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Original Article

Nursing Section

Artificial Intelligence in Nursing Education: A Cross-sectional UTAUT Analysis Study

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ABSTRACT

Introduction: Artificial Intelligence (AI) is a transformative force in nursing education, applicable in academic and clinical settings. It equips nursing students with skills to evaluate and apply AI in future patient care, preparing the nursing workforce for a healthcare landscape increasingly supported by AI. However, lack of studies focus on nursing students as AI users and the behavioural intention to accept and utilise AI.

Aim: This study investigated the factors influencing nursing students' acceptance and use of AI based on the Unified Theory of Acceptance and Use of Technology (UTAUT).

Materials and Methods: A cross-sectional study was conducted at one of the oldest and most prominent universities, collecting data from April to May 2022. The survey included 213 nursing students and aimed to evaluate the influence of the four UTAUT constructs- Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)- on behavioural intention and usage behaviour. Additionally, the study explored the moderating effects of age and gender on the UTAUT model. Data were analysed using Statistical Package for the Social Sciences (SPSS) version 29.0 for descriptive statistics and SmartPLS version 4 for Partial Least Squares (PLS) structural equation modeling.

Results: The findings indicated that PE positively influenced the behavioural intention of nursing students to adopt and use AI in nursing education. Regarding moderation effects, age moderated the relationship between PE and behavioural intention, whereas gender did not exhibit any moderation effect.

Conclusion: This study provides a foundation for its integration to enhance learning outcomes and prepare students for technology-driven healthcare. It highlights the importance of evidence-based strategies tailored to meet diverse educational needs, ensuring effective adoption and utilisation.

Keywords: Behavioural intention, Nursing students, Use behaviour

INTRODUCTION

The AI represents a transformative paradigm in nursing education, revolutionising how knowledge and competencies are imparted to prepare nurses for the evolving healthcare landscape. The advent of the Fourth Industrial Revolution- anchored in the Internet of Things, cyber-physical systems, and AI- marks a significant leap from the late 20th century's information and technological revolution powered by computers and the Internet [1]. AI leverages advanced technologies to create cognitive systems capable of learning, adapting, self-improving and expanding their functionalities [2]. Theoretical approaches within AI aim to replicate and enhance human intelligence [2], leading to its comprehensive definition as "the theory and development of computer systems are able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making and translation between languages" [3].

AI has already begun intellectualising healthcare services, becoming crucial across various sectors, including mobile health applications, virtual patient education programs, intelligent medical robots and systems for measuring and analysing human physiological parameters [4]. Its transformative potential is expected to redefine healthcare delivery, significantly influencing healthcare professionals, particularly nurses. This necessitates a reevaluation of core nursing competencies and educational requirements to integrate AI effectively into nursing practice [5]. Nurses, as frontline healthcare providers, must possess the skills to understand and implement AI technologies in clinical settings [5,6].

Furthermore, there are concerns regarding patients' legal rights, personal health information and patient safety and criticism regarding the uncertainty of the long-term effects of changes in the informatisation process [7,8]. Adopting AI will change nurses' roles and the delivery of patient care [9]. Therefore, the nursing curricula should be designed to develop competencies that prepare them for the future and specific abilities required within healthcare systems and their professional field. The educational paradigm must be transformed to keep abreast with evolving trends [5,10,4].

AI's impact on nursing education extends to instructional techniques, healthcare practices and learning outcomes, underscoring the need for curricula that address the dynamic healthcare environment [11]. For instance, Buchanan C et al. and Seibert K et al., explore AI's potential to enhance clinical decision-making and documentation processes [5,12]. Moreover, Ronquillo CE et al., emphasise the importance of collaboration between AI developers and nursing practitioners to address opportunities and challenges. The Nursing and Artificial Intelligence Leadership Collaborative highlights critical gaps requiring attention to integrate AI effectively in health systems, advocating for its inclusion in nursing education [13].

Integrating AI into nursing education necessitates a thorough understanding of nursing students' perceptions, including their attitudes and awareness of this emerging technology [14]. Without such insights, efforts to integrate AI into curricula may fail to align with students' readiness, hindering effective engagement with these innovations. Examining these perceptions is essential to ensure that AI tools and methodologies are adopted effectively, fostering both educational and clinical proficiency. To address this critical gap, the study explores the factors influencing nursing students' acceptance and use of AI by employing the UTAUT as a guiding framework. This model is pivotal in identifying and predicting behavioural intentions, focusing on four key constructs: PE, EE, SI and FC. By applying the UTAUT framework, the study seeks to uncover how these factors shape nursing students' willingness to adopt AI in their educational journey.

Understanding how users accept new technologies is fundamental for their successful adoption. The theory of reasoned action provides a foundational model to analyse the variables influencing user acceptance of technology, that individuals' beliefs shape their attitudes, which subsequently drive their intentions and behaviours

[15]. Building on this foundation, the technology acceptance model asserts that users' attitudes directly impact their intention to use technology, ultimately influencing their behaviour [16]. Although widely utilised, this model has certain limitations, such as its inability to fully capture the relationships among external factors and to analyse complex interdependencies in technology adoption. Nonetheless, it has been instrumental in explaining user acceptance of various information technologies [17,18].

UTAUT is recognised to have a greater potential for explaining behavioural intention and use, many researchers used it as a framework for their study. According to a study examining how using the UTAUT model affected students' acceptance of mobile learning applications in higher education, essential factors included perceived security, self-efficacy, consistency, and trust. They perceived awareness in addition to information quality [19].

Furthermore, a study that compared the features of utilising and adopting mobile learning in higher education in developed and developing nations using the UTAUT as a theoretical model discovered that the features and backgrounds of the two groups of countries which had a substantial impact on the use of mobile learning [20]. Study showed how students in Ghana intend to accept and use e-counselling by studying an empirical approach that applies the UTAUT model. As a result of the study, performance expectancy and social influence are proposed as the influencing constructions (factors) that affect students' behavioural intention to adopt and use video counselling [21]. According to these earlier studies on the intention to adopt novel technologies, using the UTAUT model has produced beneficial outcomes. As mentioned earlier, AI represents a paradigm shift in nursing education. AI in nursing education is essential because it enables nurses to lead in technological advancements rather than following behind, underlining the significance of promoting education in this area [22].

The UTAUT, synthesises key constructs from multiple foundational theories to provide a comprehensive framework for understanding user acceptance of information technologies. UTAUT identifies four primary constructs- PE, EE, SI and FCs- that influence behavioural intention and use behaviour [18]. This study adopts the UTAUT framework while considering age and gender as moderating variables. However, voluntariness and experience, which are often included in UTAUT-based studies, have been excluded in this context, as AI represents a novel and optional technology for nursing students. Voluntariness, which is a significant factor in organisational contexts, is not applicable here since AI adoption is self-directed and optional for the participants.

By highlighting the specific drivers and barriers to AI adoption, the study equips educators and policymakers with actionable knowledge to design AI-based interventions that align with students' expectations and needs. Addressing this gap is essential not only to prepare nursing students for an AI-driven healthcare landscape but also to ensure that their educational experiences foster confidence and competence in leveraging AI tools. Ultimately, understanding nursing students' perceptions of AI is a strategic step toward crafting a future-ready nursing workforce capable of thriving in an increasingly technology-integrated environment.

Hypotheses: The study tested several hypotheses derived from the UTAUT model:

Direct effects on behavioural intention and use behaviour:

- H1: PE positively influences behavioural intention.
- H2: EE positively influences behavioural intention.
- H3: SI positively influences behavioural intention.
- H4: FCs positively influences both behavioural intention and use behaviour.
- H5: Behavioural intention positively predicts use behaviour.

Mediating effects:

- H6a-H6d: Behavioural intention mediates the relationships between UTAUT constructs (PE, EE, SI, FC) and use behaviour.

Moderating effects:

- H7a-H7h: Gender moderates the relationships between UTAUT constructs (PE, EE, SI and FCs) and behavioural intention/use behaviour. It is hypothesised that gender facilitates these relationships by influencing perceptions and attitudes toward technology adoption.
- H8a-H8h: Age moderates the relationships between UTAUT constructs and behavioural intention/use behaviour. It is hypothesised that age may weaken these relationships, as generational differences could impact adaptability and comfort with emerging technologies.

MATERIALS AND METHODS

The present study was a cross-sectional study, conducted at the oldest and most prominent university in Saudi Arabia, from April to May 2022. This study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board (IRB) of King Saud University (KSU-HE;23-838, Date of approval: 5 April 2022). All participants provided informed consent prior to participation, ensuring ethical compliance and the confidentiality of all data collected. Nursing students enrolled in the bachelor's program were recruited as participants.

Inclusion criteria: Male and female nursing students pursuing a bachelor's degree were included in the study.

Exclusion criteria: Participants with internship program or with academic issues were excluded from the study.

Sample size and selection: A convenience sampling method was used to recruit participants. Based on Kline's (2016) rule of thumb, a minimum sample size of 200 was deemed necessary. To account for potential nonresponses or missing data, the sample size was increased to 213 students [23].

Data collection tool: A validated questionnaire developed by Venkatesh V et al., was used to measure the constructs of the UTAUT model [18]. This questionnaire has been extensively validated across diverse contexts, including Germany, Jordan [24], Finland [25] and Indonesia, with Cronbach's Alpha (CA) consistently exceeding 0.7 [26]. The questionnaire has also been employed in Iran (CA > 0.83) [27] and Germany (CA = 0.92) [28] for similar applications.

The questionnaire consisted of two sections:

1. **Demographic data:** Age, gender, Grade Point Average (GPA) and years of study.
2. **UTAUT constructs:** PE, EE, SI and FCs.

Responses were captured on a five-point Likert scale ranging from "strongly agree" to "strongly disagree." The questionnaire was distributed electronically via university email, with official approval obtained from the original author. Completion of the survey required approximately 10 minutes.

Variables: Independent variables included PE, EE, SI and FC. Behavioural intention was considered both an independent and mediating variable, while age and gender were included as moderating variables. Use behaviour was the primary dependent variable.

STATISTICAL ANALYSIS

Data were analysed using SPSS version 29.0 for descriptive statistics and SmartPLS version 4 for PLS analysis. PLS, a statistical approach based on structural equation modeling, was employed to test and validate the proposed model by assessing both measurement and structural models. Measurement model assessment included Confirmatory Factor Analysis (CFA) to evaluate convergent validity, discriminant validity and internal consistency reliability [29]. Specific methods included cross-loadings, the Fornell-Larcker criterion, the

Heterotrait-Monotrait (HTMT) ratio of correlation, outer loadings, Average Variance Extracted (AVE), Composite Reliability (CR) and CA. The structural model was assessed through collinearity diagnostics, path coefficient values, p-values, t-statistics and Confidence Interval Bias-Corrected (CIBC) estimates [29].

RESULTS

Demographic characteristics of the participants, which included age, gender, GPA and level of study are presented in [Table/Fig-1].

Characteristics	n (%)			
Gender				
Female	118 (55.4)			
Male	95 (44.6)			
Level of study				
3	12 (5.6)			
4	56 (26.3)			
5	7 (3.3)			
6	54 (25.4)			
7	23 (10.8)			
8	61 (28.6)			
Variables	**n**	**Mean±SD**	**Max**	**Min**
Age (years)	213	21.38±0.15	38	18
GPA	198	4.19±0.556	5	0

[Table/Fig-1]: Participants demographical characteristics (N=213).

Measurement Model

The measurement model was evaluated using outer loadings, internal consistency reliability, convergent validity and discriminant validity, following established guidelines [29]. Factor loadings for all items representing the constructs were assessed and found to exceed the acceptable threshold of 0.50. Consequently, no items were excluded from the analysis. These results are summarised in [Table/Fig-2].

Constrct	Outer loadings	Cronbach's Alpha (CA)	Composite Reliability (CR) (rho_a)	Composite Reliability (CR) (rho_c)	Average Variance Extracted (AVE)
Performance Expectancy (PE)		0.830	0.840	0.887	0.662
PE1 <- PE	0.783				
PE2 <- PE	0.850				
PE3 <- PE	0.842				
PE4 <- PE	0.776				
Effort Expectancy		0.770	0.777	0.853	0.592
EE1 <- EE	0.711				
EE2 <- EE	0.789				
EE3 <- EE	0.794				
EE4 <- EE	0.781				
Facilitation conditions		0.881	0.891	0.918	0.736
FC1 <- FC	0.833				
FC2 <- FC	0.880				
FC3 <- FC	0.833				
FC4 <- FC	0.884				
Social Influence		0.751	0.782	0.841	0.571
SI1 <- SI	0.706				
SI2 <- SI	0.759				
SI3 <- SI	0.847				
SI4 <- SI	0.702				
Behavioural Intention		0.698	0.717	0.832	0.625
BI1 <- BI	0.803				
BI2 <- BI	0.858				
BI3 <- BI	0.702				
Use Behaviour		0.814	0.818	0.889	0.728
UB1 <- UB	0.846				
UB2 <- UB	0.868				
UB3 <- UB	0.847				

[Table/Fig-2]: Measurement model.

Internal consistency reliability was assessed using CA and standardised CR. All constructs demonstrated CA values above the recommended threshold of 0.708 [30], except for behavioural intention, which scored 0.698. This value was deemed acceptable given the CR and AVE values fell within acceptable ranges [31].

Convergent validity was confirmed by examining the AVE values for all constructs, with all values exceeding the 0.50 criterion [31]. These results indicate that the measurement model reliably captures the constructs under investigation, as presented in [Table/Fig-2].

Discriminant validity was evaluated using the Heterotrait-Monotrait (HTMT) ratio and the Fornell and Larcker Criterion to seek to confirm the indicators of the measurement model of each construct. [Table/Fig-3] indicates that all indicators obtained discriminant validity since the HTMT ratio values were less than 0.8.

Construct	BI	EE	FC	PE	SI	UB
BI						
EE	0.616					
FC	0.378	0.665				
PE	0.675	0.673	0.494			
SI	0.491	0.717	0.591	0.071	0.545	
UB	0.668	0.309	0.223	0.109	0.322	0.37

[Table/Fig-3]: The Heterotrait-Monotrait (HTMT) ratio for each construct.

Moreover, discriminant validity was confirmed using the Fornell and Larcker Criterion by ensuring each construct has a square root of the AVE that exceeds the correlation value for another construct [31,32], as shown in [Table/Fig-4].

Construct	BI	EE	FC	PE	SI	UB
BI	0.79					
EE	0.457	0.769				
FC	0.299	0.547	0.858			
PE	0.525	0.535	0.425	0.814		
SI	0.367	0.557	0.495	0.431	0.756	
UB	0.507	0.248	0.194	0.27	0.289	0.853

[Table/Fig-4]: The Fornell and Larcker Criterion for each construct.

Structural Model

The structural model was assessed using the path coefficient (β), t-statistics, the collinearity assessment (Variance Inflated Factor (VIF) and coefficients of determination (R2 values) [33]. Since every item in the model has a VIF of less than 5, there is no collinearity issue [33], as shown in [Table/Fig-5]. The hypothesised relationship between the constructs in the model was assessed through path coefficient (β), [Table/Fig-6] indicates that PE ->BI and BI -> UB had stronger positive relationships while the EE ->BI, SI ->BI and FC ->BI had insignificant relationships; moreover, the t-values were lower than 1.960, providing support for their lack of statistical significance [34]. As [Table/Fig-7] shows, The R2 values for UB and BI are 0.257 and 0.419, respectively. A moderate link between the independent and dependent constructs is indicated by BI's R2 value of 0.419. This indicates that the model's independent variable(s) can account for about 41.9% of the variance in the dependent variable. Even though

Items	VIF
BI1	1.422
BI2	1.568
BI3	1.26
EE1	1.352
EE2	1.482
EE3	1.791
EE4	1.68
FC1	2.048
FC2	2.407
FC3	2.355
FC4	2.726
PE1	1.629
PE2	2.017
PE3	1.854
PE4	1.682
SI1	1.585
SI2	1.762
SI3	1.677
SI4	1.393
UB1	1.846
UB2	1.85
UB3	1.704

[Table/Fig-5]: Variance Inflated Factor (VIF) for each item.

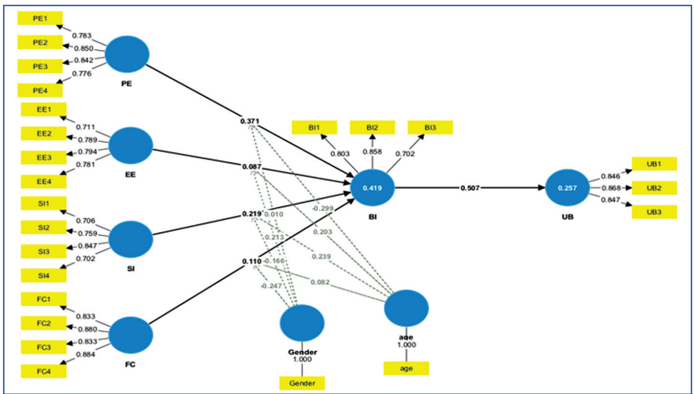
Hypothesis	Path	β	t-statistics	p-values	Hypothesis Supported or not
H1	PE -> BI	0.371	2.985	0.003	Supported
H2	EE -> BI	0.087	0.676	0.499	Not upported
H3	SI -> BI	0.219	1.633	0.102	Not supported
H4	FC -> BI	0.110	0.903	0.467	Not supported
H5	BI -> UB	0.507	6.409	0.001	Supported

[Table/Fig-6]: Structural model.

Constructs	R Square	R Square Adjusted	Comments
BI	0.419	0.378	Moderate
UB	0.257	0.254	Weak

[Table/Fig-7]: Result of the Coefficients of Determination (R^2).

compared to BI, UB's R2 score of 0.257 suggests a lesser link. It indicates that the model's independent construct may account for roughly 25.7% of the variance in the dependent construct [33,35] [Table/Fig-8] shows each construct with its related loadings.



[Table/Fig-8]: Diagram presentation of the various latent and observed constructs and their loading.

Hypotheses Testing

Direct effects on behavioural intention and use behaviour: The result from [Table/Fig-6] showed PE -> BI (t-statistics=2.985, β=0.371 p-value <0.001) and BI -> UB (t-statistics=6.409, β=0.507 p-value <0.001) were significant. while the hypothesis EE -> BI (t-statistics=0.676, β=0.087 p-value=0.499), SI->BI (t-statistics=1.633, β=0.219 p-value=0.102) and FC -> BI (t-statistics=0.903, β=0.110 p-value=0.467). were insignificant, thereby rejecting the hypothesis.

Mediating role of behavioural intention: The result in [Table/Fig-9a,b] shows that the relationship between the independent variable (PE) and the dependent variable (use behaviour) was mediated by the behavioural intention of nursing students to accept and use AI in nursing education. The lower CIBC and upper CIBC do not contain zero [33]. Therefore, mediation of behavioural intention is confirmed among supported variables. Since the direct relationship between the aforementioned independent variables is significant with use behaviour, as shown in [Table/Fig-9a], it can be affirmed that all the significant mediated effects of behavioural intention exist between the relationship: (i) PE and use behaviour; in conclusion, H6c were supported, while H6a, H6b and H6d were not.

Indirect effect (hypothsis)	β	T statistics (|O/STDEV|)	p-value	2.50%	97.50%	Decision
EE -> BI -> UB (H6a)	0.044	0.652	0.514	-0.083	0.182	Not supported
FC -> BI -> UB (H6b)	0.056	0.853	0.394	-0.051	0.205	Not supported
PE -> BI -> UB (H6c)	0.188	2.842	0.04	0.070	0.333	Supported
SI -> BI -> UB (H6d)	0.111	1.519	1.129	-0.025	0.263	Not supported

[Table/Fig-9a]: Mediation effect of BI.

Direct effect	β	T statistics (|O/STDEV|)	p-value	2.50%	97.50%	Decision
BI -> UB	0.507	6.409	0	0.345	0.656	Supported
EE -> BI	0.087	0.676	0.499	-0.159	0.344	Not supported
EE -> UB	0.044	0.652	0.514	-0.083	0.182	Not supported
FC -> BI	0.11	0.903	0.367	-0.106	0.368	Not supported
FC -> UB	0.056	0.853	0.394	-0.051	0.205	Not supported
PE -> BI	0.371	2.985	0.003	0.125	0.618	Supported
PE -> UB	0.188	2.842	0.004	0.07	0.333	Supported
SI -> BI	0.219	1.633	0.102	-0.053	0.471	Not supported
SI -> UB	0.111	1.519	0.129	-0.025	0.263	Not supported

[Table/Fig-9b]: Direct effect of UB and BI.

Moderation effect of age and gender: The results in [Table/Fig-10] show that age and gender do not have a moderate effect on any of the relationships hypothesised, except age moderates the relationship between PE and behavioural intention. To verify the acclaimed moderation effect, the lower and upper CIBC was used and it was confirmed that the moderation effect is significant since the distance between lower and upper CIBC contains zero [33].

DISCUSSION

This study investigates the factors influencing nursing students' behavioural intention to adopt and use AI in education, employing the UTAUT as a guiding framework. The constructs of PE, EE, SI and FC were analysed, with behavioural intention serving as a mediator and age and gender as moderators. The findings provide critical insights into the complex dynamics of AI adoption in nursing education.

PE was identified as the most significant predictor of behavioural intention, consistent with prior research [36-39]. Nursing students were more likely to adopt AI when they perceived it as a tool that enhances learning outcomes and academic performance. Furthermore, behavioural intention mediated the relationship between PE and use behaviour, underscoring its central role. These

Hypothesis	Path	β	T statistics (|O/STDEV|)	p-values	2.50%	97.50%	Decision
H7a	Gender × PE -> BI	0.01	0.057	0.955	-0.317	0.345	Not supported
H7b	Gender × PE -> UB	0.005	0.055	0.956	-0.159	0.187	Not supported
H7c	Gender × EE -> BI	0.213	1.261	0.207	-0.127	0.536	Not supported
H7d	Gender × EE -> UB	0.108	1.195	0.232	-0.062	0.297	Not supported
H7e	Gender × SI -> BI	-0.166	1.035	0.301	-0.478	0.15	Not supported
H7f	Gender × SI -> UB	-0.084	0.986	0.324	-0.265	0.074	Not supported
H7g	Gender × FC -> BI	-0.247	1.456	0.146	-0.594	0.07	Not supported
H7k	Gender × FC -> UB	-0.125	1.373	0.17	-0.334	0.034	Not supported
H8a	age × PE -> BI	-0.299	1.986	0.047	-0.68	-0.062	Supported
H8b	age × PE -> UB	-0.151	1.838	0.066	-0.378	-0.028	Not supported
H8c	age × EE -> BI	0.203	1.314	0.189	-0.069	0.547	Not supported
H8d	age × EE -> UB	0.103	1.246	0.213	-0.034	0.306	Not supported
H8e	age × SI -> BI	0.239	1.556	0.12	-0.039	0.571	Not supported
H8f	age × SI -> UB	0.121	1.492	0.136	-0.019	0.307	Not supported
H8g	age × FC -> BI	0.082	0.454	0.65	-0.299	0.424	Not supported
H8k	age × FC -> UB	0.042	0.437	0.662	-0.148	0.232	Not supported

[Table/Fig-10]: Moderation effect of age and gender.

results align with studies by Williams MD et al. and Ma Y et al., which emphasise the dominance of PE in technology adoption [38,39]. Contrary to expectations, EE did not significantly influence behavioural intention, suggesting that nursing students, as digital natives, may inherently find AI tools manageable and less intimidating. Bouznif MM, Basaran S and Daganni AM, Amanuail S et al., similarly noted that high technological literacy among students reduces the perceived difficulty of using advanced tools [40-43].

SI also did not significantly impact behavioural intention. A unique characteristic of the student population enrolling in nursing programs today is their familiarity with technology. Further evidence of technology's critical role in contemporary nursing education comes from research conducted by Van Houwelingen CTM et al., which emphasises the importance of improving nursing students' ability to use technology for educational purposes [44]. This study's findings align with previous research that revealed no significant relationship between SI and usage intention within the UTAUT model [45], reflecting findings by Erjavec J and Manfreda A, Alharbi et al., and Andersen BL et al., which suggest that intrinsic motivation often outweighs social pressures in technology adoption decisions [46-48].

FCs, representing organisational and technical support, was not significantly related to behavioural intention or use behaviour. This finding challenges earlier studies that emphasised the importance of external resources in technology adoption [49-51]. It suggests that nursing students' willingness to use AI is more closely tied to their intrinsic motivation and perceived benefits rather than institutional support.

Behavioural intention demonstrated a significant direct effect on use behaviour, confirming its reliability as a strong predictor of actual technology use [47-49]. However, the R^2 values for behavioural intention (41.9%) and use behaviour (25.7%) indicate that additional factors beyond the UTAUT constructs may influence AI adoption. Variables such as trust, ethical concerns and individual differences are likely to play a significant role. Lockey S et al., highlight trust-specifically perceived security, accuracy and dependability- as a key determinant in AI adoption [52]. Ethical concerns, including privacy and data security, may also influence nursing students' attitudes toward AI as noted by Acquisti A et al., [53].

Age was found to moderate the relationship between PE and behavioural intention, indicating that younger students may perceive AI's benefits more positively, as they tend to be more adaptable to emerging technologies [54-57]. However, gender did not moderate behavioural intention or use behaviour, consistent with studies suggesting that AI's intuitive and accessible design fosters gender-neutral adoption patterns [58-61].

These findings highlight the critical role of PE in driving AI adoption in nursing education, emphasising that students' perceptions of utility and benefits are central. Addressing students' specific needs and motivations can support effective integration into nursing curricula, contributing to improved educational and clinical outcomes.

Limitation(s)

This study had limitations. It examined UTAUT constructs, excluding factors such as trust, ethical considerations and contextual variables, which may also play a significant role in AI adoption. The cross-sectional design restricts the ability to determine causality and the findings may lack generalisability due to the sample being limited to a single institution. Furthermore, reliance on self-reported data may have introduced response bias, impacting the accuracy of the results.

CONCLUSION(S)

PE significantly influences nursing students' behavioural intention to adopt AI, while EE, SI and FCs showed no significant effects. Age moderates the relationship between PE and behavioural intention, whereas gender does not. Behavioural intention mediates the relationship between PE and use behaviour, underscoring its critical role in AI adoption. These findings highlight the importance of aligning AI tools with nursing students' perceived utility to enhance acceptance and integration effectively.

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