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Investigating the intention to use technology among medical students: An application of an extended model of the theory of planned behavior

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Though the integration of technology into the health sector has been touted as one of the conduits for enhancing efficiency and effectiveness in health and service delivery, research reports of not only a slow pace of adoption, but also medical practitioner's negative tendency regarding technology adoption. Considering that medical students are likely to constitute the future work force to use technology for enhancing accuracy in medical decisions, their intention to use technology constitutes a cardinal factor for guiding the implementation of technology-based initiatives in healthcare settings. By integrating descriptive norm, the study seeks to extend the theory of planned behavior (TPB) to investigate correlates of prospective users' behavioral characteristics relative to technology adoption. A field survey is conducted with 322 medical students from different medical schools undertaking mandatory clinicals in health facilities in Ghana. The structural equation modeling analysis of collected data revealed that, attitude, subjective norm, perceived behavioral control, and descriptive norm, all have significant positive relationship with student's technology adoption intention. The results of data analysis further revealed that, the core TPB constructs contributed 26% of the variance in technology adoption intention whiles the extended variable contributed to increasing the explanation of variance in student's adoption intention to 33%. Hence, the inclusion of descriptive norm increased the explained variance by 7% (ΔR^2 = 7%, p < .001). The results confirm the predictive potential and appropriateness of the TPB model. Arising from the empirical results, study implications are discussed.

1 | INTRODUCTION

The adoption of information and communication technology (ICT) has been globally acknowledged to be fraught with immense potentials to anchor professionalism, drive service delivery and enhance sector performance. In recent times, health delivery has been influenced by a concatenation of technological developments. Essentially, advancements in computer technology, and the availability of accessories thereof have spurred the development and implementation of innovative strategies for healthcare settings (Arkorful, Shuliang, Muhideen, Basiru, & Hammond, 2019; Hopson, Simms, & Knezek, 2002). In the developing world to be precise, the desire to tap into this enormous resource has compelled governments to make strides toward implementing policy initiatives meant to drive technology usage across sectors. To this end, substantial capital has been injected to provide sustainable support for ICT drive across sectors including the health sector.

More particularly in Ghana, the information communication technology for development (ICT4D) has been initiated. Coupled with this, the electronic health (e-health) strategy intended to drive health

sector technology integration was also implemented in the year 2010. This however said, in the face of the implementation of the e-health strategy and the overwhelming benefits that technology offers, its deployment has remained peripheral and minimal (Acquah-Swanzy,-2015; Zhao & Cziko, 2001).

This situation has been attributed to the hurdles confronting the integration and subsequently, the deployment of technology. These hurdles may include infrastructure, technology satisfaction, individual specific characteristics (Surry, Ensminger, & Haab, 2005) and other behavioral elements (Hossain, Quaresma, & Rahman, 2019). Under this circumstance, it is apparent that, gaining a fair knowledge, or perhaps a much deeper understanding of factors likely to influence technology adoption and use by medical students who constitute prospective medical practitioners, may be sufficient to provide insights into driving and pursuing health technology integration in challenged healthcare settings (Hossain et al., 2019; Mun & Hwang, 2003) including Ghana.

Hitherto, in the corporate world, it was conventional for management and authorities to impose technology on employees. In contemporary times however, corporate reforms have significantly shifted greater adoption responsibility and discretion to users who cannot be ignored in terms of decision-making relative to the formation of adoption intentions and possible utilization (Legris, Ingham, & Collerette, 2003). In the domain of health technology, many researches have been conducted to investigate factors that influence individuals in forming adoption intention.

In a study involving 524 medical student respondents, Dockweiler and Hornberg (2014) investigated knowledge and attitude-based factors likely to influence technology adoption among medical students in Germany. In another study involving 400 physicians, utilizing an integrated model, Chau and Hu (2001) investigated factors pertinent to individual acceptance of telemedicine technology. Furthermore, Briz-Ponce, Pereira, Carvalho, Juanes-Méndez, and García-Peñalvo (2017) researched into driver factors relative to mobile technology usage for learning among medical students in the University of Coimbra. Chau and Hu (2001) in a study in Hong Kong involving 400 physicians empirically proved a combination of models to understand technology acceptance among health practitioners practicing in public tertiary hospitals. Among other things, the study results underscored the effectiveness and pertinence of the models in predicting and explaining intention.

To the best of the knowledge of the authors, there has not been any study investigating factors influencing medical student's technology adoption intention. As such, on the basis of prior research, all against the backdrop of the reported slow technology adoption among medical practitioners in Ghana (Acquah-Swanzy, 2015; Arkorful et al., 2019) and other developing countries (Hossain et al., 2019) this seminal study would provide insights into factors likely to influence practitioners' technology adoption. This may also help overcome health sector technology integration challenges. Against this backdrop, this paper sets out to investigate factors influencing technology adoption intention among medical students using an extended version of the theory of planned behavior (TPB) model.

At the same time, in agreement with Lederer, Maupin, Sens, and Zhuang (2000), Teo and Wong (2013), and Wong, Teo, and Russo (2013) who assert the centrality of a comprehensive understanding of users' belief to technology and users' intention to use, we undertake this study to explore the predictive power of an extended TPB version. Moreover, in recognition of the recommendations of Ajzen (2002) who recognized the relevance of "others" in generating approval or otherwise for the conduct of a behavior, whether desirable or not, the study integrated descriptive norm to check the variability of the construct, especially within health technology studies. This will help to confirm the findings of Rivis and Sheeran (2004) regarding the contribution of descriptive norm to increasing explained variance in intention.

Given the importance of empirical data to substantiating conceptual debates, the aim of this paper is to examine the efficacy of an integrated model to investigate factors influencing medical student's technology adoption. Arising from this interest, the research hypothesizes that; the three core TPB variables, thus, (attitude toward use, subjective norm, perceived behavioral control) and the extended variable, thus, descriptive norm will have significant relationship with behavioral intention to use technology. The remaining parts of this paper is segmented as follows; theory and hypotheses are captured under "*theoretical background and hypotheses*" segment. The "*research methodology*" component discusses the methods employed for the study. Furthermore, study results are also covered under "*data analysis and results*." Also, detailed elaboration of the study is highlighted in the "*discussion and conclusion*" part. And finally, the study concludes by delineating strengths and shortcomings in the "*implications and limitations*" segment.

2 | THEORETICAL BACKGROUND AND HYPOTHESES

The TPB, proposed by Ajzen (1991) as an extension of the theory of reasoned action (TRA) by Ajzen and Fishbein (1980) has been established in research as an efficacious model capable of predicting behavioral intentions. The theory fosters an understanding of human behaviors, and the proximate intentions underlying them. According to Ajzen (1991), a person's action is predicated on behavioral intention. Behavioral intention is further influenced by attitude toward behavior and subjective norms. In addition to attitude and subjective norms, as captured in the TPB, perceived behavioral control can equally influence intention as well. Summarily, the TPB posits that, attitude, subjective norm and perceived behavioral control are all cognitive constructs that influence intention. The TPB is regarded as an appropriate model for studying human behavior intentions. Because of the appropriateness of the theory, though steeped in social psychology, the TPB has been employed for various studies across diverse study domains including, but not limited to Internet banking (Rouibah, Khalil, & Hassanien, 2009), e-commerce (Ramayah, Rouibah, Gopi, & Rangel, 2009), and technology use intention (Teo & Zhou, 2014).

And to further improve the predictive power of the model, prior studies have attempted integrating additional variables into the model. In predicting consumer intention to adopt hybrid electric vehicles in china using the TPB model, Wang, Fan, Zhao, Yang, and Fu (2016) added personal moral norm. Another study by Ramayah et al. (2009) explores the predictive power of TPB by integrating injunctive norm. In conducting a comprehensive investigation into what influences technology adoption intention by medical students, the research used the TPB model, incorporating descriptive norm as an additional variable to confirm and verify its predictive potential.

3 | HYPOTHESES DEVELOPMENT

3.1 | Attitude

Attitude toward behavior is conceptualized as the effective evaluation toward a given assignment or task (Ajzen & Fishbein, 1977). In the views of Teo and Lee (2010), attitude represents the positive or negative evaluation of an adoption behavior. Essentially, attitude regards the individual's response to and disposition in relations to an object. More precisely, attitude toward technology adoption could be summarized as a representation of users' like or otherwise, relative to technology use. The success or otherwise of any technology-based initiative is predicated on attitude. The implementation of same in health settings in Ghana cannot be successful without the support and positive attitude of practitioners involved.

On this basis, practitioner's perception or belief relative to the usefulness of technology to fulfilling professional needs could largely influence behavioral intention. The more fulfilling the perception, the more likely the formation of behavioral intention to adopt. Conversely, the less fulfilling, the less likely the intention. Under this circumstance, the attitude of future medical practitioners, now students, whether negative or positive are largely informed by the perceived usefulness in the professional working space. With respect to technology usage, Bellone and Czerniak (2001) contend that, an individual's positive assessment of technology, significantly increases technology use intention.

Various studies have corroborated attitude as a significant predictor of adoption intention (Dickinger & Kleijnen, 2008) which further predicts factors that influences a behavior. Behavior within the precincts of this study is technology adoption. The relationship between attitude and intention is prominently underscored in TPB models. This amply clarifies that; individual attitude represents an evaluative predisposition to behavior as a function of its determinant personal consequences (Ajzen, 1985). As such, the demonstration of a positive attitude by medical students is likely to influence the formation of a strong and positive intention. Based on the foregoing discourse, the following hypothesis is suggested:

H1 Attitude toward technology has a significant positive relationship with adoption intention.

3.2 | Subjective norm

Subjective norm (SN) primarily represents an individual's perception that people who matter most to him or her think he or she ought or not perform a behavior (Fishbein & Ajzen, 1975). This amply proves that; the opinion of other persons motivates the individual's compliance and tendency to perform a behavior. For instance, an individual practitioner may either feel the need or be compelled to use technology because a regulatory authority like the Ghana Health Service (GHS), the Ministry of Health (MoH), or a professional body like the Ghana Medical Council has issued a mandate to that effect. Teo and Lee (2010) confirm the significance of subjective norm in a study of technology adoption, and further establishes the predictive potency of the construct on intention to perform a behavior. Relative to this study on medical student's technology use intention, subjective norm is conceptualized as the individual's tendency or disposition to perform behavior (i.e., technology use in professional health practice and settings) based on the expectation of a referent group (i.e., important person[s]). In this regard, it could be speculated that, the more people think of others to perform a certain behavior, the more likely the intention to perform such behavior- owing to a higher degree of social influence. Against the backdrop of the foregoing discourse, it is important to emphasize that, a co-worker's perception of the usefulness of a technology system is likely to have a contagious imitative effect on others (Venkatesh & Davis, 2000). In relations to this study, we generalize that, the expectation of important people to medical students can significantly exert a bandwagon influence on the formation of health technology adoption intention. In view of these reasons, the following hypotheses is subsequently suggested:

H2 Subjective norm has a significant positive relationship with adoption intention.

3.3 | Perceived behavior control

Perceived behavior control (PBC) summarily represents the individual's anticipated difficulty or otherwise of undertaking a task or performing a behavior and the perceived degree of mastery the individual holds in relations to the realization of the goals from the performance of the said behavior. In terms of performing behavior, individuals may be significantly constrained by some degree of capability deficiencies which may encumber or perhaps impair his or her perception of the mastery or control over an action, results or the outcome of performing a behavior. Real or perceived shortcomings in performing behavior can interfere with the individual's ability to perform a behavior. In the views of Ajzen (1991), among other things, the TPB is introduced with the proximate reason of evaluating or assessing a situation whereby the individual has less or no tacit control over the performance of a behavior.

Seminal research (Compeau & Higgins, 1995) has established a strong correlation between individual's perceived ease or difficulty of use of technology and adoption intention. In relations to the

performance of technology behavior, PBC has been established to be significantly synonymous with perceived ease or difficulty of use. These have been well established as factors cardinal to predicting technology use intention (Compeau & Higgins, 1995). This further accentuates that, the stronger the perception of ease of use of a technology, the stronger the self-belief of the individual in the use of the system to gratify a need. The converse equally holds. From the foregoing, it is hypothesized that:

H3 Perceived behavior control has a significant positive relationship with adoption intention.

3.4 | Descriptive norm

Central to behavioral studies is descriptive norm. Descriptive norm is construed as subjective norm. In as much as they all belong to the broader classification of social norm, they however differ. Whereas subjective norm summarizes a presentation of what important people think and expect of an individual, descriptive norm on the other hand refers to the performance of a particular behavior by the people the individual thinks or considers to be important, for which reason the individual thinks he or she should replicate or do same. Essentially, descriptive norm concerns what others are doing. It captures what is perceived as common or normal, that is, what most people do. In relations to system adoption like health technology, the behavior of others is likely to exert a bandwagon effect or influence on others to perform same behavior. It is important to state that, the higher the performance of adoption behavior by the others, the more likely the performance of same by others. On the other hand, the less the adoption, the less likely for others to perform same behavior. More significantly, the greater the descriptive norm, the greater the adoption likelihood. And the less the subjective norm, the less the adoption intention.

Ajzen (2002) recognized that, since important others generally are perceived to approve of desirable behaviors and disapprove of undesirable behaviors, subjective norm is likely to have weak variability. In view of this, he recommended for the inclusion of items designed to capture descriptive norm, in addition to subjective norm. In a meta-analysis, Rivis and Sheeran (2004) found descriptive norm to have increased the variance explained in intention by 5% after the TPB components. In view of the results of Rivis and Sheeran (2004) and the recommendations of Ajzen (2002), it is expected that descriptive norm will have an impact on student's technology adoption intentions. Extending same logic to investigate medical student's technology adoption intention, it could be suggested that, adoption intention is more likely to be performed, especially in situation where individuals perceive such a behavior as one commonly performed by others. On this basis, the study hypothesizes that:

H4 Descriptive norm has a significant positive relationship with adoption intention.

3.5 | Intention

The TPB model perceives intention prediction as a subsequent predicate of a set of corresponding open action. As such, intention is viewed as a capture or a representation of influential factors of behavior which demonstrates willingness or otherwise of people to perform a particular behavior. Intention is a representation of the difficulty of individuals to perform a behavior. This further informs the degree of effort they are willing or ready to exert in the performance of same behavior (Sheeran, 2002).

Attitude is determined through an investigation of individual's set of beliefs relative to the ramifications generated from the performance of behavior. The prediction of intention within the TPB framework is central to predicting behavior. Armitage and Conner (2001) corroborate the significance of intention in predicting the performance of a behavior in 185 studies. Also, it is important to state that, attitude, subjective norm, perceived behavioral control, and descriptive norm will integrate additively, and incrementally contribute to predicting intention. Therefore, it could be concluded that, the prediction of intention is derived from the influence of other collective factors. In relations to this study, intention will be determined by the additive and subsequent incremental contribution of factors such as attitude, subjective norm, perceived behavioral control and descriptive norm.

4 | RESEARCH METHODOLOGY

4.1 | Sample and data collection

The study employs the structural equation modeling (SEM) method to develop and verify the research model and further establish construct relationships (Figure 1). To test the research hypotheses, the study used a questionnaire survey to draw data from medical students undertaking mandatory clinical assignments in different health facilities across Ghana. The study participants were made up of students from various tertiary institutions in Ghana studying medicine. The study randomly selected participants on the basis of their availability, readiness, and willingness to participate. The study targeted medical students because, given the urgency of driving universal health coverage goals, after school, they are expected to use technology in their work as medical practitioners to propel health sector outcomes. Prior to questionnaire administration, the study participants were briefed on the study purpose. They were further informed of their liberty to either accept or decline participation at any time; thus, before, during and even after. Averagely, in completing a questionnaire developed in the English language, participants took less than 30 min. The study made responses anonymous to protect participants' identity. To avoid biases which could skew results, study participants were not offered any incentive. Regarding the selection of proper samples for studies, various opinions have been expressed. A sample size of 200 is regarded as fair and 300 is considered good for SEM statistical analysis (Kline, 2010). Also, a sample of 200 is also considered as appropriate

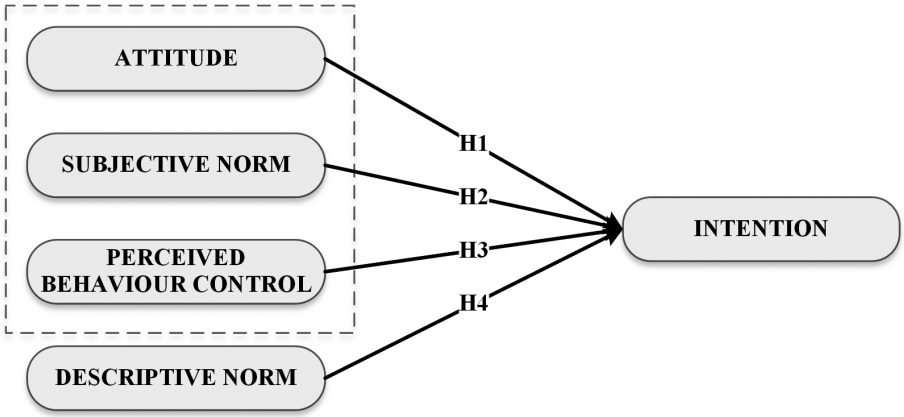

FIGURE 1 Research framework of technology adoption intention

TABLE 1 Descriptive information of the sample

Measures	Frequency	Percentage
Gender		
Male	178	55.3
Female	144	44.7
Age		
18–25	94	29.2
26–32	137	42.5
33–39	44	13.7
40+	47	14.6
Duration of computer utilization		
Less than 1 year	155	48.1
Between 1 and 2 years	99	30.7
Between 3 and 4 years	22	6.8
Five or more years	46	14.3

for SEM analysis (Hair, Anderson, Tatham, & Black, 1998). In view of these recommendations, and subsequently drawing validation from them, the research team distributed 360 questionnaires. In total, 344 questionnaires were retrieved. After reviewing retrieved questionnaires, incomplete questionnaires, as well as those with missing data were discarded. In the end, 322 valid and useable questionnaires were finally retrieved, representing 88% response rate. The descriptive information of the study sample is presented in Table 1. Participation in this study was voluntary.

5 | MEASURES

Survey items for this study involved 15 items spread across constructs adapted from instruments validated by prior studies. The researchers made significant changes in the word arrangements of the questions to suit and reflect the measurements of study constructs. Latent variables for this study were measured on a 5-point Likert scale ranging from 1 (strongly agree) to 5 (strongly disagree). Measurement items for individual attitude toward technology adoption, subjective and perceived behavioral control and technology adoption intention were adapted from prior studies by Ajzen (2002), Kaiser and Scheuthle (2003), Manning (2009), Wang et al. (2016), and Yadav and Pathak (2016). Similarly, items for descriptive norm were also adapted from Fornara, Pattitoni, Mura, and Strazzera (2016), Jun and Arendt (2016), Rivis and Sheeran (2004), and Webb, Soutar, Mazzarol, and Saldaris (2013). Construct and measurement items are presented in Table A1.

6 | DATA ANALYSIS AND RESULTS

Based on the theoretical framework and the hypothesis employed for the study, the analysis of moments structures (AMOS) version 24 was used for SEM analysis, and for establishing the model. The SEM technique was used because it facilitates the use of some observed variables to measure an unobserved variable. Analysis of data involved two processes. Firstly, in confirming the validity and reliability of constructs, the measurement model was verified (Table 2). Subsequently, hypothesis testing was carried out by using the structural model approach. In examining values of factor loadings greater than 0.5, using SPSS version 24, an exploratory factor analysis (EFA) was performed. The results indicated that, indices were consistent with standard values. This is a sufficient validation of the proposed study model. Also, results of confirmatory factor analysis (CFA) were used for measuring model test comprising validity and reliability test. Factor analysis was used for item cleaning. Afterwards, factor loadings were found to be above 0.7. Based on these acceptable results, SEM was run. Reliability test, as evidenced in Cronbach alpha values were found to be higher than .7 which is a sufficient proof of a good reliability scale (Fornell & Larcker, 1981; Hair, Black, Babin, & Anderson, 2010). Results are presented in Table 3. Using average variance extracted (AVE) and composite reliability (CR) measures (Table 3), test of convergent validity was carried out. Composite reliability scores were all found to be above 0.7. This is an indication of the sufficiency and representativeness of the study constructs and reliability (Hair et al., 1998; Wu, 2010). According to Fornell and Larcker (1981) AVE values beyond 0.5 demonstrates good convergent validity for the research instrument. Essentially, AVE values could also be used to explain discriminant validity, especially when it does not match with a

TABLE 2 Loading and cross-loadings

Constructs	Indicators	ATT	DN	AI	SN	PBC
ATT	ATT1	**.896**	−.038	.033	.016	.019
	ATT2	**.929**	.002	.034	−.013	.010
	ATT3	**.977**	.030	−.060	.000	−.021
DN	DN1	.018	**.923**	.013	−.025	−.012
	DN2	.005	**.926**	−.020	−.022	.030
	DN3	−.025	**.898**	.022	.051	−.020
AI	AI1	−.020	−.060	**.927**	.010	.017
	AI2	.004	.017	**.921**	−.005	.003
	AI3	.019	.064	**.906**	−.009	−.018
SN	SN1	.052	−.039	.045	**.884**	−.006
	SN2	−.016	.075	−.032	**.883**	.053
	SN3	−.030	−.030	−.015	**.956**	−.042
PBC	PBC1	−.018	−.062	.092	.021	**.847**
	PBC2	.004	−.001	−.037	−.019	**.931**
	PBC3	.017	.059	−.041	−.001	**.897**

Note: Bold values show loadings of measurement items on specified constructs.
Abbreviations: AI, adoption intention; ATT, attitude towards adoption; DN, descriptive norm; PBC, perceived behavioral control; SN, social norm.

TABLE 3 Results of factor analysis

Constructs	Indicators	Factor loadings	Cronbach's alpha	CR	AVE
ATT	ATT1	**.896**	.928	.906	.874
	ATT2	**.929**			
	ATT3	**.977**			
DN	DN1	**.923**	.907	.940	.838
	DN2	**.926**			
	DN3	**.898**			
AI	AI1	**.927**	.908	.941	.843
	AI2	**.921**			
	AI3	**.906**			
SN	SN1	**.884**	.895	.934	.825
	SN2	**.883**			
	SN3	**.956**			
PBC	PBC1	**.847**	.875	.921	.796
	PBC2	**.931**			
	PBC3	**.897**			

Abbreviations: AI, adoption intention; ATT, attitude towards adoption; AVE, average variance extracted; CR, composite reliability; DN, descriptive norm; PBC, perceived behavioral control; SN, social norm.

measure for which it must vary. Table 4 presents correlation where the diagonals represent the square roots of the AVE. This is an indication of a good discriminant validity.

7 | MEASUREMENT AND STRUCTURAL MODEL EVALUATION

Using AMOS version 24, the study evaluated goodness of fit of measurement and structural model to find out the extent of significance of the respective hypothesis path. The indices checked include; degree of freedom (df), comparative fit index (cfi), normed fit index (nfi), incremental fit index (IFI), parsimonious comparative fit index, and root mean square error of approximation (RMSEA).

The study used fit indices to signify varying and diverse classifications of model fitness along with acceptance fit level as presented in Table 5.

As shown in the table, it is apparent that, measures are good fit and consistent with the recommended criterions (Wu, 2010). Per the accepted values of Bentler (1992), Elkaseh, Wong, and Fung (2016),

TABLE 4 Composite reliability, average variance extracted, and correlation

Constructs	Mean	*SD*	ATT	DN	AI	SN	PBC
ATT	9.540	3.893	**.935**				
DN	10.236	3.245	.085	**.915**			
AI	11.488	2.767	.401**	.347**	**.918**		
SN	10.705	3.094	.220**	.226**	.305**	**.908**	
PBC	10.935	3.084	.420**	.090	.410**	.264**	**.891**

Abbreviations: AI, adoption intention; ATT, attitude; DN, descriptive norm; PBC, perceived behavioral control; SN, subjective norm.
**Off-diagonal elements are the correlations among constructs.
Correlation is significant at .01.

TABLE 5 Fit indices for the measurement and structural model

			Results	
Measurement	Indices	Criterion	Measurement model	Structural model
Absolute fit measures	AGFI	>.8	0.939	0.882
	GFI	>.9	0.963	0.915
	RMSEA	<.08	0.043	0.068
Incremental fit measures	NFI	>.9	0.972	0.939
	CFI	>.9	0.989	0.963
	IFI	>.9	0.989	0.963
	CMIN/DF	<3.00	1.588	2.476

Abbreviations: AGFI, adjusted goodness-of-fit-index; CFI, comparative fit index; DF, degree of freedom; GFI, goodness-of -fit-index; IFI, incremental fit index; NFI, normed fit index; RMSEA, root mean square error of approximation.

TABLE 6 Results of path coefficient

Constructs	Estimates (β)
ATT → AI	.162***
DN → AI	.223***
SN → AI	.097**
PBC → AI	.206***

Abbreviations: AI, adoption intention; ATT, attitude; DN, descriptive norm; PBC, perceived behavioral control; SN, subjective norm.
**p < .01.
***p < .001.

Hair et al. (1998), Miles and Shevlin (2007), Quintana and Maxwell (1999), the research model is considered fit. For this reason, it is reasonable to conclude that, both structural and measurement model for the study are appropriate and acceptable.

8 | HYPOTHESIS TESTING AND EFFECTS

The study hypotheses were tested after confirming the validity and reliability of the study. Table 6 and Figure 2 capture the results of path analysis using AMOS version 24.

The results of analysis indicated that, Attitude toward technology (β = .162, p < .001), subjective norm (β = .97, p < .001), perceived behavioral control (β = .206, p < .001) and descriptive norm (β = .223, p < .001) all have significant positive relationship with technology adoption intention. These findings were in support of proposed H1, H2, H3, and H4, respectively. Study results show that, all proposed study hypotheses were significantly supported.

9 | DISCUSSION AND CONCLUSION

The study sought to research into technology adoption intention of medical students using an extended version of the TPB. With reference to findings from previous seminal studies, the study proposed a research theoretical framework as the research model. With recourse to the study model, four hypotheses were proposed to signify the correlation between the TPB constructs. Whiles extensively exploring social, psychological, and related behavioral factors underpinning technology adoption and usage, the study significantly contributes to IS studies by presenting an integrated TPB model to investigate technology adoption intention.

The adoption of technology and its usage has the potency to contribute more significantly to improving health sector outcomes, foster collaboration between not only diverse health system, but also between patients and practitioners through an interoperable common platform, intensify and expand efforts to building a healthy population, whiles at the same time, helping to achieve global health related goals, specifically, universal health coverage. Furthermore, the use of technology enhances high synchronization, information exchanges and amplifies health sector efficiency and effectiveness. At the same time, the utilization of a technology innovation platform, compared to

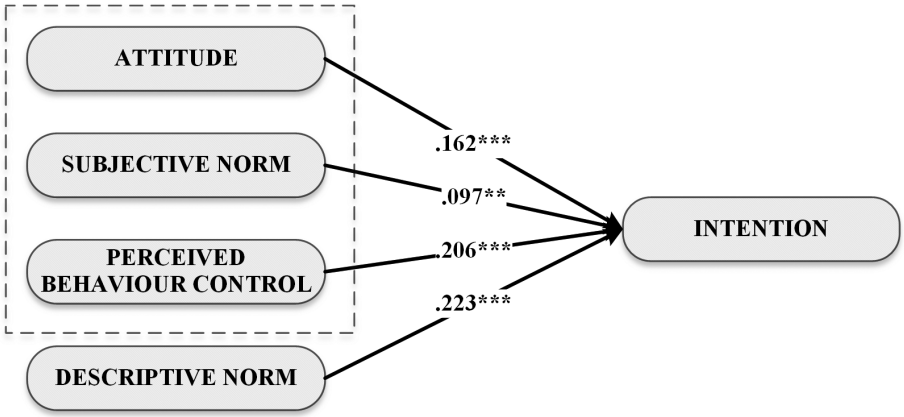

FIGURE 2 Structural equation modeling results

a traditional nontechnology-based method of healthcare service delivery has been proved to have cutting edge precision, efficiency and potency (Hossain et al., 2019).

Our findings indicated that, attitude (β = .162, $p < .001$) had a positive significant relationship with medical student's technology adoption intention. This significance is consistent with Bellone and Czerniak (2001) who asserted that students' positive evaluation of technology, significantly impacts on the use of technology by others. This finding is also in agreement with Azizi and Khatony (2019), Macharia and Pelser (2014), Teo (2006, 2008, 2009), Teo and Lee (2010), Teo and Zhou (2014), Teo, Zhou, and Noyes (2016), and Wong et al. (2013). Even though the relationship is significant, attitude, per this research outcome, is not the strongest predictor of intentions as corroborated by prior research findings. As the third least predictor of intention, this finding is inconsistent with Rivis and Sheeran (2004), Teo (2006, 2008, 2009), and Teo and Lee (2010).

Moreover, results of data analysis revealed subjective norm to have a significant positive relationship with intention (β = .97, $p < .001$). Though subjective norm was found to have the least relationship with technology adoption intention, it is positively and significantly related. This is consistent with the findings of Bellone and Czerniak (2001) and Teo et al. (2016) who underscored the significance of technology users' positive evaluation on the use of technology by others. Situating this within our study context, it could be proffered that, capitalizing on social pressures brought about by perception and/or expectations of others to perform a behavior can help promote technology adoption intention.

Furthermore, the study findings revealed perceived behavioral control to have a significant positive relationship with technology adoption intention. Though this is inconsistent with Teo and Lee (2010), the positive relationship could be attributed to the level of perceived personal adequacy with regards to the amount of control a medical student may have over the use of technology to attain goals, by forming intention and subsequently performing a behavior. This may imply that; health students are likely to use technology whenever they think they have the confidence and mastery over the technology (Azizi & Khatony, 2019). Conversely, technology adoption intention may decline in cases or instances when and where the level of confidence and perception of mastery over the technology usage is in doubt (Teo et al., 2016). Summarily, the degree of ease or difficulty of use, could significantly impact on intention to use technology.

This could be interpreted to mean that, as much as participants recognize the efficacy of technology use in propelling healthcare and service delivery, the degree of technology efficacy may be of greater significance in influencing the formation of user intention. Under this circumstance, it is important to note that, as much as the inception of ICT training outfits for in-school and out-of-school medical students will be cardinal to promoting technology adoption behavior, it could in much the same way foster an appreciation of technology. This can impel technology adoption intention in medical students.

More so, the study demonstrated that, the additional TPB variable, thus, descriptive norm, also had a significant positive relationship with adoption intention. These results from the data analysis adequately revealed that, the three TPB constructs supported the three proposed study hypotheses. At the same time, the integrated construct, thus descriptive norm, also supported the proposed hypothesis. The study outcomes, as demonstrated by the results of path analysis confirmed that, the path coefficient from descriptive norm toward technology adoption intention was the strongest (β = .223, $p < .001$). This is an indication that, relative to this study bordering on medical student's technology adoption intention, descriptive norm exerted the strongest significance.

From this finding, it could be concluded that, technology adoption intention could be facilitated by stimulating and taking advantage of social group relations. Even though prior research findings of Tsai, Hung, Yu, Chen, and Yen (2019) on intention-based models have reported attitude to be strongest predictor of intentions, which is inconsistent with this study outcome, there is a plausible reason to explain why descriptive norm is reported as the strongest predictor of intention. Given the collective and communal nature of the Ghanaian society where relations, more especially group relations are assigned greater paramountcy (Adu-Febiri, 1995), it is understandable that group relations could compel technology adoption intention among health students. This finding could also be possible because of varying external factors often generated by a population's sociodemographic characteristics as confirmed by Burton-Jones and Hubona (2005).

Collectively, whereas the core TPB constructs contributed 26% of the variance in technology adoption intention, the integrated

variable contributed to increasing the explanation of variance in adoption intention to 33%. As such, the inclusion of descriptive norm increased explained variance by 7% (ΔR^2 = 7%, p < .001). This is a little above the increase in explained variance in intention threshold (5%) empirically proven by Rivis and Sheeran (2004). Compared with other research, in as much as the research findings offer interesting outcomes, it has the potential to explain the intricate and complex factors underpinning technology adoption intention among medical students in Ghana.

10 | IMPLICATIONS AND LIMITATIONS OF THE STUDY

This research has several implications. Theoretically, this research contributes to extant literature on the role and impact of psychological and behavioral factors in decision-making relative to performing technology adoption behavior. The study further reveals the TPB as a promising paradigm, with a greater prospect for predicting intention. In the same light, the study contributes to enriching our understanding of factors undergirding individual decision-making, as it empirically points out factors that can drive the decision-making process.

Furthermore, in prior IS literature, few studies have undertaken seminal research of empirical value to prove how behavioral factors could influence technology adoption intention. To the best of the knowledge of the authors, no study has been conducted within the Ghanaian context. Given this gap, the research lends sufficient support and credence to the levels of coordination between social and psychological factors on one hand and individual behavior on the other. More significantly, this research finds varying impacts of behavioral factors on technology adoption intention and recommend the conduct of further research to confirm the hypotheses. This suggestion does not however invalidate the results of this study.

Besides, in practice, the research findings may proffer guidelines and pointers to stakeholders such as government, educationist, policy makers and the general civil society on how to plan and allot resources for driving technology to elevate health care, service delivery and overall outcomes. Stakeholders must acknowledge that; behavioral factors are very essential to be considered in terms of implementing policies.

For the purposes of enhancing and improving public health interventions, life expectancy and other factors with the potential to account for public health service delivery improvements, which is a matter of global public interest, driving technology integration requires undertaking several measures to boost individual adoption intention. Specifically, with regards to technology adoption intention, strategies are more likely to succeed if individuals, especially prospective users are targeted more than organizations (Gagnon et al., 2016). Also, to increase student's positive appreciation of technology systems, it is relevant to provide relevant professional training to enhance familiarization with technology (Rozenblum et al., 2011). Furthermore, stakeholders like medical service providers, health administrators, health policy makers among others should consider that, in addition to technology specific characteristics, social, psychological and behavioral factors have significant baring on user's intention.

In as much as our research projects insightful, yet enthralling theoretical and practical implications, it is pertinent to point out the shortcomings of this study. Firstly, the data analysis for this study was based on a cross-sectional data which is not entirely a sufficient basis for measuring the causal relationship between an independent and dependent variable. This threatens generalization and replication across populations. We therefore strongly recommend the design of a longitudinal study to elicit, and further explore causal relationships anchored on technology adoption. Research could also be more specific on the precise or specific kind of technology. This will make future investigations more robust, distinct, precise and effective.

Finally, the findings of this research were based on data drawn from respondents in different locations. For this reason, the generalizability of these findings must be limited. And caution must be exercised in this regard. The outcome may not be replicable in other countries who evince characteristics like individualism, which is in sharp contrast, and diametrically opposed to the communal and collectivist culture of Ghana. Coupled with other cultural factors, generalization of the findings may be perilous. Thus, the research suggests future research to prioritize collecting data from different countries, composed of a more diverse population with heterogenous sociodemographic characteristics, to further verify and establish construct relationships.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

ETHICS STATEMENT

All procedures performed in this study are in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants included in the study.

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APPENDIX A

TABLE A1 Measurement items

Constructs	Items	Questions
ATT	ATT1	For me, adoption technology is favorable
	ATT2	For me, adopting technology is desirable
	ATT3	For me, adopting technology is positive
SN	SN1	Most people who are important to me think I should use technology
	SN2	People whose opinions I value would prefer I adopt technology in my work
	SN3	If I use technology, most people who are important to me would also use
PBC	PBC1	I can easily find technology when needed
	PBC2	The maintenance and use of technology are important to me when I adopt
	PBC3	I can use technology efficiently when I decide to use
DN	DN1	My colleagues have taken actions to use technology
	DN2	A number of my colleagues I know have decided to use technology
	DN3	Others who are important to me have decided to use technology.
AI	AI1	I am ready to adopt technology in the near future
	AI2	I intend to use technology when I start work in future
	AI3	I plan to use technology in my profession in future

Abbreviations: AI, adoption intention of technology; ATT, attitude; DN, descriptive norm; PBC, perceived behavioral control; SN, subjective norm.