies since it is the most dependable. The distribution of product approach, the Sobel test (Preacher, 2010), and casual steps are some methods for assessing mediation. Moreover, many researchers prefer bootstrapping over other methods since it is the most reliable mediation methodology. The results of a particular indirect relation analysis are shown in Table IV, which illustrates how three distinct independent variables (HB, Conv, and SF) affect the dependent variable (HAA) via a mediator (CHH). The indirect effect of HB on HAA through CHH is statistically significant ($p < 0.05$) with a beta value of 0.199. This suggests that CHH mediates the statistically significant beneficial indirect effect of HB on HAA. H4 is acceptable since β=0.190, t=3.672, and $P<0.05$ support it. The indirect effect of Conv on HAA through CHH is statistically significant ($p < 0.05$) with a beta value of 0.162. This implies that Conv, through CHH, has a statistically significant positive indirect influence on HAA. H5 is approved because t=3.796, β=0.162, and $P<0.05$. The indirect effect of SF on HAA through CHH is statistically significant ($p < 0.05$) with a beta value of 0.172. This indicates that SF, through CHH, has a statistically significant positive indirect effect on HAA. H6 is approved because t=3.176, β=0.172, and P<0.05. Fig. 3 indicates the SEM path model among the variables.

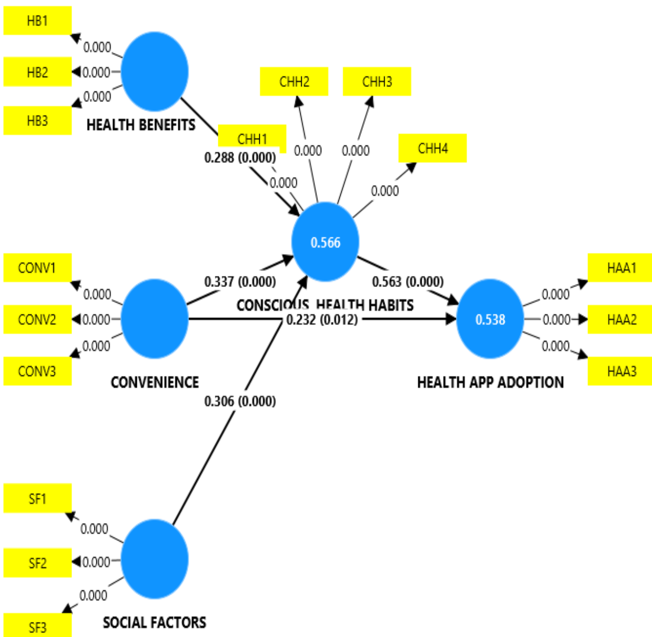

Fig. 3 PLS SEM Path Model

V. Discussion and Conclusion

A. Findings and Discussions

This study aims to find possible contributing elements to consumers' adoption of health apps (HAA). To do this, a conceptual framework is developed based on hypotheses. The sole dependent variable is the use of health applications. Convenience, social influences, and health advantages are the three independent variables. A mediating variable is used to analyze the association between the variables is conscious health habits. The study is quantitative, and a survey questionnaire employing a purposeful convenience sample technique was used to collect data from users of Indian health apps. Data analysis used was Smart PLS 4. 185 responses were also used for further research. The data's reliability and validity were evaluated using various methods. The results show that each variable falls within a range. Table II shows that the Cronbach's Alpha values for the independent and dependent variables are all over 0.8, meaning that they are all within acceptable ranges. The hypotheses were tested using bootstrapping and algorithm mediation. In line with previous studies, the test results show that hypotheses 1, 2, and 3 were accepted. The theories H4, H5, and H6 are supported by the findings of other scholars, including (Pu et al., 2020).

Furthermore, the examination of these apps' features demonstrated the quick development of health technology. Features that can improve patient engagement, treatment plan adherence, and overall health outcomes include personalized health tracking, real-time monitoring, telemedicine capabilities, and behavior change support. However, issues including data privacy, app usability, interoperability, and equitable access across a range of demographics must be addressed for integration into mainstream healthcare to be successful (Malhotra, 2005).

B. Theoretical & Practical Implications

The variables we used for the study were based on the HITAM and UTAUT frameworks. The results together highlight the significance of social considerations, convenience, and health advantages, along with the mediation of mindful health practices, in explaining the adoption of health applications (HAAs). Additionally, the likelihood of downloading health applications is higher among those who follow conscientious health practices including consistent exercise, a healthy diet, and adequate sleep. To maintain a healthy lifestyle, users should focus on other factors (Rahaman et al., 2023b). In conclusion, data collected from users of health apps shows that the adoption of health apps is significantly connected with social, convenient, and health benefits and is mediated by conscious health habits. The range of products and services, which include everything from fitness and wellness applications to aids for managing chronic illnesses, shows how mobile health technology may revolutionize healthcare delivery and enable people to take control of their health.

With an emphasis on the significance of user-centred design that gives priority to convenience, social interaction, and health benefits, the analysis provides insightful advice for developers and marketers of health applications. Marketing strategies that highlight these components might attract a larger audience and encourage acceptance. Enhancing components that promote mindful health behaviors can increase user loyalty and engagement. Policymakers and healthcare institutions can use these findings to support digital health efforts. Furthermore, tailored advertising efforts that cater to user interests may encourage the long-term uptake of health apps in India.

C. Limitations and Recommendations for Future Research

This study has certain drawbacks, which investigates how conscious health behaviors (CHH) influence Indian users' use of health apps (HAA). First, the study's geographic scope is limited because it only looks at India. Because of this, the results might not apply entirely to users in other areas, especially those from diverse socioeconomic and cultural backgrounds. To obtain a more thorough knowledge of the factors driving the adoption of health apps, future research could benefit from broadening the study to include users from different cities or nations. This study emphasizes the need to incorporate managerial strategies into app design to enhance user engagement. Future research could investigate the long-term effects of health app usage on maintaining lifestyle changes.

Abbreviation

HITAM: Health Information Technology acceptance model, UTAUT: Unified theory of acceptance and use of technology, HAA: Health app adoption, HB: Health benefits, SF: Social factors, CONV: convenience.

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Author Contributions

Vidhya J: Conceptualization, Methodology, Data collection, Analysis, manuscript writing and preparation. Shanthi Venkatesh: Review, editing, supervision, writing.

Conflict of Interest

The author(s) reported no potential conflicts of interest.

Ethics Approval

Not applicable

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