



# The Influence of Personal Innovation in Information Technology (PIIT) and Factors on Behavior Intention of 3DBody Anatomy Software in Liaoyang Vocational and Technical College

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## Abstract

**Background and Aim:** This research explores the key factors influencing nursing students' intention to use 3D body anatomy software at Liaoyang Vocational and Technical College, China. Based on these models, seven hypotheses and seven latent variables were proposed: Personal Innovation in Information Technology (PIIT), Performance Expectancy (PE), Effort Expectancy (EE), Subject Norms (SN), Attitude (ATT), Perceived Behavior Control (PBC), and Behavior Intention (BI).

**Materials and Methods:** This study adopts a quantitative method, through an operationalized questionnaire, and conducts reliability and validity tests. The sampling method is purposive sampling and stratified sampling. Data analysis was performed through confirmatory factor analysis (CFA) and structural equation modeling (SEM).

**Results:** The research findings indicate that all hypotheses are supported, with effort expectancy exerting the most significant influence on behavioral intention. The results show  $\beta = 0.320$ ,  $p < 0.001$ . This result indicates that EE has the greatest impact on BI. Next are Performance Expectancy (PE), Attitude (ATT), Subject Norms (SN), and Perceived Behavior Control (PBC). PIIT also shows a significant positive impact on PE and EE.

**Conclusion:** This study indicates that in the comprehensive prediction of vocational nursing students' behavioral intention to use the 3Dbody anatomy software, performance expectancy (PE), effort expectancy (EE), subjective norm (SN), attitude (Att), and personal innovativeness (PIIT) all have a significant impact on behavioral intention (BI). According to the research results, software designers can simplify operations, while teachers can enhance students' confidence through guided learning. These improvements can enhance the user experience, thereby increasing students' adoption intention and usage retention.

**Keywords:** Vocational Nursing Students; 3Dbody Software; Technology Adoption; Nursing Education

## Introduction

Undeniably, e-learning technologies are influencing the consumption of educational content in today's teaching methodologies. Although e-learning offers various advantages, it fails to maintain learners' motivation, which is a key component of any type of learning, including online learning (Bekele, 2010; Jones & Issroff, 2005). For certain courses, such as those involving physical experiments like human body structure and function, the application of technology can effectively strengthen the learning outcomes. Due to limited opportunities for students to access labs with cadavers and physiology resources, information technology has become a valuable means of supplementation. Consequently, the trend of digitizing anatomy and physiology courses is becoming increasingly apparent. It provides supplementary learning resources to help students understand fundamental knowledge and complex theories in the curriculum. Therefore, to enhance the learning experience and remain competitive, many universities have adopted e-learning practices (Rodrigues et al., 2011; Njenga & Fourie, 2010).

3Dbody anatomy software provides high-precision 3D anatomical models that users can freely view from different angles through operations such as rotation, scaling, and translation. This method of 3D visualization enables learners to better understand the relationships between organs and their spatial arrangements (Brazina et al., 2014). In medical education, 3Dbody anatomy software provides medical and nursing students with a learning experience different from traditional anatomy courses. Studies have shown that using 3D models can improve students' mastery of anatomical knowledge and enhance spatial cognitive abilities (Liu et al., 2016).

[833]

## Citation



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Currently, research on 3DBody software focuses on its impact on teaching quality and student performance, rather than exploring it from the perspective of student acceptance and the software's characteristics. Despite increasing digitalization in nursing education, limited research explores vocational students' acceptance of 3D anatomy software. This study addresses this gap by applying the UTAUT and TPB frameworks to analyze behavioral intention among students at Liaoyang Vocational and Technical College.

The Theory of Planned Behavior (TPB), proposed by Ajzen (1991), is used to explain individuals' behavioral intentions and actual behaviors. TPB suggests that three key factors influence behavioral intention: attitude, subjective norms (SN), and perceived behavioral control (PBC). When students have a positive attitude toward the software or receive recommendations from peers or teachers, their intention to use the software may increase.

UTAUT theory (Venkatesh et al., 2003) aims to deeply explore individuals' adoption and application intentions and influencing factors when facing new technologies. This theory believes that by analyzing the part of expected benefits and social influence, we can more accurately predict individual acceptance and actual application of new technologies. In short, the UTAUT theory provides us with a powerful framework for understanding and predicting individuals' psychological mechanisms and behavioral patterns in the process of adopting new technologies.

In addition to the UTAUT factors that explain e-learning behavioral intention, scholars also recommend considering other factors that influence e-learning intention, such as personal innovation ability in information technology (PIIT) (Gunasinghe et al., 2020; Pinho, Franco, & Mendes, 2021) and expected financial costs of e-learning (Chang & Tung, 2008, 2008). Agarwal and Prasad (1998) argued that PIIT can be used not only to describe individuals who early adopt innovations but also as a personality trait describing "A person's readiness to experiment with any new information technology."

## Objectives

This study aims to examine the impact of behavioral intentions on 3D body anatomy software among higher vocational nursing students in Liaoyang Vocational and Technical College. An extensive investigation of the complex psychological and behavioral factors influencing vocational college students' use of 3Dbody software aims to fill existing research gaps in the literature, providing a fresh perspective and empirical support for the effective application of digital learning tools in vocational education.

## Literature review

### Personal Innovation in Information Technology

PIIT can assess an individual's willingness to explore new technologies (Agarwal & Prasad, 1998; Twum et al., 2022). In both the PIIT theory and the UTAUT theory, it is considered a key variable. Individuals with high PIIT are more sensitive to the potential of new technologies to enhance work or learning efficiency, thus having a significant impact on perceived usefulness (PE) (Kapoor et al., 2021). At the same time, individuals with high PIIT are more willing to experiment with new technologies, making it easier for them to master these technologies (Rogers, 2003).

Previous studies have shown that PIIT has a significant positive impact on PE and EE, indicating that individuals with high PIIT are more likely to perceive new technologies as useful and easy to use during the adoption process. In the promotion of educational technology, enhancing individuals' technological innovativeness can increase their acceptance of new technologies, improve perceived usefulness and perceived ease of use, and ultimately facilitate the continuous use of technology.

H1: The PIIT has a positive influence on the Performance Expectancy of the use of 3Dbody anatomy software by vocational nursing students.

H2: The PIIT has a positive influence on the Effort Expectancy on the use of 3Dbody anatomy software by vocational nursing students.

### Performance Expectancy

The performance expectancy framework within the UTAUT model is defined as "the anticipation that using a particular technology will lead to actual benefits or improvements in outcomes" (Venkatesh et al., 2003; Chao, 2019). Among the factors influencing the intention of vocational nursing students to use 3Dbody software, Performance Expectancy is considered an important determinant influencing their intention to adopt the software.

H3: Performance Expectancy has a positive influence on Behavior Intention on the use of 3Dbody anatomy software by vocational nursing students.

### **Effort Expectancy**

Venkatesh et al. (2003) identified "Effort Expectancy" as a crucial factor, describing it as the perceived ease of use of technology, which directly influences users' intention to accept the technology. The complexity of the technology directly impacts users' Effort Expectancy (Chao, 2019). User Experience: Users' prior experience and familiarity with technology can reduce their Effort Expectancy for new technologies. User Support: The availability of technical support and training can affect users' Effort Expectancy, making them perceive the technology as easier to use.

H4: Effort Expectancy has no positive influence on the Behavior Intention on the use of 3Dbody anatomy software by vocational nursing students.

### **Subjective Norms**

Subjective norms refer to the pressure an individual feels from their social environment when deciding whether to engage in a particular behavior (Ajzen, 1991). A key component of the Theory of Planned Behavior (TPB) and the Theory of Reasoned Action (TRA). These theories are primarily used to explain and predict individual behavior, especially when behavior is influenced by social and environmental factors. Subjective norms reflect whether individuals believe that important others (such as colleagues, supervisors, and friends) expect them to use a particular information technology. Recent studies have also proved the significant impact of SN on BI (Al-Rahmi et al., 2020).

H5: The Subjective norm has a positive influence on the Behavior Intention on the use of 3Dbody anatomy software by vocational nursing students.

### **Attitude**

Attitude is an important concept in the fields of psychology and behavioral sciences. Ajzen (1991) further elaborated that attitude consists of three components: affective response, cognitive evaluation, and behavioral intention. Affective response refers to an individual's emotional reaction to the attitude object, cognitive evaluation indicates the individual's views about the attitude, and behavioral intention is the individual's expected response to a specific behavior. Recent studies have demonstrated that consumers' biospheric values significantly influence their pro-environmental purchase behavior (Nguyen et al., 2016).

H6: Attitude has a positive influence on the Behavior Intention on the use of 3D body anatomy software by vocational nursing students.

### **Perceived Behavioral Control**

One variable in the Theory of Planned Behavior (TPB) is perceived behavioral control (Ajzen, 1991). PBC reflects an individual's confidence and a perceived ability to regulate and execute a specific behavior. The study by Hagger, Cheung, Ajzen, and Hamilton (2022) supports the effect of perceived behavioral control (PBC) on behavioral intention (BI).

H7: Perceived behavior control has a positive influence on the Behavior Intention on the use of 3Dbody anatomy software by vocational nursing students.

### **Behavioral intention**

Taylor and Todd (1995) found that behavioral intention plays a crucial mediating role in both models. They emphasized that understanding the formation process of behavioral intention is important for predicting and promoting individual behavior. BI is a commonly used core variable in research on the adoption of new technology (Chao, 2019).

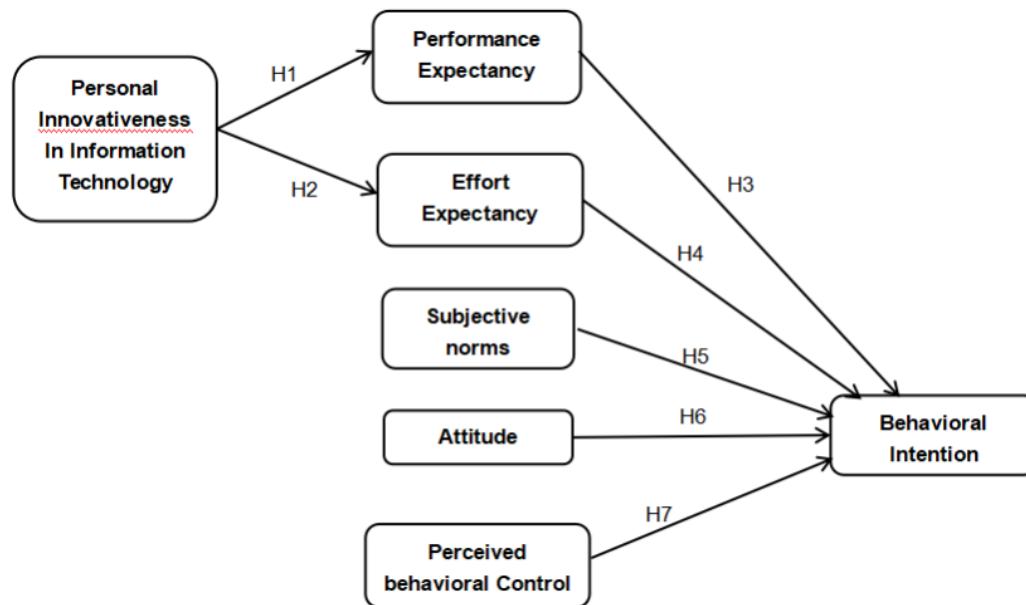


**Table 1** Theories and Their Connection to This Study

Theoretical Model	Core Concept	Key Elements	Application in This Study
Theory of Planned Behavior (TPB)	Attitude, subjective norms, and perceived behavioral control collectively determine behavioral intention.	Attitude (ATT) Subjective Norm (SN) Perceived Behavioral Control (PBC) Behavioral Intention (BI)	The intention of nursing students to use 3D anatomy software is determined by their attitude (whether they believe the software aids learning), subjective norms (the influence of teachers and peers), and perceived behavioral control (whether they possess the ability to use the software).
Unified Theory of Acceptance and Use of Technology (UTAUT)	The adoption of technology by individuals is influenced by a confluence of social and environmental factors.	Performance Expectancy (PE) Effort Expectancy (EE) Social Influence (SI) Facilitating Conditions (FC)	Nursing students are more likely to use 3D anatomy software if they believe it enhances learning efficiency (PE) and is easy to use (EE).
Personal Innovation in Information Technology (PIIT)	An individual's innovativeness in technology determines their propensity to adopt new technologies.	Personal Innovativeness (PIIT)	Nursing students with higher PIIT are more willing to try 3D anatomy software because they have a positive attitude toward new technology and tend to explore its potential value.

### Conceptual Framework

This study's conceptual framework is constructed based on the existing theories and previous research outlined in the literature review. The model consists of 7 variables, as illustrated in the diagram. These 7 variables are grouped into three sets, Performance Expectancy and Effort Expectancy, drawing from the Technology Acceptance Model (Venkatesh et al,2003). Subjective Norms, Attitude, Perceived Behavioral Control, Behavior Intention from the Theory of Planned Behavior, and a Theoretical Perspective on IT Innovativeness Derived from Innovation Diffusion Theory. Causal relationships exist among the 7 variables, aimed at analyzing various factors influencing the behavioral intention of nursing students at Liaoyang Vocational and Technical College toward the use of 3Dbody software.



**Figure 1** Conceptual Framework

## Methodology

This research utilizes a quantitative approach, targeting students in a nursing program at a vocational college. The survey design includes structured questions aimed at evaluating students' perceptions and experiences with the use of 3Dbody anatomy software in anatomy courses.

### Research Instrument

This study uses questionnaires as the main research tool. This questionnaire aims to collect data on the factors that influence students' use of 3Dbody anatomy software in anatomy courses, including personal innovation, performance expectations, effort expectations, attitudes, subjective norms, perceived behavioral control, and behavioral intentions. Variables play an important role in understanding students' use of 3Dbody anatomy software in anatomy courses.

This questionnaire was carefully crafted to gain a more detailed understanding of students' thinking. The study comprises seven variables, each measured through questions on a 5-point Likert scale (Table 2), where students express their degree of agreement or disagreement.

To ensure that the questions in the questionnaire were good and appropriate, we first used CVI, according to Polit and Beck (2006), to determine that the survey items in this study were valid. Furthermore, to ensure the questionnaire functioned effectively and provided consistent information each time, a pilot test was conducted. The mathematical calculation method of Cronbach's Alpha was employed. If the value exceeded 0.9, the questionnaire was considered reliable. It is widely recognized that Cronbach's Alpha (CA) is the most appropriate reliability test before distributing the questionnaire to the target group (Bardhoshi et al., 2017).

The results confirm that Cronbach's Alpha value is sufficient, indicating that the questionnaire is reliable for collecting actual data for the research.





**Table 2** Operationalization Table of Questionnaire

Variables	Definition	Operationalization	Source	Scale
Personal Innovativeness in Information Technology	The willingness of an individual to try out any new information technology. (Agarwal & Prasad, 1998).	1. If I heard about new information technology, I would look for ways to experiment with it. 2. Amongst my peers, I am usually the first to try out new information technologies. 3. In general, I am not hesitant to try out new information technologies. 4. I like to experiment with new information technologies.	Agarwal and Prasad (1998)	5-point Likert Scales 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree
Performance Expectancy	The degree to which an individual believes that using the system will help him or her attain gains in job performance. (Venkatesh et al., 2003, p. 447)	1. 3D body anatomy software can help students fulfill their needs quickly and effectively. 2. The use of 3D body anatomy software can create a more equitable learning environment for all students. 3. Implementing 3D body anatomy software could lead to time savings for students. 4. Incorporating 3D body anatomy software into education can enhance the quality of the learning experience.	Venkatesh et al (2003)	5-point Likert Scales 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree
Effort Expectancy	The degree of ease associated with the use of the system. (Venkatesh et al. (2003))	1. I find 3Dbody anatomy software easy to use. 2. My interaction with 3Dbody anatomy software is clear and understandable.	Venkatesh et al (2003)	5-point Likert Scales 1=Strongly Disagree, 2=Disagree,



Variables	Definition	Operationalization	Source	Scale
		3. It is easy for me to become skillful at using 3D anatomy software 4. I find the 3D body anatomy software flexible to interact with 5. I find it easy to get 3Dbody anatomy software to do what I want it to do.		3=Neutral, 4=Agree, 5=Strongly Agree
Subject norms	Subjective norms are defined as the perceived social pressure to perform or not perform a particular behavior. Ajzen (1991)	1. People who are important to me think I should use 3D body anatomy software 2. People who are important to me would support my decision to use 3Dbody anatomy software 3. People who are important to me would understand the importance of using 3D body anatomy software 4. People who are important to me would recommend using 3Dbody anatomy software	Taylor and Todd (1995a)	5-point Likert Scales 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree
Attitude	Attitude represents subjective feelings toward performing a behavior. Fishbein and Ajzen (1975)	1. Using 3Dbody anatomy software is a wise idea. 2. I like the idea of 3D body anatomy software 3. Using 3Dbody anatomy software is pleasant 4. Using the 3Dbody anatomy software service is beneficial 5. Using 3D body anatomy software is interesting	Taylor and Todd (1995a)	5-point Likert Scales 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree



Variables	Definition	Operationalization	Source	Scale
Perceived behavior control	Perceived behavioral control represents subjective perceptions of obstructions and resources affecting behavior. Ajzen (1991)	1. I have the necessary resources to use 3Dbody anatomy software 2. I have the necessary knowledge to use 3Dbody anatomy software 3. 3D body anatomy software is compatible with other technologies that I use 4. I can get help if I have difficulty using 3Dbody anatomy software.	Taylor and Todd (1995a)	5-point Likert Scales 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree
Behavior Intention	BI refers to the willingness and effort of the individual to perform the underlying behavior. Fishbein and Ajzen (1975)	1. I will use 3Dbody anatomy software regularly in the future. 2. I will frequently use 3Dbody anatomy software in the future. 3. I intend to use 3Dbody anatomy software to assist my learning. 4. Assuming I had access to the 3Dbody anatomy software, I would use it.	Davis (1989)	5-point Likert Scales 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree

### Population and Sample

The population of this study is defined as nursing students at Liaoyang Vocational and Technical College, with a total population of 1000. These students have used the 3Dbody anatomy software in their anatomy courses. The sample includes all students participating in this course to ensure the thoroughness and reflectiveness of the data.

This study adopted Purposive sampling and Stratified Random Sampling as quantitative methods. The total sample size is 500, and we randomly select samples based on the proportion of each grade. A stratified sampling method was used to ensure representation across different academic years (first-year: 30%, second-year: 44.6%, third-year: 25.4%). To minimize response bias, the questionnaire emphasized anonymity and voluntary participation.

### Data Collection Process

We strictly adhere to research ethics to ensure comprehensive privacy safeguarding and the rights of participating students and teachers. Throughout the process of conducting surveys and collecting data, we





emphasize the voluntary participation of students and rigorously safeguard their personal information. We persistently follow research ethical guidelines to ensure their rights to informed consent and autonomy in decision-making are protected. In the course of the questionnaire survey, we obtained informed consent from the interviewed students, an ethical consideration that is integral throughout the entire data collection process.

The questionnaire was distributed via Tencent Forms to nursing students at Liaoyang Vocational and Technical College who had prior experience with the 3Dbody software. The questionnaires were distributed through the class representatives of each nursing class, with supervision from the respective student management teachers. Before distributing the questionnaires, the purpose and significance of the survey were explained to the students. Emphasis was placed on the anonymity and confidentiality of the survey to enhance student trust. Students were encouraged to fill out the questionnaire according to the instructions, ensuring their understanding of the questions' content.

### Data Analysis

This study conducted data analysis and hypothesis testing using the widely used comprehensive statistical software Amos in the field of social science. The primary analytical approach employed in this research is CFA and SEM, aiming to examine the impact of the use intention of 3Dbody anatomy software among vocational nursing students. Confirmatory Factor Analysis (CFA) was performed to examine the factor loadings, composite reliability, convergent validity, discriminant validity, and goodness of fit of the measurement model. The structural model was executed under the Structural Equation Model (SEM) to determine significant relationships and hypotheses in this research.

## Results

### Demographic Information

The final sample included 500 students. This part outlines the demographic attributes of the research sample and analyzes the data using descriptive statistical methods.

Among the 500 samples, there were 150 first-year students (30%), 223 second-year students (44.6%), and 127 third-year students (25.4%). In terms of gender, there were 188 male students, accounting for 37.6%, and 312 female students, making up 62.4%. Regarding age distribution, 127 students (25.4%) were aged 18-20, 189 students (37.8%) were aged 21-23, 184 students (36.8%) were above 23 years old.

**Table 3** Demographic Information

Variable	Category	Frequency	Percentage
Year of Study	1	150	30.0%
	2	223	44.6%
	3	127	25.4%
	<b>Total</b>	<b>500</b>	<b>100%</b>
Age	18-20	127	25.4%
	21-23	189	37.8%
	23+	184	36.8%
	<b>Total</b>	<b>500</b>	<b>100%</b>
Gender	Male	188	37.6%
	Female	312	62.4%
	<b>Total</b>	<b>500</b>	<b>100%</b>

### Statistics of standard deviation and mean



In this study, a 5-point Likert scale questionnaire (Agreement) was used to assess participants' attitudes toward the measured variables. To facilitate the interpretation of the collected data, the following predefined criteria were applied to analyze the mean values for each variable.

**Table 4** Statistics of standard deviation and mean

Variable	Mean	Std	Interpretation
PIIT	4.108	0.78	Agree
Performance Expectancy	3.700	0.852	Agree
Effort Expectancy	3.808	0.841	Agree
Subject norms	4.000	0.826	Agree
Attitude	4.006	0.81	Agree
Perceived behavior control	3.896	0.849	Agree
Behavior Intent	4.059	0.811	Agree

#### Skewness and Kurtosis

In this study, the maximum absolute values of skewness and kurtosis fall between -2 and 2, which is generally considered indicative of a distribution that approximates normality (West, Finch, & Curran, 1995). Based on the aforementioned criteria, this indicates that the data are approximately normally distributed, thereby meeting the normality assumptions required for subsequent statistical analyses. (Tabachnick, B. G., & Fidell, L. S., 2007).

#### Confirmatory Factor Analysis

As shown in the table, all model fit indices, including CMIN/DF, GFI, RMSEA, AGFI, NFI, CFI, and TLI, meet the required standards, indicating that the structural validity of the PIIT, SN, Att, PBC, PE, EE, and BI scales is well established.

**Table 5** Construct Validity

Fit Index	Fit Index	After
CMIN/DF	< 3.00 (Awang, 2012; Al-Mamary and Shamsuddin, 2015)	1.224
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.942
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.929
NFI	≥ 0.80 (Wu & Wang, 2006)	0.934
CFI	≥ 0.80 (Bentler, 1990)	0.987
TLI	≥ 0.80 (Sharma et al., 2005)	0.985
RMSEA	< 0.08 (Pedroso et. al., 2016)	0.021
Model Summary		Acceptable Model Fit

According to the results, the factor loadings for PIIT, SN, Att, PBC, PE, EE, and BI across their respective items are all greater than 0.5, indicating that the items corresponding to each latent variable exhibit high representativeness. All latent variables have AVE values above 0.50, and their composite reliability (CR) values exceed 0.70, confirming an ideal level of convergent validity.

**Table 6** Convergent Validity

Latent Variables	Item Amount	Factors Loading	CR	AVE
PIIT	4	0.715-0.771	0.833	0.555
PE	4	0.677-0.828	0.837	0.564



Latent Variables	Item Amount	Factors Loading	CR	AVE
EE	5	0.733-0.819	0.875	0.583
SN	4	0.746-0.799	0.858	0.603
ATT	5	0.678-0.847	0.853	0.538
PBC	4	0.711-0.830	0.840	0.568
BI	4	0.735-0.823	0.851	0.589

The correlation coefficients among PIIT, SN, Att, PBC, PE, EE, and BI are all lower than the square root of their corresponding AVE values, indicating that while the latent variables are correlated to some extent, they also maintain a certain level of distinction from each other. This demonstrates that the scale data exhibit adequate discriminant validity (Fornell & Larcker, 1981).

**Table 7** Discriminant Validity

	PIIT	SN	Att	PBC	PEPE	EE	BI
PIIT	<b>0.745</b>						
SN	0.171	<b>0.751</b>					
Att	0.239	0.217	<b>0.764</b>				
PBC	0.332	0.284	0.329	<b>0.777</b>			
PEPE	0.467	0.217	0.232	0.290	<b>0.733</b>		
EE	0.455	0.188	0.275	0.337	0.379	<b>0.754</b>	
BI	0.203	0.293	0.391	0.459	0.395	0.492	<b>0.767</b>

### Structural Equation Modeling (SEM)

Based on the evaluation results of model fit, CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA all meet the established fit criteria. The values of these indices fall within the threshold ranges recommended by relevant literature, indicating that the overall structural fit of the model is satisfactory. Therefore, it can be reasonably inferred that the mediating model exhibits a good fit, effectively reflecting the alignment between the data structure and the theoretical framework, thereby supporting subsequent hypothesis testing and path analysis.

**Table 8** Model fitting criteria and results from the structural modeling

Fit Index	Fit Index	Value
CMIN/DF	< 3.00 (Awang, 2012; Al-Mamary and Shamsuddin, 2015)	1.697
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.914
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.899
NFI	≥ 0.80 (Wu & Wang, 2006)	0.905
CFI	≥ 0.80 (Bentler, 1990)	0.959
	≥ 0.80 (Sharma et al., 2005)	0.955
RMSEA	< 0.08 (Pedroso et. al., 2016)	0.037
Model Summary		Acceptable Model Fit

Note: CMIN/DF Ratio of the Chi-Square Value to Degree of Freedom, GFI=Goodness of-Fit Index, AGFI=Adjusted Goodness-of-Fit Index, CFI=Comparative Fit Index, NFI= Normed Fit Index, RMSEA = Root-Mean-Square Error of Approximation.

### Hypotheses Testing

According to the proposed model, this study employed Structural Equation Modeling (SEM) regression analysis to investigate the seven hypotheses. The hypotheses were examined using SEM regression weights (including standardized and unstandardized coefficients).

The Pearson correlation coefficient test shows that the correlation coefficients between different dimensions are all below 0.5, indicating that there is no collinearity among the dimensions.

**Table 9** Multicollinearity

	PIIT	PE	EE	SN	Att	PBC	BI
PIIT	1						
PE	.390**	1					
EE	.391**	.323**	1				
SN	.142**	.196**	.157**	1			
Att	.203**	.217**	.254**	.183**	1		
PBC	.278**	.257**	.296**	.247**	.292**	1	
BI	.176**	.341**	.429**	.255**	.349**	.400**	1

Note: \*\*p<0.01

The acceptance or rejection of research hypotheses was determined based on significance levels (p-values). In this study, a significance threshold of  $p < 0.05$  was set, meaning that when p-values are below 0.05, the hypothesis test results are statistically significant, resulting in the confirmation of the research hypothesis while dismissing the null hypothesis. This significance level indicates that the probability of the results occurring due to random sampling error is less than 5% (Hair et al., 2016).

**Table 10** Structural Equation Model (SEM) Path Analysis

Number	Hypothesis	$\beta$	t	Results
H1	PIIT->PE	0.479	8.881***	Supported
H2	PIIT->EE	0.465	8.599***	Supported
H3	PE->BI	0.176	3.532***	Supported
H4	EE->BI	0.320	6.240***	Supported
H5	SN->BI	0.128	2.698**	Supported
H6	Att->BI	0.212	4.406***	Supported
H7	PBC->BI	0.262	5.319***	Supported

Note: \*\*\*p<0.001, \*\*p<0.01

Table 9 summarizes the influence of each factor on behavioral intention, with effort expectancy ( $\beta = 0.320$ ) as the strongest predictor. These results align with previous research by Deng et al. (2021), which found that ease of use significantly impacts e-learning engagement. PIIT has a significant positive effect on PE ( $\beta=0.479$ ), thus H1 is supported. This indicates that when an individual's technology acceptance is higher, their expected benefits from the technology will also be greater, which is consistent with previous research (Twum et al., 2022). PIIT has a significant positive effect on EE ( $\beta=0.465$ ), thus H2 is supported.

This suggests that individuals with higher levels of PIIT are more likely to perceive new technology as useful and easy to use, which in turn strengthens their willingness to adopt these digital innovations (Lu et al., 2005). PE has a significant positive effect on BI ( $\beta = 0.176$ ), thus H3 is supported. In an educational environment, if students believe that the software can improve their academic performance or efficiency, it is likely to enhance their intention to use the software. This finding is consistent with the conclusions of Tang et al. (2021). SN has a significant positive effect on BI ( $\beta = 0.128$ ), thus H5 is supported. This result indicates that in a learning environment, if the majority of students and teachers believe that using a certain technology or platform can improve learning outcomes, this social validation will further encourage students to use the technology and enhance their behavioral intention. El-Masri and Tarhini (2021) underscore the importance of incorporating social influence into the design of educational technologies to enhance user engagement and adoption. Att has a significant positive effect on BI ( $\beta = 0.212$ ), thus H6 is supported. The results indicate that a positive attitude can influence students' behavioral intention to use the software. The students are more willing to try using it. This is consistent with the findings of Chao (2019), who examined the factors influencing behavioral intention to use mobile learning by applying and extending the UTAUT model. PBC has a significant positive effect on BI ( $\beta = 0.262$ ), thus H7 is supported. It indicates that when students face a new technology, if they feel they can easily master its use, they will exhibit a stronger behavioral intention. This finding is also supported by Al-Rahmi et al. (2020), who investigated factors influencing students' intention to use e-learning systems.

### Mediation Test

The results from the Bootstrap test ( $n=5000$ ) show that, with PE as the dependent variable, PIIT has a direct effect on PE, with an effect size of 0.479. PE explains the dependent variable to a certain extent, with an explanatory power of 22.9%.

With EE as the dependent variable, PIIT has a direct effect on EE, with an effect size of 0.465. The independent variable explains PE to a certain extent, with an explanatory power of 21.6%.

### Discussion

The data analysis reveals that effort expectancy (EE) is the most critical factor influencing behavioral intention (BI) in this study. As software designers, it is essential to enhance human-computer interaction to improve user engagement, introduce intelligent algorithms for personalized content delivery, and optimize interface design to reduce cognitive load. These improvements can enhance the user experience, thereby increasing students' adoption intention and usage retention.

The significant positive impact of performance expectancy (PE) and effort expectancy (EE) on student usage behavior provides a scientific basis for teachers and educational administrators to develop more targeted teaching strategies. Similarly, research by Deng et al. (2021) also confirmed that functional expectations of online learning platforms have a significant positive impact on students' learning engagement and willingness to use them.

The variables in this study highlight the significant impact of individual user characteristics, such as perceived risk control and attitude, in the technology adoption process. This finding provides a new theoretical perspective for understanding the complexity of technology acceptance behavior and offers a theoretical foundation for the design and promotion of personalized learning tools. This finding is consistent with previous studies. In the use of 3Dbody anatomy software, PIIT exhibits a substantial positive association with effort expectancy.

The results emphasize that institutions should prioritize user-friendly software interfaces and provide comprehensive training to improve perceived ease of use. Establishing technical support teams or student peer-assistance groups can address issues encountered during usage. Designing progressive learning tasks and transitioning from simple operations to complex functions can help students build confidence in using the software. Future research should explore how AI-driven adaptive learning can enhance vocational students' engagement with 3D anatomy tools.





## Conclusion

This study builds upon existing literature and research findings to establish a predictive framework for the behavioral intention of vocational nursing students to use the 3Dbody anatomy software. The study integrates multiple variables, including performance expectancy (PE), effort expectancy (EE), subjective norms (SN), attitude, and behavioral intention (BI). Additionally, this study examines the indirect impact of PIIT on BI through PE and EE. The findings indicated that performance expectancy (PE), effort expectancy (EE), subjective norms (SN), attitude (Att), and personal innovativeness in information technology (PIIT) all had significant effects on behavioral intention (BI).

Effort expectancy (EE) had the most significant impact on behavioral intention, suggesting that vocational nursing students preferred software that was easy to operate and user-friendly. This implied that reducing the learning cost, optimizing the user interface, and providing sufficient technical support were key factors in enhancing students' willingness to use the software. Additionally, performance expectancy (PE) enhanced behavioral intention, indicating that students tend to develop a decisive intention to use 3Dbody anatomy software if they recognize its benefits in improving learning outcomes. Therefore, promoting the software should have emphasized its role in enhancing anatomical knowledge comprehension, strengthening practical skills, and improving learning efficiency.

The insights from this research demonstrate that PBC has a significant positive impact on vocational nursing students' readiness to utilize 3Dbody anatomy software. When students perceive a higher sense of control over the use of the software, such as receiving adequate technical training and a supportive environment, they are more likely to adopt the software for learning.

Additionally, personal innovativeness in information technology (PIIT) indirectly affected behavioral intention (BI) through performance expectancy (PE) and effort expectancy (EE). This suggested that students with higher technological innovativeness were more likely to perceive the value of the software and were more willing to overcome technological barriers. This finding highlighted the need to focus not only on software functionality optimization but also on fostering students' technological innovation awareness. Strategies such as training programs, online learning resources, and virtual reality (VR) interactive experiences could have been employed to enhance students' acceptance of new technologies.

## Recommendation

### For students

In the process of using 3Dbody anatomy software, students should enhance their technology acceptance awareness and improve their adaptability to new technologies. During software functionality training and usage instruction, efforts should be made to reduce the cognitive burden associated with software usage. At the same time, students should reinforce their performance expectancy by understanding the actual value that the software brings, such as improving their grasp of anatomical knowledge and enhancing spatial thinking abilities. Students can strengthen their trust in technology by joining learning communities, engaging in peer discussions, and adopting teachers' recommendations, thereby increasing the frequency of software usage and enhancing learning outcomes.

### For teachers

As key advocates and enablers of educational technology, teachers play a crucial role in shaping students' willingness to engage with learning software through their instructional approaches, attitudes, and guidance strategies. Structured learning support should be provided to alleviate perceived usage difficulties. By demonstrating the software's ease of operation and high educational value, educators can enhance students' effort expectations (EE) and lower perceived cognitive barriers.

### For a software designer

The software can enhance students' willingness to use it by improving functionality and adaptability. For instance, adding features such as peer learning communities allows users to receive positive feedback from others during use, thereby increasing motivation. Additionally, customizable features can be provided,



enabling users to adjust learning progress and select suitable learning modes based on individual needs, thus enhancing their sense of autonomy.

### Future research

Future research should examine long-term student retention and engagement with 3D anatomy tools, particularly in comparison to traditional cadaver-based learning methods. Additionally, integrating AI-driven customization in e-learning platforms may further enhance user experience and acceptance.

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