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Empirical Investigation of User Attitudes towards Emerging Technologies in Healthcare: Using the SOHI Model

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ABSTRACT
The advancement of technology and the internet have increased social media platforms' popularity in recent years. Intending to extend the social media healthcare information [SOHI] model, this study incorporates attitudes towards social media [ATTSM] to extend the model. The model was tested using SmartPLS in a quantitative study with 310 participants. The results reveal that performance expectancy of social media (PESM) has a positive and significant influence on ATTSM and satisfaction with social media (SATSM), respectively. The findings show that both ATTSM and SATSM are significantly impacted by social influence on social media (SISM). In addition, ATTSM and SATSM significantly affected the behavioural intention of social media (BISM). Furthermore, the outcome indicated that BISM has a major effect on how people use SOHI. By testing SOHI with the integration of ATTSM, it has been proven that attitude plays a critical role in users' decisions to use social media for healthcare.

Keywords: *attitude, healthcare information, performance expectancy, social influence, satisfaction, sohi, users*

I. INTRODUCTION

Currently, people rely on ICT and, by extension, social media for almost everything they do, from basic and generic information gathering to complex tasks. Social media is the pinnacle of technologists' efforts to create a virtual environment (Ikpi et al., 2022). According to Ofori and Oduro-Asante (2022), since the development of the internet, digital sites have seen a surge in user traffic and interest. This emerging healthcare technology is bridging the gap in healthcare delivery, thereby making digital healthcare accessible. Kapoor *et al.* (2020) suggested that digital systems are appropriate since new ideas for health solutions are provided. With the increasing development of social media platforms, users have adopted them for accessing personal and health-related information. There have been various studies on social media and healthcare in the past few years. Marar, Al-madaney, and Almousawi (2019) in Saudi Arabia outline reasons why people rely on social media for vital health information for their family members and its relevance. Similarly, Malik *et al.* (2019) assessed how social media could be used to support diabetic patients in managing their condition. It was evident from the study that social media communication can help enhance communication beyond clinic visits to optimise diabetes management. It was concluded that using social media for these purposes enables diabetic patients to self-manage their condition. Jin et al. (2019) conducted a study on how social media is used for healthcare. The results show that trust in the source and the usefulness of healthcare information were the key factors that health seekers focused on. In another study, Shang et al. (2020) investigated how older adults embrace digital healthcare. The study revealed that perceived susceptibility had the best effect on people's intentions to share health information.

Ofori and Wang (2022) conducted research on the application of cutting-edge technologies in health. As part of the research, a conceptual framework was developed by modifying existing variables from the UTAUT model to create a new model. In developing the SOHI model, the primary constructs that were adapted were performance expectancy, social influence, behavioural intention (Venkatesh et al., 2003), and satisfaction (Silver, Subramaniam, and Stylianou, 2020; Ofori, Antwi, and Owusu-Ansah, 2021). In their study, Ofori and Wang (2022) recommended that new variables be added to increase the explanatory power of the model. Hence, this study seeks to fill that gap with an expansion of the SOHI model to include an extra variable. We intend to add attitude because studies (Jung, Choi, and Oh, 2020; Zaremohzzabieh *et al.*, 2021) have shown that it is a crucial factor in shaping future behaviour. The purpose of adding this variable is that users' attitudes play a key role in their decision to accept a new system. In developing countries, digital healthcare is still at an emerging stage.

1.1 Literature Review and Hypothesis Development

There are many benefits to getting health information on the Internet (Jaks et al., 2019). The most common methods for receiving health information today are through the use of social media platforms (Zhang et al., 2017). It is anticipated that the expectations of patients and requirements about their interactions with their physicians will shift in response to the increasing prevalence of patients' use of the internet to search for health information (Tan and Goonawardene, 2017). The process of making decisions about one's health requires one to actively seek out, comprehend, and use relevant information (Chen et al., 2018). When compared to using a standard internet resource, accessing health information via a mobile device presents unique opportunities (Zhang, Jung, and Chen, 2019). On the basis of the theoretical model we now examine, the proposed hypotheses.

1.2 Performance Expectancy of Social Media (PESM)

The comprehensiveness of a person's social media usage has been demonstrated to reflect their technical abilities and development in the context, as well as the degree to which an invention is congruent with their views, experiences, and needs (Chatterjee and Kumar Kar, 2020). The performance requirements of a system are essential, and virtual platforms are no different. This suggests that the customers' hope for the efficacy of social media platforms has a direct bearing on their decision to engage with these sites (Gruzd, Staves, and Wilk, 2012). A study shows that when consumers recognise the extra benefits of using social media, such as increasing access to a wider range of health information and connecting with members of the network, they adopt the platform (Puspitasari and Firdauzy, 2019). Praveena and Thomas (2018) indicated that performance expectancy has a significant relationship with social media adoption. It has been suggested by the literature that performance expectancy will influence attitude, which further influences behavioural intention and use behaviour. In a recent study, it was found that users need education on how a social media health platform may aid them before they will use it for health management (Ofori, Antwi, and Asante-Oduro, 2021). From the discussions above, the following hypotheses have been developed:

H1: *The performance expectancy of social media is significantly influenced by users' attitudes towards adopting social media health information.*

H2: *The performance expectancy of social media is influenced favourably by users' SATSM.*

1.3 Social Influence on Social Media (SISM)

An individual's intention to utilise an information management system will grow if social influence is greater (Nurhayati, Anandari, and Ekowati, 2019). The level at which social networking impacts one's intention to adopt an information system may differ in various fields (Venkatesh and Davis, 2000). For instance, a study revealed that participants' level of understanding of social media use transformed their intentions towards teaching and learning practices in higher education institutions (Tachie and Brenya, 2022). Social media is being used to increase users' attitudes, social ties, and social influence (Wang & Sun, 2016). Studies have shown that users may adopt technology suggested to them by others because they want to deepen their ties with them (Hernandez et al., 2011; Ifinedo, 2016). Additionally, social influence and attitudes have varying effects across various social media platforms (Wang & Sun, 2016). Assessed from this standpoint, we formulated these hypotheses:

H3: *SISM is significantly influenced by users' attitudes towards social media.*

H4: *The SISM will have a positive impact on users' satisfaction with using social media.*

1.4 Attitude towards Social Media (ATTSM)

Attitude, as a concept, is mainly used with other variables to measure a particular procedure. Icek Ajzen's theory of planned behaviour (TPB) indicates that action towards a specific behaviour is determined by attitude (Karimy et al., 2019). Eagle & Chaiken (1993) defined attitude as the "tendency to evaluate an entity with some degree of favour or disfavour." Ajzen & Fishbein (2000) describe attitude as a judgement of a goal, a concept, or an action to like or dislike. A person's attitude towards an act can have a significant impact on their actions. Studies have shown that attitude determines an individual's behavioural intention (Devries & Ajzen, 1971; Godin et al., 1993; Ajzen, 2001; Karimy *et al.*, 2019). Mclean (2020) revealed in a recent study that good attitudes towards an application may impact a person's desire to acquire the app. Another study indicates that intention positively relates to attitude on social media (Tran, 2017). Passafaro (2019) suggested that users' attitudes can influence important direct determinants of intentions. Current studies have shown that a person's attitude has a great impact on their actions, especially with the use of technology (Hee et al., 2019; Chatterjee & Bhattacharjee, 2020; Altalhi, 2020). The explanation for this is that consumers' perceptions of social media influence their willingness to accept digital health-related issues (Ofori, Antwi, and Owusu-Ansah, 2021). Accordingly, we defined "attitude towards social media" as a person's actions after choosing to use social media. Based on the discussion that attitude affects behavioural intention, the following hypotheses are formulated:

H5: *Attitude towards social media positively influences users' behavioural intentions to utilise social media.*

1.5 Satisfaction with Social Media (SATSM)

A correlation may be shown between satisfied consumers and intention. Satisfaction is achieved when the users' perceptions of quality service are met (Marinković et al. 2019). Satisfaction on an online platform increases patients' use of the internet for health information (Liu, Zhang, and Lu, 2018). The findings of a recent investigation indicate that social media platforms are an important resource for disseminating health information in emergency settings (Li and Liu, 2020). This notwithstanding, users' satisfaction with information management is influenced by social interaction (Hsu and Chiu, 2004). It is to be noted that individuals' satisfaction with social media health information is crucial to sustaining healthcare benefits (Wang et al., 2016). According to Khatoon et al. (2020), it is possible to demonstrate a link between satisfied customers and their intentions. Per the input, we hypothesised that:

H6: *Social media satisfaction positively impacts healthcare users' behavioural intentions on social media.*

1.6 Behavioural Intention to Use Social Media (BISM)

Users' behavioural intentions are vital in an individual's decision to accept a system. A thorough examination of the relationship between behavioural intention and system usage has revealed that behavioural intention is a reliable predictor of technology adoption (Venkatesh & Davis, 2000). Venkatesh et al. (2003) came to the same conclusion, which showed that behavioural intention greatly impacts how people use technology. Kim & Malhotra (2005) posit that the amount of experience that a person has directly correlates to the likelihood that they will continue their habits. Digital technologies and behavioural intentions heavily influence health seekers' adoption and use of digital health (Hoque & Sorwar, 2017). A study has shown that if a customer has had a positive interaction and seen positive results in their situation, particularly their health conditions, they are more inclined to utilise platforms like digital networking in the future (Puspitasari and Firdauzy, 2019). It was confirmed in a similar study that indicated behaviour intention affects healthcare wearable devices (Dai et al., 2019). The use of social networking websites for medical purposes suggests that the system can motivate the public to modify their behaviour (Li and Liu, 2020). Following is a hypothesis that was formulated as a result of the discussion: behavioural intention influences SOHI:

H7: *Users' behavioural intentions towards social media positively affect social media health information usage.*

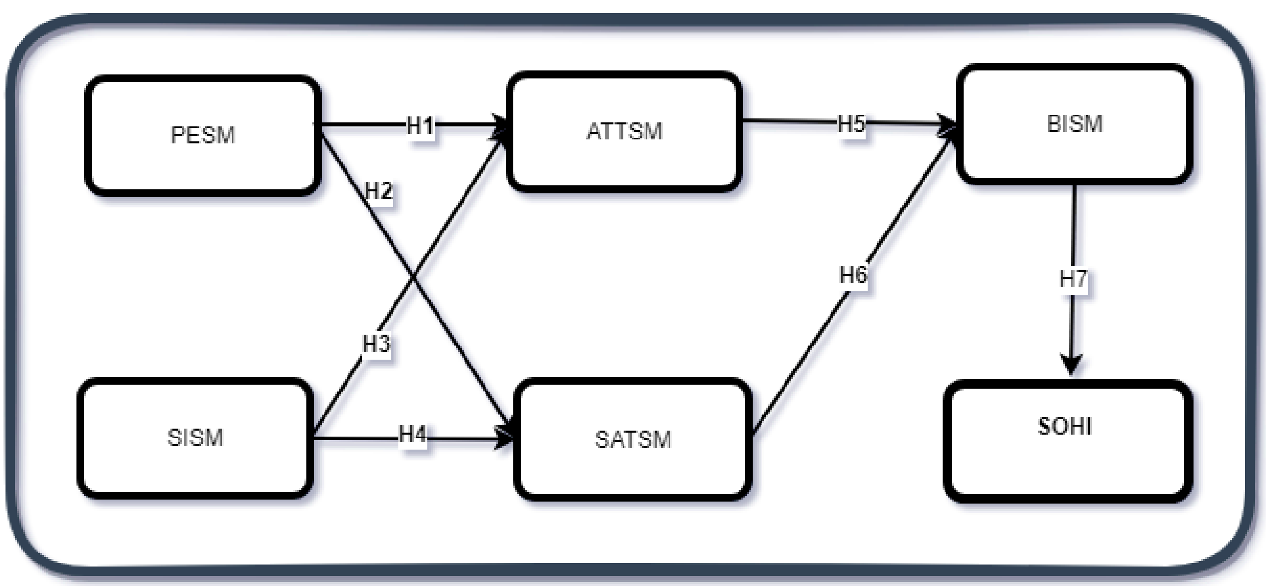

Figure 1: Research model with hypotheses development

Abbreviations: PESM: performance expectancy of social media, SISM: social influence on social media, BISM: behaviour intention of social media, ATTSM: attitude towards social media, SATSM: satisfaction with social media, SOHI: social media health information usage.

II. METHODOLOGY

2.1 Sample and Procedure

The data for this study was gathered from respondents using the Microsoft 365 forms platform. The study was conducted at Ghana Communication Technology University, and the reason for selecting the university for the study was based on the respondents' desires. The participants for this study were undergraduate students from various departments under the Faculties of Computing and Information Systems, Engineering, and IT Business. A link to a closed-ended question was sent to the participants via the WhatsApp social media platform. The survey was grouped into two sections. The first part of the questionnaire included demographic information. The second part had questions from PESM, SISM, SATSM, ATTSM, BISM, and SOHI. The study employed a 5-point Likert scale and anchored it from strongly disagree (1) to strongly agree (5). Respondents were aware that there was no risk in the study and were assured of the anonymity of their data. Based on these, respondents voluntarily completed the questionnaire through social media. With a total of 321 responses received, 310 were good for the analysis. Using 310 responses from the data gathered, the statistical analysis was performed using SmartPLS version 3 software.

2.2 Method of Data Analysis

The data were examined for validity and reliability, and the relationship between the predicted components was checked using PLS based on its estimates and statistical power (Reinartz, Haenlein, and Henseler, 2009). For primary statistical analysis, the survey data was converted from Microsoft Office form to Microsoft Excel. Internal consistency was examined using the measurement model approach. Once more, the convergent validity was examined by making use of factor loadings and the average variance extracted (AVE) (Davis, Bagozzi, and Warshaw, 1989). We examined the discriminant validity using the Heterotrait-Monotrait Ratio Test (HTMT) (Henseler, Ringle, and Sarstedt, 2015). The study used SmartPLS for statistical analysis. The researcher employed a consistent algorithm, bootstrapping, and blindfolding for the measurement and structural models.

III. EMPIRICAL RESULTS

3.1 Demographic Results

The details of the respondents are indicated in Table 1, and the sample used for the study was 310. The demographic characteristics used in the study were gender, age, and educational background. Although the link for the survey was sent out, the percentage of males participating was higher than that of females. The reason may be that many of the male respondents showed an interest in the study. However, gender was not the focus. Many of the respondents were aged 18 to 24, and this may be attributed to the fact that they were students.

Table 1: The Results of Demographics

Parameters	Frequency N (310)	Percentage (%)
Gender		
Male	267	87
Female	41	13
Age		
Under 18	4	1
18-24	273	88
25 and above	33	11
Educational background		
Diploma	14	5
Degree	246	79
Other	50	16

3.2 Measurement Model

To evaluate the data, we assessed the outer loading, average variance extracted (AVE), Cronbach's alpha, composite reliability (CR), and the Heterotrait-Monotrait Ratio Test (HTMT). The item loading range was between 0.637 and 0.864, while the AVE was from 0.515 to 0.637, which was greater than 0.5 (Hair et al., 2016). The Cronbach alpha had values that ranged from 0.797 to 0.865, while the composite reliability ranged from 0.797 to 0.875. The measurement for composite reliability and Cronbach alpha (α) was greater than 0.7 (Fornell and Larcker, 1981), demonstrating high internal reliability. The HTMT had values less than 1, which shows discriminant validity (Henseler et al., 2015) (see Table 3).

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Table 2: Construct Reliability Results

Construct	Items	Convergent Validity		Internal Consistency	
		Outer Loading	AVE	α	CR
	PESM1	0.764			
PESM	PESM2	0.662	0.515	0.808	0.809
	PESM3	0.740			
	PESM4	0.701			
	SISM2	0.745			
SISM	SISM3	0.786	0.566	0.796	0.797
	SISM4	0.726			
	ATTSM1	0.838			
	ATTSM2	0.719			
ATTSM	ATTSM3	0.728	0.560	0.865	0.863
	ATTSM4	0.637			
	ATTSM5	0.804			
	SATSM1	0.801			
SATSM	SATSM2	0.794	0.637	0.873	0.875
	SATSM3	0.864			
	SATSM4	0.728			
	BISM1	0.737			
BISM	BISM2	0.835	0.621	0.829	0.831
	BISM3	0.789			
	SOHI1	0.742			
SOHI	SOHI2	0.759	0.567	0.839	0.840
	SOHI3	0.755			
	SOHI4	0.756			

Abbreviations: PESM: performance expectancy of social media, SISM: social influence on social media, BISM: behaviour intention of social media, ATTSM: attitude towards social media, SATSM: satisfaction with social media, SOHI: social media healthcare information adoption

Table 3: Results of Variance Inflation Factors (VIF) and the Heterotrait-Monotrait Ratio Test (HTMT)

Variance Inflation Factors (VIF)

Construct	ATTSM	BISM	SATSM	SOHI
ATTSM	-	3.697	-	
BISM	-	-	-	1.000
PESM	1.228	-	1.230	-
SATSM	-	3.697	-	-
SISM	1.228	-	1.228	-

Heterotrait-Monotrait Ratio Test (HTMT)

Construct	ATTSM	BISM	PESM	SATSM	SISM
ATTSM	-				
BISM	0.766	-			
PESM	0.768	0.649	-		
SATSM	0.858	0.795	0.659	-	
SISM	0.446	0.459	0.432	0.517	-
SOHI	0.701	0.633	0.544	0.726	0.429

Abbreviations: PESM: performance expectancy of social media, SISM: social influence on social media, BISM: behaviour intention of social media, ATTSM: attitude towards social media, SATSM: satisfaction with social media, SOHI: social media healthcare information adoption

3.3 Structural Model

In terms of the direct connectivity between the constructs of the framework, the hypothesis relationships were confirmed. PESM had a statistically significant effect on ATTSM and SATSM (β =.706, t-value = 14.384, p.000); (β =.538, t-value = 8.560, p.000), supporting H1 and H2. SISM had a significant positive effect on ATTSM and SATSM (β =.145, t-value = 2.156, p < .031); (β =.283, t-value = 4.015, p <.000), which supported H3 and H4. Both ATTSM and SATSM had a positive and significant effect on BISM: (β = .349, t-value = 2.095, p <.036); (β = .492, t-value = 2.903, p <.004), which supported H5 and H6. In terms of H7, the relationship between BISM and SOHI H7 was supported because it was both positive and significant (β =.631, t-value = 9.197, p.000). The interpretation of the hypotheses is shown in Table 4 and Figure 2. The variance inflation factors (VIF) were checked to assess the common method bias. Table 3 shows that VIF values were less than 5 (Hair et al., 2011). The outcome revealed that multicollinearity was not an issue in this study.

Table 4: Summary of hypothesis results

Hypothesis	Path	Path Coefficient	T-Statistics	P-Values	Remarks
H1	PESM -> ATTSM	0.706	14.384	0.000	Supported
H2	PESM -> SATSM	0.538	8.580	0.000	Supported
H3	SISM -> ATTSM	0.145	2.156	0.031	Supported
H4	SISM -> SATSM	0.283	4.015	0.000	Supported
H5	ATTSM -> BISM	0.349	2.095	0.036	Supported
H6	SATSM -> BISM	0.492	2.903	0.004	Supported
H7	BISM -> SOHI	0.631	9.197	0.000	Supported

Abbreviations: PESM: performance expectancy of social media, SISM: social influence on social media, BISM: behaviour intention of social media, ATTSM: attitude towards social media, SATSM: satisfaction with social media, SOHI: social media healthcare information adoption

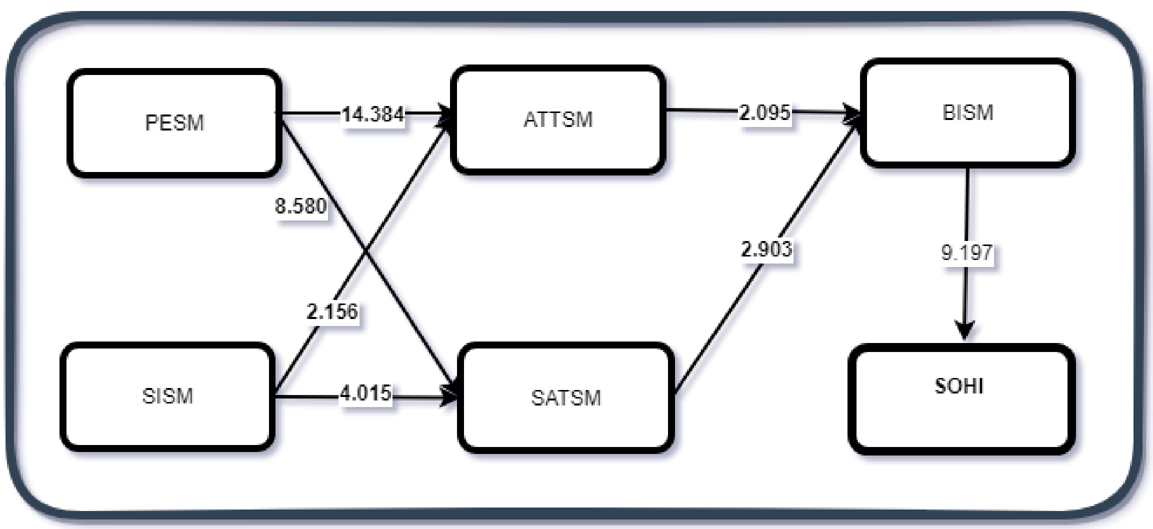

Figure 2: Structural Model Results

3.4 The Coefficient of Determination and Predictive Relevance

The values of the R^2 were 0.657 for BISM, 0.608 for ATTSM, 0.501 for SATSM, and 0.398 for SOHI. From the results, the values show substantial and moderate predictability of the constructs (Chin 1998). Stone (1974) and Geisser (1975) state that when the Q^2 values are greater than 0, it indicates that the values have predictive importance for the variables that are being measured.

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Table 5: Results of Predictive relevance and accuracy

Constructs	Coefficient of Determination	Predictive Relevance
	R^2	Q^2
BISM	0.657	0.375
ATTSM	0.608	0.278
SATSM	0.501	0.266
SOHI	0.398	0.185

IV. DISCUSSION

The current study aims to develop an extension to describe the social networking sites' healthcare information usage. First, our study extended the SOHI model with one added variable: attitude towards social media (ATTSM). Using SmartPLS, the model was analysed for the current results. Since SOHI was developed to explain user context, the model was chosen as the foundation for this study. The attitude was chosen for the extension because studies have shown that it is a significant element in user adoption of digital platforms.

The findings of this study show that the performance expectancy of social media (PESM) has a significant effect on users' attitudes towards using social media (ATTSM). This implies that people evaluate a social media site critically, which is a factor in the platform's overall level of acceptability. The findings show that PESM is important to users as it would motivate them to use the platform for other essential activities, especially health needs. Again, the results demonstrate that a site that performs the task for which it was created would persuade users to embrace it for healthcare information. The outcome of this study was in line with Ofori, Antwi, and Owusu-Ansah (2021), who suggested that users' expectations of how well social media will function have a significant bearing on their disposition, which influences, hence, whether or not they would utilise the platform for health purposes. Again, related studies confirm that performance expectance has a significant effect on users' attitudes (Ryu and Fortenberry, 2021; Afrizal, 2021).

PESM was found to affect SATSM, as proposed in H2, and the findings were supported. The results show that users' emphasis on PESM has a considerable impact on SATSM, which affects people's openness to using social networking sites to get health advice. The research model accounts for 50.1% of the variance in SATSM and represents a significant percentage of the model's explained variance. The findings demonstrate that users place a high value on the platforms they use. It also shows that as users' expectations are met, they are encouraged to continue their search on the social networking platform and, most importantly, to use it to seek health information. The impact of PESM on SATSM is consistent with similar studies (Ofori, Antwi, and Owusu-Ansah, 2021; Rahman et al., 2020; Silver et al., 2020).

In addition to this, the data demonstrated that the SISM exerts a favourable impact on the ATTSM. The research model explained 60.8% of the variance in ATTSM, and the results backed up the hypothesis. This finding indicates that users' attitudes towards social media will alter, especially if friends and family members endorse it. This strategy encourages them to utilise social media and increases their use of the platform for health information.

In a similar vein, SISM exerts a considerable influence on SATSM among users of social media. The results also reveal that SISM has a great impact on users, mainly on their satisfaction with the platforms. The results show that SISM is important when people use social media to get health information. The findings were in line with a similar study by Silver et al. (2020). In another study, Afrizal (2021) posited that users' attitudes influence the relationship between social influence and behavioural intention.

Furthermore, ATTSM had a significant impact on BISM, which supported H5. The outcome posits that a user's positive attitude towards a system is important since it influences individuals' decisions to embrace a digital platform for health information. The results from this study agree with previous studies (Ofori, Antwi, and Owusu-Ansah, 2021). Other studies have confirmed that users' attitudes have a significant effect on intentions (Mhina, Md Johar, and Alkawaz, 2019; Adov et al., 2020; Ryu and Fortenberry, 2021).

Again, H6 was shown to be significant, indicating that SATSM has a considerable impact on BISM. The results show that, despite the numerous social media platforms available, people will only accept platforms that fit the standards of their relationships and exceed their expectations. The results demonstrate that if a platform is well-designed and has solid functionalities, it has a good chance of attracting users. The results revealed that users would want to use such a platform to educate themselves and learn more about health-related issues. The findings of this investigation were in line with earlier research (Deng et al., 2010; Lopez et al., 2019; Rahman et al., 2020).

As proposed, BISM showed a significant positive relationship with SOHI, which supported the suggested hypothesis. The findings show that people who want to get health information from social media are more likely to do so if they have good intentions about how social media platforms will benefit them. The outcome of the current study supports similar literature (Ofori and Wang, 2022; Puspitasari and Firdauzy, 2019; Wu et al., 2018).

4.1 Theoretical Implications

Our major theoretical contribution is extending the SOHI model by integrating it with another construct. The previous study focused on BISM and SATSM as the main predictors of SOHI (Ofori and Wang, 2022). In the case of extending the model, another driver comes to the fore. One such factor included in SOHI is the attitude towards social media (ATTSM). The paths for the current study were changed due to the integration of ATTSM. The empirical results suggest that in accessing social networking sites for healthcare information, users' attitudes are an important driver for their adoption.

4.2 Practical Implications

Our empirical findings about research have implications for online healthcare providers. Particularly, our study suggests that a positive attitude can impact users' decisions regarding social media usage. For instance, there are various social media platforms that users can use for different purposes. However, if a platform channel for healthcare information will provide a vital benefit, then it is likely that users will accept its usage. This result will give providers an understanding of what users look at on a platform and ensure that they incorporate that into their online activities. Furthermore, online healthcare educators can prioritise their focus on determining factors that greatly influence users' adoption of social media health information. PESM emerged as the higher predictor of ATTSM, while BISM was the strongest determinant of SOHI. Using these findings, it will be appropriate for digital healthcare educators to create an appealing social media platform that can attract users. Finally, as social influence impacts PESM and ATTSM, continued interaction may lead users to connect with other individuals who may need digital health information.

4.3 Limitations and Future Research

This study, like other empirical studies, has some limitations. This research mostly focuses on students who are general customers rather than patients; hence, future studies can focus on patients. The current study focused solely on digital health information, excluding pharmaceutical and insurance businesses; a subsequent study can consider this area. Lastly, the majority of the respondents in the study were below the age of 35. Although younger consumers tend to use social media more than older adults, older consumers should be considered in future studies. A future study can expand our study by testing the SOHI in different countries' contexts and in other fields other than healthcare information.

V. CONCLUSION

The researchers developed an integrated model to investigate the factors that influence people's willingness to seek healthcare information from social media. Extending the SOHI model, the findings demonstrate that users' attitudes towards social media usage are influenced by the performance expectations of social media, which impacts their satisfaction and influences their decision towards SOHI. In our study, we validated the importance of users' attitudes and satisfaction on behavioural intention towards SOHI. Finally, users' perceptions of a system, as well as SISM, influence their use of digital health information. Users' attitudes and satisfaction are factors that influence the adoption of digital healthcare information. According to the findings, social media influence affects users' attitudes towards using social media for health information.

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