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Determinants of Artificial Intelligence Adoption Intention Among Moroccan Nursing Students: An Extended UTAUT-Based Cross-Sectional Study

Houyam Jelloul[1*], Malika Rmili[2], Souad Arhouh[3] and Youssef Nafidi[4]
[1,4]Laboratory of Education and Social Dynamics, Faculty of Educational Sciences, Mohammed V University, Rabat, Morocco
[2,3]RIPDS, Higher Normal School, Abdelmalek Essaadi University, Tetouan, Morocco

*Corresponding author: Houyam Jelloul (e-mail: houyam_jelloul@um5.ac.ma).

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Abstract **Background:** Artificial Intelligence (AI) is increasingly entering higher and professional education, yet evidence on students' pre-implementation readiness remains limited in North African health professions education. This study examined factors associated with undergraduate nursing students' behavioral intention to use AI in Moroccan paramedical education using an extended UTAUT-informed model. **Methods:** An analytical cross-sectional survey was conducted among 359 second- and third-year nursing students enrolled in public paramedical training institutes in the Casablanca-Settat region, Morocco. The questionnaire assessed performance expectancy, effort expectancy, social influence, facilitating conditions, AI readiness, positive attitude toward AI, AI literacy and behavioral intention. Descriptive statistics, reliability analyses, group comparisons, Spearman correlations and multiple linear regression were performed. **Results:** The regression model explained 59.6% of the variance in behavioral intention. Performance expectancy was the strongest independent predictor ($\beta = 0.267$, $p<0.001$), followed by social influence ($\beta = 0.217$, $p<0.001$), positive attitude toward AI ($\beta = 0.206$, $p<0.001$), academic level ($\beta = 0.204$, $p = 0.004$), AI readiness ($\beta = 0.109$, $p = 0.018$) and facilitating conditions ($\beta = 0.087$, $p = 0.041$). Effort expectancy and AI literacy were not independent predictors after adjustment. **Conclusions:** Students' intentions to adopt AI are predominantly shaped by factors such as perceived educational value, social influence, positive attitudes, readiness and conducive institutional conditions. These insights offer preliminary evidence to support the responsible integration of AI in Moroccan health professions education and similar settings.

Key Words Artificial Intelligence, Health Professions Education, Nursing Education, Behavioral Intention, UTAUT, Morocco

INTRODUCTION

Artificial Intelligence (AI) is becoming increasingly prominent in higher education. Its main documented applications include the personalization of learning paths, support for the analysis of student performance, the partial automation of formative feedback and the development of more adaptive learning environments [1,2]. Tools based on natural language processing, particularly generative language models and virtual teaching assistants, expand this reach by offering continuous, individualized support that can respond more directly to learners' needs [3,4].

The availability of such tools does not solely determine the educational value of AI. It also depends on students' perceptions of their utility, their readiness to use them and the extent to which institutional and pedagogical conditions support meaningful integration.

These elements are particularly common in medical and health professions education, where the curriculum aims to integrate theoretical knowledge with applied reasoning, practical decision-making and preparation for real-world professional roles. Nursing education exemplifies this significant challenge due to its high-stakes nature. In this context, artificial intelligence is increasingly regarded as a valuable resource to enhance learning experiences, support simulation-based activities, assist in case analysis and aid students in preparing for clinical and professional practice [5-7].

Studies from various contexts have reported generally favorable effects on student engagement and some learning outcomes, particularly through algorithm-generated clinical scenarios, augmented simulations and generative AI tools used to support self-directed study [8-11]. These findings,

however, should be interpreted carefully, as the heterogeneity of tools, educational contexts and pedagogical approaches limits their generalizability. Moreover, evidence remains less consistent regarding AI's effects on higher-order educational outcomes such as clinical reasoning, critical thinking and professional judgment [6,12,13]. This distinction is particularly relevant in nursing, where clinical reasoning is a dynamic, iterative cognitive process directly linked to clinical judgment, appropriate decision-making and professional autonomy [14].

What the literature also consistently shows is a gap between students' growing interest in AI and their actual readiness to use it. A meta-analysis by Amiri *et al.* [15], conducted among medical, dental and nursing students, found that generally favorable attitudes toward AI frequently coexist with more limited levels of knowledge and literacy. The integrative review by El Arab *et al.* [7], which synthesized 37 studies involving more than 10,000 nursing students and practicing nurses, similarly found that AI readiness, literacy and adoption intentions are strongly shaped by perceived usefulness, prior digital skills, previous AI training and the availability of facilitating institutional conditions. Labrague *et al.* [16] reported that nursing students' readiness to adopt AI is shaped by individual and contextual factors, yet constrained by limited access, insufficient training and a lack of institutional support. These findings point to AI adoption in education as a process shaped by multiple intersecting factors, not a natural consequence of tool availability.

The issue is particularly pertinent in Morocco, where health professions education faces mounting pressure to develop a qualified and adaptable healthcare workforce. The Higher Institutes of Nursing and Health Technical Professions (ISPITS), which are public institutions overseen by the Ministry of Health, serve as a primary institutional framework for the education of nurses and health technicians in Morocco [17]. Yet nursing education at ISPITS continues to face documented challenges in curriculum design, cross-cutting skills development, research culture and pedagogical innovation [18,19]. AI could represent a meaningful resource for improving educational quality, provided its integration is pedagogically grounded and institutionally supported.

Formal AI integration in health professions education across the region appears uneven and still developing. Across the MENA region, only a minority of health sciences students receive formal AI training; most of what they know about AI comes from informal channels, social media, online tutorials and peer conversations, without sufficient assurance of depth or reliability [20-22]. Available evidence on Moroccan ISPITS and related paramedical training contexts suggests persistent challenges in pedagogical innovation, digital integration, instructor preparation and institutional support, which may also affect the conditions for AI integration [18,19]. Delayed or poorly supported AI integration may fail to reduce educational gaps and could risk reinforcing existing inequalities in access, preparedness and pedagogical support, particularly as AI applications in medicine and nursing practice expand. These contextual conditions make it important to examine students' intention to use AI before assuming that AI tools can be meaningfully or responsibly integrated into nursing education.

Research on technology acceptance shows consistently that actual use depends less on tool availability than on how users perceive usefulness, ease of use, social legitimacy and the practical conditions surrounding implementation. Among available frameworks, the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh *et al.* [23] is particularly well suited to this purpose. UTAUT provides a theoretically grounded basis for examining behavioral intention through four core constructs: performance expectancy, effort expectancy, social influence and facilitating conditions. Existing UTAUT-based studies on AI adoption in health professions education, including nursing and medical education, have been conducted primarily in Asian and Middle Eastern contexts such as China [24], South Korea [25] and Saudi Arabia [26]. In Moroccan higher education, recent research has investigated how university students in various disciplines accept AI. Nonetheless, there is limited evidence regarding AI adoption in professional health education, where it is linked not only to academic practices but also to future career readiness, clinical education and institutional readiness [27]. This creates a significant gap in the context of North African paramedical training, where institutional conditions, AI exposure, curriculum structure and training cultures might differ considerably from those observed in other higher education settings.

Studying behavioral intention through UTAUT alone, however, leaves important dimensions unaddressed. First, the original UTAUT does not capture students' subjective sense of preparedness to engage with AI. This construct has emerged as a distinct predictor of adoption intention in healthcare education contexts [16,28]. In the present study, AI readiness was assessed using items adapted from the Shinners Artificial Intelligence Perception (SHAIP) instrument, originally developed for healthcare professionals [29,30] and reformulated for the educational context. Second, positive attitude toward AI, while not a canonical UTAUT construct, is consistently identified in the emerging nursing literature as an independent predictor of adoption intention, operating distinctly from instrumental beliefs about usefulness or ease [28,31] and was therefore included as a complementary predictor. Third, AI literacy, defined as the ability to understand, evaluate and use AI critically and ethically [32], was assessed using a purpose-built 10-item multiple-choice questionnaire. Given the exploratory nature of this study, this measure focused primarily on declarative and conceptual knowledge rather than the full multidimensional scope of applied AI literacy and its role as a direct predictor of adoption intention remains underexplored in paramedical education contexts. For this reason, an extended UTAUT-informed model may offer a more context-sensitive understanding of AI adoption intention than the original UTAUT model alone.

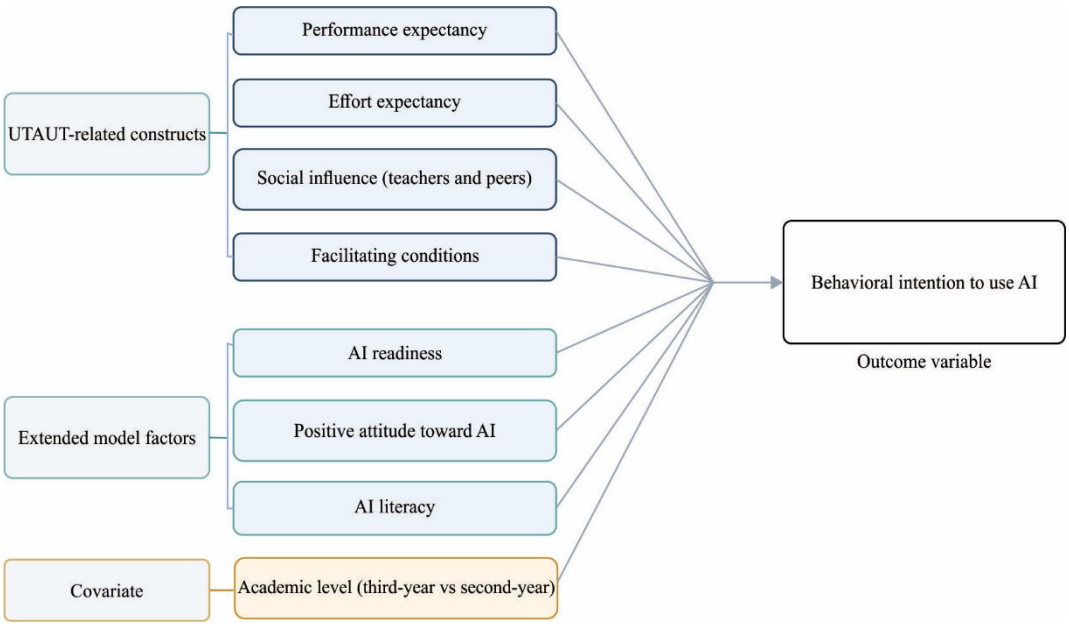


Figure 1: Extended UTAUT-Informed Model of Behavioral Intention to Use Artificial Intelligence Among Nursing Students
The model was informed by the UTAUT framework and extended with AI readiness, positive attitude toward AI, AI literacy and academic level. Behavioral intention to use AI was specified as the dependent variable. Academic level was included as a covariate

While research on AI adoption in education is expanding, three gaps remain particularly relevant for professional health education. First, most studies on students' intention to adopt AI have been conducted outside North African health professions education contexts. Second, attitudes, readiness and AI literacy are often examined separately, rather than integrated within a theoretically grounded technology acceptance model. Third, limited pre-implementation evidence is available to guide how professional education institutions should prepare students for responsible AI use before formal curricular integration. To our knowledge, no published study has quantitatively examined the determinants of nursing students' behavioral intention to use AI in Moroccan paramedical education using an extended UTAUT-informed model that combines UTAUT constructs, AI readiness, positive attitude toward AI, AI literacy and academic level.

This study addresses these gaps by providing an empirical pre-implementation baseline from an underrepresented North African health professions education context. It contributes to educational technology and health professions education by testing an extended UTAUT-informed model among undergraduate nursing students and by generating evidence that may inform pedagogically grounded, ethically guided and institutionally supported AI integration in professional education settings.

The study was conducted among second- (L2) and third-year (L3) nursing students enrolled at ISPITS in the Casablanca-Settat region of Morocco. The L2-L3 comparison was selected because these two cohorts represent the more clinically oriented stages of the undergraduate nursing training and because academic level, as a proxy for clinical exposure and professional socialization, has been identified as a relevant variable in prior studies of AI attitudes and adoption intention in nursing education [28,33]. The primary objective was to identify factors independently associated with students' behavioral intention to use AI, using a multiple linear regression model. The secondary objectives were to describe AI readiness and AI literacy levels across both cohorts and to compare key study variables between L2 and L3 students.

In line with the extended UTAUT-informed model, we hypothesized that performance expectancy, effort expectancy, social influence, facilitating conditions, AI readiness, positive attitude toward AI, AI literacy and academic level would be related to behavioral intention to use AI. Figure 1 presents the extended UTAUT-informed model used to guide the empirical analysis.

METHODS

Research Design

An analytical cross-sectional survey was conducted among second- and third-year undergraduate nursing students enrolled in public paramedical training institutes in the Casablanca-Settat region of Morocco. The reporting of this analytical cross-sectional study followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) checklist for cross-sectional studies [34]; the completed checklist is provided as Supplementary File S1.

Setting and Samples

A non-probability sampling strategy stratified by academic level was used to ensure the inclusion of both second- and third-year nursing students. The accessible population comprised 1,651 undergraduate nursing students (L2: n = 833; L3: n = 818).

The minimum required sample size was estimated using Cochran's [35] formula for proportions in finite populations, assuming an expected proportion of 0.50 (maximum variance), a margin of error of 5 and a 95% confidence level, yielding a minimum of 312 participants. To account for anticipated incomplete responses, the target recruitment number was set at 367. A total of 359 complete questionnaires were ultimately retained for analysis, exceeding the minimum required sample size.

Inclusion criteria were: (i) Enrollment as an L2 or L3 nursing student in the selected public paramedical training institutes in the Casablanca-Settat region at the time of data collection; (ii) Provision of informed consent and (iii) Submission of a complete questionnaire. Students who did not provide consent were excluded from the analysis.

Measurement and Data Collection

Data were collected between November 2025 and January 2026 using a self-administered questionnaire available in two parallel formats: paper-based and online (Google Forms). The dual-format approach was adopted to maximize accessibility and participation across varying levels of digital access among students. The online survey link was disseminated through institutional communication channels, including course coordinators and student communication groups. Paper questionnaires were distributed and collected during scheduled academic sessions under the supervision of a research team member and students were informed that participation was voluntary with no effect on their academic standing.

Despite the inability to completely prevent duplicate participation across formats due to the absence of personal identifiers, participants were explicitly instructed to complete the questionnaire only once, irrespective of the format. For the online version, response timestamps were scrutinized to identify any submissions made in an unreasonably short time. Each returned questionnaire was subjected to a completeness check prior to data entry. The survey remained accessible throughout the entire recruitment phase, with a single reminder issued midway through the data collection period.

The questionnaire was administered in French, the language of instruction in the selected public paramedical training institutes. Items originally developed in English were translated into French by one bilingual researcher and reviewed for semantic equivalence by a second bilingual researcher. Items were adapted to AI use in health professions education, with attention to pedagogical relevance and clarity for undergraduate nursing students. Items were phrased in the present or near-future tense to reflect the anticipated nature of AI integration into students' educational experience.

After the adaptation process, a panel consisting of three experts, two specializing in nursing education and one in educational technology, conducted a thorough evaluation of the questionnaire. They assessed the clarity, relevance and contextual suitability of each item. Based on their insights, minor adjustments were made to the wording and order of the items before finalizing the questionnaire. Unless otherwise noted, constructs with multiple items were measured using a five-point Likert scale, where 1 indicated strong disagreement and 5 indicated strong agreement. Composite scores were calculated as the average of the relevant items, with higher scores signifying greater endorsement of each construct.

Determinants of AI acceptance were assessed using a scale informed by the Unified Theory of Acceptance and Use of Technology (UTAUT), as originally proposed by Venkatesh *et al.* [23]. Four UTAUT-related constructs were operationalized: performance expectancy (PE; 3 items; Cronbach's $\alpha = 0.831$), effort expectancy (EE; 3 items; $\alpha = 0.788$), facilitating conditions (FC; 3 items; $\alpha = 0.558$) and behavioral intention to use AI (INT; 3 items; $\alpha = 0.849$). Items related to performance expectancy and behavioral intention were contextualized around educational uses of AI in nursing training, including understanding complex clinical concepts and practicing with AI-generated case scenarios. The remaining constructs reflected broader conditions influencing AI adoption in nursing education.

The internal consistency of the facilitating conditions subscale ($\alpha = 0.558$) was below the conventional threshold of 0.70 [36]. This subscale was retained given its theoretical centrality within the UTAUT framework and the small number of items (three), which may partly limit alpha estimates. An item-deletion analysis confirmed that removing any single FC item did not yield a meaningful improvement in alpha (deletion range: $\alpha = 0.43$-0.56). Findings related to facilitating conditions are therefore interpreted with caution throughout this paper.

AI readiness was assessed using four items (Cronbach's $\alpha = 0.652$) adapted from the conceptual domains of the Shinners Artificial Intelligence Perception (SHAIP) instrument, originally developed for healthcare professionals through an e-Delphi approach [29] and subsequently piloted psychometrically [30]. Items were reformulated to reflect students' perceived readiness for the supervised educational use of AI in nursing training, rather than clinical AI applications. Given this adaptation to a different population and setting, the scale was treated as an exploratory measure. The alpha coefficient of 0.652 indicated moderate internal consistency and was considered acceptable for exploratory purposes. The readiness score was computed as the mean of the four items (range: 1-5).

Positive attitude toward AI was assessed with two items (Cronbach's $\alpha = 0.733$) and summarized as a mean score (range: 1-5). Concern about AI-related risks was measured with a single item and treated as an exploratory indicator. Social influence was operationalized as the mean of two items reflecting perceived influence from teachers and peers (inter-item Pearson's $r = 0.557$, $p<0.001$; Spearman-Brown reliability = 0.715). A third social influence item, capturing perceived expectations from important others in general, was

analyzed separately as a single-item indicator of subjective norm, owing to the modest internal consistency of the three-item composite (α = 0.563). A single governance item assessed students' expectations regarding clear institutional rules regulating AI use in educational settings. Single-item variables were used as exploratory indicators and were not interpreted as multidimensional psychometric constructs.

AI literacy was assessed with a 10-item Multiple-Choice Questionnaire (MCQ) covering foundational concepts of AI's general functioning, principal limitations and core principles of responsible use. Each item was scored dichotomously (1 = correct; 0 = incorrect), yielding a total score from 0 to 10. The same expert panel reviewed the MCQ for item clarity, relevance and contextual appropriateness; minor revisions were made based on their feedback. Internal consistency for the dichotomous items was estimated using the Kuder-Richardson formula 20 (KR-20), yielding a coefficient of 0.659, indicating moderate internal consistency, which was considered sufficient for exploratory purposes [37]. Item-level performance statistics are reported in Supplementary Table S2.

Data Analysis

All statistical analyses were conducted in jamovi version 2.6.44. Descriptive statistics, including means, standard deviations, frequencies and proportions, were used to characterize participants and summarize study variables. Between-group differences across academic levels (second-year vs third-year students) were assessed with independent-samples t-tests and Welch's correction was applied when Levene's test indicated a violation of the homogeneity of variance assumption. Effect sizes were quantified using Cohen's d [38], with values of 0.20, 0.50 and 0.80 interpreted as small, medium and large, respectively. Spearman's rank-order correlations were used to provide a conservative assessment of bivariate associations involving Likert-derived scores.

A multiple linear regression model was estimated with behavioral intention to use AI as the dependent variable. Predictors were entered simultaneously in accordance with the extended UTAUT-informed conceptual model and included: performance expectancy, effort expectancy, the two-item social influence composite, facilitating conditions, AI literacy total score, positive attitude toward AI, AI readiness and academic level (dummy-coded with L2 as the reference category). Multicollinearity was assessed using Variance Inflation Factors (VIF); values above 5 were considered indicative of potential concern and values above 10 of serious collinearity [39]. Regression assumptions were verified through residuals-versus-fitted plots and normal Q-Q plots. Influential observations were identified using Cook's distance with a threshold of 4/n and multivariate outliers were screened using Mahalanobis distance. Statistical significance was set at a two-tailed $p<0.05$.

To examine the potential for common method bias, an inherent concern in cross-sectional self-report surveys [40], Harman's single-factor test was conducted. All self-reported Likert-type items were entered into an exploratory factor analysis with extraction constrained to a single factor. A single factor explaining less than 50% of the total variance was interpreted as not indicating a dominant single-factor structure. However, this procedure was treated as a diagnostic check rather than definitive evidence that common method bias was absent [40]. The result of this test is reported in the Results section.

Ethical Considerations

The study received a formal institutional waiver/exemption from full ethics review, jointly issued by the Director and the Deputy Director for Scientific Research, Continuing Education and Cooperation of the Higher Institute of Nursing and Health Technical Professions (ISPITS), Casablanca-Settat Region, Ministry of Health and Social Protection, Morocco, under reference number 634/2026, dated 8 September 2026. The waiver/exemption was granted because the study was an anonymous, non-interventional, minimal-risk, questionnaire-based educational survey that did not involve patients, clinical interventions, biological material, clinical data or identifying personal data. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and relevant institutional and national regulations for research involving human participants. Participation was voluntary and anonymous and informed consent was obtained from all participants before questionnaire completion.

RESULTS

Participant Characteristics

A total of 359 undergraduate nursing students at ISPITS completed the survey: 184 in second year (L2) and 175 in third year (L3). The sample was predominantly female (84.4%, n = 303). Age composition differed sharply by cohort; most L2 students were under 20 (66.8%), while most L3 students were in the 20-22-year range (79.4%). Sociodemographic characteristics are presented in Table 1.

Descriptive Statistics

Mean scores on Likert-type measures were generally above the scale midpoint in both cohorts, reflecting a broadly favorable orientation toward AI use in nursing education (Table 2). Performance expectancy was nearly identical across years (L2: 3.90 [SD 0.92]; L3: 3.91 [SD 0.86]), as was AI readiness (3.69 [SD 0.73] vs. 3.64 [SD 0.72]). Behavioral intention was higher in L3 students (4.02 [SD 0.81] vs. 3.77 [SD 0.97]), as were social influence from teachers and peers (3.97 [SD 0.91] vs. 3.71 [SD 1.01]) and institutional policy clarity expectations (3.70 [SD 1.18] vs. 3.44 [SD 1.23]). AI literacy scores were moderate in both groups (L2: 5.64 [SD 2.25]; L3: 5.89 [SD 2.17] on a 0-10 scale) and risk concern scores were nearly the same (3.84 [SD 1.08] vs. 3.83 [SD 1.00]).

Table 1: Participant Characteristics by Academic Level (L2 vs. L3)

Characteristic	L2 (n = 184)	L3 (n = 175)	Total (n = 359)
Sex			
Female	153 (83.2)	150 (85.7)	303 (84.4)
Male	31 (16.8)	25 (14.3)	56 (15.6)
Age category (years)			
<20	12H3 (66.8)	29 (16.6)	152 (42.3)
20-22	57 (31.0)	139 (79.4)	196 (54.6)
23-25	2 (1.1)	6 (3.4)	8 (2.2)
>25	2 (1.1)	1 (0.6)	3 (0.8)

Values are n (%), Percentages are calculated within columns

Table 2: Descriptive Statistics of Study Variables by Academic Level (L2 vs. L3)

Study variable	L2 (n = 184) (Mean (SD))	L3 (n = 175) (Mean (SD))
AI readiness	3.69 (0.73)	3.64 (0.72)
Performance expectancy	3.90 (0.92)	3.91 (0.86)
Effort expectancy	3.86 (0.84)	3.93 (0.80)
Facilitating conditions	3.77 (0.86)	3.69 (0.79)
Behavioral intention	3.77 (0.97)	4.02 (0.81)
AI literacy score (0-10)	5.64 (2.25)	5.89 (2.17)
Positive attitude toward AI	3.90 (0.99)	4.05 (0.86)
Risk concern	3.84 (1.08)	3.83 (1.00)
Social influence (teachers & peers)	3.71 (1.01)	3.97 (0.91)
Subjective norm (important others)	3.34 (1.20)	3.17 (1.20)
Expectation of policy clarity	3.44 (1.23)	3.70 (1.18)

Values are Mean (SD), Likert-type variables range from 1 to 5. AI literacy ranges from 0 to 10

Table 3: Internal Consistency Reliability of Study Measures

Construct	Items	Reliability metric	Estimate	Notes
AI readiness	READ1-READ4	Cronbach's α	0.652	4-item scale
Performance expectancy	PE1-PE3	Cronbach's α	0.831	3-item scale
Effort expectancy	EE1-EE3	Cronbach's α	0.788	3-item scale
Facilitating conditions	FC1-FC3	Cronbach's α	0.558	3-item scale
Social influence (SI_2)	SI1-SI2	Inter-item r/Spearman-Brown	r = 0.557; SB = 0.715	2-item score
Behavioral intention	INT1-INT3	Cronbach's α	0.849	3-item scale
Positive attitude	ATT1-ATT2	Cronbach's α	0.733	2-item scale
AI literacy quiz	LIT1-LIT10 (0/1)	KR-20	0.659	Dichotomous items

Cronbach's α is reported for Likert-type scales, KR-20 is reported for dichotomous items, SB: Spearman-Brown reliability, SI3 was analyzed separately as a single-item indicator of subjective norm

Table 4: Group Comparisons of Study Variables by Academic Level (L2 vs. L3)

Variable	L2 (n = 184) (Mean (SD))	L3 (n = 175) (Mean (SD))	Test (t, df)	p	Cohen's d
AI readiness	3.69 (0.73)	3.64 (0.72)	t = 0.692, df = 357	0.490	0.073
Performance expectancy	3.90 (0.92)	3.91 (0.86)	t = -0.088, df = 357	0.930	-0.009
Effort expectancy	3.86 (0.84)	3.93 (0.80)	t = -0.839, df = 357	0.402	-0.089
Social influence (SI_2)	3.71 (1.01)	3.97 (0.91)	t = -2.499, df = 357	0.013	-0.264
Subjective norm (SI3)	3.34 (1.20)	3.17 (1.20)	t = 1.395, df = 357	0.164	0.147
Policy clarity (GOV)	3.44 (1.23)	3.70 (1.18)	t = -2.019, df = 357	0.044	-0.213
Facilitating conditions	3.77 (0.86)	3.69 (0.79)	t = 0.945, df = 357	0.345	0.100
Behavioral intention*	3.77 (0.97)	4.02 (0.81)	t = -2.729, df = 351	0.007	-0.287
AI literacy (0-10)	5.64 (2.25)	5.89 (2.17)	t = -1.071, df = 357	0.285	-0.113
Positive attitude	3.90 (0.99)	4.05 (0.86)	t = -1.498, df = 357	0.135	-0.158

Values are Mean (SD), Two-tailed independent-samples t-tests were used; Welch's correction was applied for behavioral intention due to violation of homogeneity of variance (*), Negative Cohen's d values indicate higher scores in L3 students

Internal Consistency of Measures

Internal consistency estimates are reported in Table 3. Reliability was good for behavioral intention (Cronbach's α = 0.849), performance expectancy (α = 0.831) and effort expectancy (α = 0.788) and acceptable for positive attitude toward AI (α = 0.733). AI readiness showed moderate internal consistency (α = 0.652), considered sufficient for exploratory purposes. Facilitating conditions yielded a lower coefficient (α = 0.558); findings for this subscale are interpreted with caution throughout. For the two-item social influence composite, the inter-item Pearson correlation was 0.557 ($p<0.001$), with a Spearman-Brown coefficient of 0.715, supporting use of a mean score. The AI literacy quiz showed a KR-20 coefficient of 0.659, indicating moderate consistency for a dichotomous exploratory instrument.

Comparisons by Academic Level

Group comparisons are presented in Table 4. Third-year students reported higher behavioral intention than second-year students (Welch's $t(351) = -2.729$, $p = 0.007$, Cohen's $d = -0.287$), stronger social influence from teachers and peers ($t(357) = -2.499$, $p = 0.013$, $d = -0.264$) and higher

Table 5: Predictors of Behavioral Intention to Use Artificial Intelligence

Predictor	B	SE	T	P	Std. β	95% CI for Std. β, lower	95% CI for Std. β, upper	VIF
Academic level (L3 vs. L2)	0.184	0.063	2.930	0.004	0.204	0.067	0.340	1.05
AI readiness	0.135	0.057	2.382	0.018	0.109	0.019	0.199	1.81
Performance expectancy	0.271	0.051	5.273	<0.001	0.267	0.168	0.367	2.22
Effort expectancy	0.069	0.053	1.298	0.195	0.063	-0.032	0.158	2.02
Social influence (SI_2)	0.203	0.045	4.460	<0.001	0.217	0.121	0.313	2.05
Facilitating conditions	0.096	0.047	2.052	0.041	0.087	0.004	0.171	1.57
AI literacy	-0.0001	0.015	-0.010	0.992	-0.0004	-0.072	0.071	1.14
Positive attitude toward AI	0.200	0.049	4.078	<0.001	0.206	0.107	0.305	2.20

Model fit (N = 359): R^2 = 0.596, adjusted R^2 = 0.587, F(8, 350) = 64.5, p<0.001, Behavioral intention to use AI was specified as the outcome variable, Academic level was dummy-coded with L2 as the reference category, B: Unstandardized regression coefficient, SE: Standard error; Std, β: Standardized regression coefficient, CI: Confidence interval, VIF: Variance inflation factor

institutional policy clarity expectations (t(357) = -2.019, p = 0.044, d = -0.213). All three differences were small. The policy clarity difference, in particular, was close to the conventional significance threshold and should be read cautiously. No significant differences were found for AI readiness, performance expectancy, effort expectancy, facilitating conditions, AI literacy, positive attitude or subjective norm (all p>0.05).

Bivariate Associations with Behavioral Intention

Spearman rank-order correlations between each study variable and behavioral intention are reported in Supplementary Table S1. All study variables were positively and significantly associated with behavioral intention (all p<0.001). The strongest correlations involved positive attitude toward AI (ρ = 0.640), performance expectancy (ρ = 0.621) and social influence from teachers and peers (ρ = 0.605). Effort expectancy (ρ = 0.559) and AI readiness (ρ = 0.523) showed moderate associations, followed by facilitating conditions (ρ = 0.460). AI literacy (ρ = 0.203), subjective norm (ρ = 0.208), risk concern (ρ = 0.271) and policy clarity expectation (ρ = 0.327, p<0.001) were more weakly correlated with intention, though all reached statistical significance.

These bivariate associations are reported to describe the overall pattern of relationships with behavioral intention. The multivariable regression model was subsequently specified based on the extended UTAUT-informed theoretical framework, prioritizing theoretically central constructs and multi-item predictors; single-item exploratory indicators (subjective norm, risk concern and policy clarity expectation) were not included in the adjusted model.

Multiple Linear Regression: Predictors of Behavioral Intention

The regression model was statistically significant (F(8, 350) = 64.5, p<0.001) and explained 59.6% of the variance in behavioral intention (R^2 = 0.596, adjusted R^2 = 0.587). Residual diagnostics did not indicate major assumption violations and VIF values ranged from 1.05 to 2.22, with no evidence of problematic multicollinearity (Table 5).

Performance expectancy was the strongest independent predictor (standardized β = 0.267, 95% CI [0.168, 0.367], p<0.001). Social influence from teachers and peers (β = 0.217, 95% CI [0.121, 0.313], p<0.001) and positive attitude toward AI (β = 0.206, 95% CI [0.107, 0.305], p<0.001) were also independently associated with intention, each with a similar effect size. Academic level remained significant after adjustment, with third-year students reporting higher intention (β = 0.204, 95% CI [0.067, 0.340], p = 0.004). AI readiness (β = 0.109, 95% CI [0.019, 0.199], p = 0.018) and facilitating conditions (β = 0.087, 95% CI [0.004, 0.171], p = 0.041) each contributed modestly.

In the adjusted model, effort expectancy (β = 0.063, p = 0.195) and AI literacy score (β ≈ 0.000, p = 0.992) were not independently associated with behavioral intention.

Common Method Bias Assessment

Harman's single-factor test was conducted on all self-reported Likert-type items. The single-factor solution explained 42.6% of the total variance, below the conventional 50% threshold, which did not indicate a dominant single-factor structure. Common method bias is therefore unlikely to fully account for the observed associations [40], though this test cannot exclude it entirely, as method bias remains an inherent concern in cross-sectional self-report designs.

In general, performance expectancy, social influence, positive attitude toward AI, academic level, AI readiness and facilitating conditions were identified as independent predictors of behavioral intention to use AI in the adjusted regression model. Neither effort expectancy nor AI literacy was independently associated with behavioral intention after adjustment. Both variables were positively correlated with behavioral intention in bivariate analyzes.

DISCUSSION

Principal Findings

This study examined AI adoption intention among undergraduate nursing students in Moroccan health professions education and identified factors independently associated with this intention, using an extended UTAUT-informed conceptual model [23] complemented by measures of AI readiness, positive attitude and AI literacy. The adjusted model explained 59.6% of the variance in behavioral intention (R^2 = 0.596). This substantial explanatory value may partly reflect the inclusion of complementary predictors such as positive attitude toward AI and AI readiness, although comparisons

across studies should be made cautiously because of differences in samples, instruments, AI exposure and educational contexts [25,26]. Performance expectancy, social influence, positive attitude, AI readiness, facilitating conditions and academic level remained independently associated with behavioral intention after adjustment, whereas effort expectancy and AI literacy did not retain independent effects. Collectively, these findings suggest that students' intention to use AI is not shaped by declarative IA knowledge alone but by perceived educational value, social norms and enabling personal and institutional conditions; a profile consistent with recent evidence that nursing students often hold more favorable attitudes toward AI than their levels of formal knowledge or operational readiness would predict [15,28].

Key Determinants of AI Adoption Intention in Health Professions Education

Performance expectancy emerged as the strongest independent predictor of behavioral intention ($\beta = 0.267$, $p<0.001$), suggesting that students' intention to use AI may be primarily driven by the educational value they attribute to it. This result aligns with Tao *et al.* [24], who applied UTAUT to intention to use AI chatbots among medical students and with Kwak *et al.* [25], who found performance expectancy to independently predict AI use intention in 210 South Korean nursing students. The systematic review by El Arab *et al.* [28] similarly identifies perceived usefulness as one of the most recurrent determinants of adoption intentions across 37 studies. These findings indicate that the appeal of AI among nursing students rests on the recognition that it could concretely support learning and clinical preparation and that integration strategies should be designed around field-specific applications where this value is visible.

Social influence from teachers and peers was the second strongest predictor ($\beta = 0.217$, $p<0.001$), indicating that behavioral intention to use AI is embedded in a normative social environment rather than being a purely individual decision. Third-year students reported higher social influence scores than second-year students, alongside higher expectations regarding institutional policy clarity. These cross-sectional associations do not imply directionality but are consistent with El Arab *et al.* [28] emphasis on institutional climate and peer norms as enabling factors for AI readiness and adoption intention. In a context where formal AI-integrated pedagogy is still emerging, the social and institutional environment may be as influential as the technology itself. Educators, classmates and institutional regulations can play a significant role in legitimizing the use of AI, elucidating acceptable practices and mitigating uncertainty regarding its application in educational contexts.

Positive attitude toward AI was independently associated with intention ($\beta = 0.206$, $p<0.001$), with an effect size comparable to that of performance expectancy and social influence. Evidence from Turkey documents associations between nursing students' AI readiness, positive attitudes and anxiety [41,42], while Han *et al.* [43] find that attitude, perceived acceptance and institutional guidance interact to shape adoption intention. A favorable attitude toward AI appears less as a passive background disposition than as an active enabler of students' willingness to engage with AI-supported learning. Effort expectancy, however, did not retain a significant independent effect ($\beta = 0.063$, $p = 0.195$) once performance expectancy, social influence and attitude were held constant; a pattern consistent with prior UTAUT-based nursing studies in which ease of use was similarly attenuated in multivariable models [25,26].

AI readiness, literacy and pedagogical preparation for responsible AI integration

AI readiness ($\beta = 0.109$, $p = 0.018$) and facilitating conditions ($\beta = 0.087$, $p = 0.041$) each contributed independently to behavioral intention after adjustment, indicating students' perceived readiness to work with AI and perception of an enabling learning environment were associated with higher intention to adopt AI, over and above motivational and attitudinal factors. These findings converge with El Arab *et al.* [28], who identify readiness and facilitating conditions as recurring factors associated with AI adoption intention and with Labrague *et al.* [16], who showed that nursing students' readiness to adopt AI is shaped by personal preparedness and contextual support while remaining constrained by barriers of access and training. Choe and Woo [44] identified a comparable direct effect of facilitating conditions on the intention to use generative AI among nurses employed in a tertiary hospital in South Korea. However, this evidence should be interpreted cautiously in relation to the current study, as it derives from a professional clinical context rather than an undergraduate educational environment. Additionally, the facilitating conditions subscale in the present study demonstrated relatively low internal consistency, suggesting that this finding should be considered exploratory.

The absence of an independent contribution of AI literacy ($\beta \approx 0.000$, $p = 0.992$) is among the most theoretically informative findings of this study. Factual AI knowledge showed a positive bivariate association with intention ($\rho = 0.203$, $p<0.001$) but this association was not significant after controlling for perceived usefulness, social influence, attitudes, readiness, facilitating conditions and academic level. This pattern suggests that declarative AI knowledge may not be a direct predictor of adoption intention when students' motivational, attitudinal and contextual perceptions are taken into account. This is consistent with Alenazi and Alhalal [26] and Akca Sumengen *et al.* [41], who found that AI knowledge was associated with more positive attitudes but did not independently drive adoption decisions. This result should not be read as dismissing the importance of AI education. What it suggests, specifically, is that factual knowledge appears relevant but insufficient on its own to explain adoption intention and that what students may need is not more declarative knowledge but applied AI literacy: The

capacity to use AI tools critically, reflectively and ethically in situated educational and clinical contexts.

The 10-item MCQ used here captured only declarative knowledge; instruments encompassing critical appraisal, practical skills and ethical reasoning [45] may reveal different associations with intention in future research. A further explanation is that AI literacy scores were relatively homogeneous and moderate across both cohorts at the time of data collection (L2: M = 5.64/10; L3: M = 5.89/10), likely reflecting the absence of formal AI curricula at ISPITS. This limited variability may have constrained the ability to detect an independent association between AI literacy and behavioral intention.

Academic Level and Professional Socialization

Academic level was a significant independent predictor of behavioral intention ($\beta = 0.204$, $p = 0.004$), with third-year students reporting higher adoption intention than second-year students. While the effect size was modest, this pattern is consistent with El Arab *et al.* [28], whose systematic review found that senior nursing students tended to express more enthusiasm for AI than juniors and with Majidpanah *et al.* [33], who found that academic semester was significantly associated with all domains of AI knowledge, attitudes and practice among Iranian nursing students. In this study, this difference could be a reflection of the greater clinical exposure and professional socialization of third year students that might make the potential relevance of AI for learning, case analysis and professional preparation more visible. This finding implies that the integration of AI in professional health education may be enhanced by a graduated curricular approach, consistent with students' growing clinical experience and professional development rather than uniformly applied across all years of training.

Implication and Limitations

Implications for Professional Health Education

Three practical directions for AI integration emerge from the data.

First, integration efforts should demonstrate pedagogical value before scaling. Since performance expectancy is the dominant predictor of behavioral intention, AI integration should begin with educational activities in which students can clearly perceive the added value of AI for learning and professional preparation. Examples may include AI-assisted case-based reasoning, simulated clinical scenarios or structured documentation exercises. This is consistent with recent scholarship arguing that AI education in health professions should support the joint development of competence, confidence and critical judgment, rather than simply introducing students to tools [45,46].

Second, faculty development appears to be a strategic requirement for responsible AI integration. The central role of social influence in predicting behavioral intention implies that students' adoption intentions are partly shaped by whether their teachers and educational supervisors visibly endorse and model responsible AI practices. Institutions that invest in faculty AI literacy and pedagogical preparation may be better positioned to support students' intention and readiness for responsible AI use. In Moroccan paramedical health professions education, where AI-integrated pedagogy is still nascent, structured faculty development that includes pedagogical applications, ethical use, assessment practices and institutional governance would represent an important prerequisite for meaningful curricular integration.

Third, clear institutional governance appears to be an important condition for responsible AI use. Although the governance item (GOV) used in this study was exploratory and the observed difference between L2 and L3 students was small and close to the conventional significance threshold, the broader ethical requirements of AI use in health professions education independently support the need for explicit institutional guidance on academic integrity, data confidentiality and the limits of AI use in assessed work and clinical settings. Transparent governance frameworks may reduce uncertainty, reinforce responsible practice and create the enabling conditions for students to engage with AI tools confidently and ethically.

CONCLUSIONS

This study suggests that undergraduate nursing students in Moroccan health professions education are not resistant to artificial intelligence but rather approach it with conditional openness. Their intention to use AI was mainly associated with perceived educational usefulness, social influence, positive attitudes, personal readiness and enabling institutional conditions. This finding is important because it suggests that AI integration in nursing education cannot be reduced to the simple availability of digital tools. It depends on whether students perceive AI as meaningful for their learning, whether teachers and peers legitimize its use and whether institutions provide clear guidance and support.

The absence of an independent effect of AI literacy in the adjusted model does not diminish the importance of AI education. Instead, it highlights the limits of declarative knowledge alone. Students need more than factual information about AI; they need applied AI literacy, developed through guided, contextualized and ethically grounded learning experiences.

These findings provide a pre-implementation baseline for the intention to adopt artificial intelligence among the nursing students in Moroccan paramedical health professions education and provide practical directions for a responsible curricular integration. To responsibly integrate AI into educational settings, it is crucial to focus on applications that align with educational goals, involve faculty oversight, evaluate student readiness and ensure institutional governance. Future research should investigate whether students' intentions translate into actual AI adoption, enhance educational experiences and lead to measurable outcomes, such as improved clinical reasoning skills in nursing education.

Limitations

The findings of this study should be interpreted in light of several limitations. First, its cross-sectional design precludes causal inference and the findings should be interpreted as associations rather than evidence of adoption behavior, learning effectiveness or improvement in clinical reasoning outcomes. Second, the use of self-reported measures may have introduced social desirability bias and common method variance. While Harman's single-factor test did not indicate a dominant single-factor structure, with the single factor explaining 42.6% of the variance, this test does not fully exclude common method bias. Third, some measures should be interpreted cautiously: the facilitating conditions subscale ($\alpha = 0.558$) and the AI readiness scale ($\alpha = 0.652$) showed internal consistency below the conventional 0.70 threshold; the AI literacy measure captured only declarative knowledge and did not cover the full multidimensional scope of AI literacy, including critical appraisal, practical use and ethical reasoning [45] and subjective norm, risk concern and governance expectations were assessed using single-item exploratory indicators. Finally, the non-probability sampling strategy, mixed paper-and-online data collection mode and recruitment from a single Moroccan region may limit generalizability; duplicate participation across formats could not be completely ruled out because no identifying data were collected.

Future research should examine whether students' behavioral intention translates into actual AI use over time and whether predictors change as students gain clinical experience. Longitudinal and multi-institutional studies across different Moroccan regions and comparable professional health education contexts would strengthen external validity. Future studies should also use multidimensional AI literacy instruments and validated multi-item measures of institutional governance, risk perception and subjective norm. Structural equation modeling may also be useful for testing both measurement and structural components of extended AI adoption models while accounting for measurement error.

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Ethical Approval

The study received a formal institutional waiver/exemption from full ethics review, jointly issued by the Director and the Deputy Director for Scientific Research, Continuing Education and Cooperation of the Higher Institute of Nursing and Health Technical Professions (ISPITS), Casablanca-Settat Region, Ministry of Health and Social Protection, Morocco, under reference number 634/2026, dated 8 September 2026. The waiver/exemption was granted because the study was an anonymous, non-interventional, minimal-risk, questionnaire-based educational survey that did not involve patients, clinical interventions, biological material, clinical data or identifying personal data. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and relevant institutional and national regulations for research involving human participants. Participation was voluntary and anonymous and informed consent was obtained from all participants before questionnaire completion.

REFERENCES

[1] Crompton, H. and D. Burke. "Artificial Intelligence in Higher Education: The State of the Field." *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, April 2023. https://doi.org/10.1186/s41239-023-00392-8.

[2] Ouyang, F. *et al.* "Artificial Intelligence in Online Higher Education: A Systematic Review of Empirical Research from 2011 to 2020." *Education and Information Technologies*, vol. 27, no. 6, July 2022, pp. 7893-7925. https://doi.org/10.1007/s10639-022-10925-9.

[3] Hariyanto *et al.* "Artificial Intelligence in Adaptive Education: A Systematic Review of Techniques for Personalized Learning." *Discover Education*, vol. 4, no. 1, 28 October 2025. https://doi.org/10.1007/s44217-025-00908-6.

[4] Labrague, L.J. and S.A. Sabei. "Integration of AI-Powered Chatbots in Nursing Education: A Scoping Review of Their Utilization, Outcomes and Challenges." *Teaching and Learning in Nursing*, November 2024. https://doi.org/10.1016/j.teln.2024.11.010.

[5] Alrazeeni, D.M. *et al.* "Transforming Nursing Education with Artificial Intelligence: A Systematic Review (2010-2025)." *SAGE Open Nursing*, vol. 12, 20 February 2026. https://doi.org/10.1177/23779608261424597.

[6] Bozkurt, S.A. *et al.* "A Systematic Review and Sequential Explanatory Synthesis: Artificial Intelligence in Healthcare Education, a Case of Nursing." *International Nursing Review*, vol. 72, no. 2, 2025. https://doi.org/10.1111/inr.70018.

[7] El Arab, R.A. *et al.* "Integrative Review of Artificial Intelligence Applications in Nursing: Education, Clinical Practice, Workload Management and Professional Perceptions." *Frontiers in Public Health*, vol. 13, 2025. https://doi.org/10.3389/fpubh.2025.1619378.

[8] Athilingam, P. and H.G. He. "ChatGPT in Nursing Education: Opportunities and Challenges." *Teaching and Learning in Nursing*, vol. 19, no. 1, January 2024, pp. 97-101. https://doi.org/10.1016/j.teln.2023.11.004.

[9] Han, J.W. *et al.* "Analysis of the Effect of an Artificial Intelligence Chatbot Educational Program on Non-Face-to-Face Classes: A Quasi-Experimental Study." *BMC Medical Education*, vol. 22, no. 1, December 2022. https://doi.org/10.1186/s12909-022-03898-3.

[10] Liaw, S.Y. *et al.* "Artificial Intelligence Versus Human-Controlled Doctor in Virtual Reality Simulation for Sepsis Team Training: Randomized Controlled Study." *Journal of Medical Internet Research*, vol. 25, no. 1, 26 July 2023. https://doi.org/10.2196/47748.

[11] Padilha, J.M. *et al.* "Clinical Virtual Simulation in Nursing Education: Randomized Controlled Trial." *Journal of Medical Internet Research*, vol. 21, no. 3, 18 March 2019. https://doi.org/10.2196/11529.

[12] Saban, M. and I. Dubovi. "A Comparative Vignette Study: Evaluating the Potential Role of a Generative AI Model in Enhancing Clinical Decision-Making in Nursing." *Journal of Advanced Nursing*, vol. 81, no. 11, 2025, pp. 7489-7499. https://doi.org/10.1111/jan.16101.

[13] Jelloul, H. *et al.* "Artificial Intelligence-Enabled Educational Tools and Clinical Reasoning in Undergraduate Nursing Education: A Systematic Review." *Journal of Pioneer Medical Sciences*, vol. 15, no. 2, 5 March 2026, pp. 192-203. https://doi.org/10.47310/jpms2026150226.

[14] Mohammadi-Shahboulaghi, F. *et al.* "Clinical Reasoning in Nursing Students: A Concept Analysis." *Nursing Forum*, vol. 56, no. 4, 2021, pp. 1008-1014. https://doi.org/10.1111/nuf.12628.

[15] Amiri, H. *et al.* "Medical, Dental and Nursing Students' Attitudes and Knowledge towards Artificial Intelligence: A Systematic Review and Meta-Analysis." *BMC Medical Education*, vol. 24, no. 1, 15 April 2024. https://doi.org/10.1186/s12909-024-05406-1.

[16] Labrague, L.J. *et al.* "Student Nurses' Attitudes, Perceived Utilization and Intention to Adopt Artificial Intelligence (AI) Technology in Nursing Practice: A Cross-Sectional Study." *Nurse Education in Practice*, vol. 73, November 2023. https://doi.org/10.1016/j.nepr.2023.103815.

[17] World Health Organization. *State of the World's Nursing 2025: Investing in Education, Jobs, Leadership and Service Delivery*. World Health Organization, 2025. https://www.who.int/publications/i/item/9789240110236.

[18] Barich, F. *et al.* "La Formation en Soins Infirmiers et Techniques de Santé dans le Système Licence-Master-Doctorat au Maroc: Analyse des Descriptifs de Formation, Étude Analytique Descriptive." *Revue Francophone Internationale de Recherche Infirmière*, vol. 5, no. 4, December 2019. https://doi.org/10.1016/j.refiri.2019.100183.

[19] Benijjane, M. *et al.* "The Social Accountability of Nursing Training Institutes in Morocco: The Knowledge, Perceptions and Realization of Its Aspects." *Journal of Advances in Medical Education and Professionalism*, vol. 9, no. 4, October 2021, pp. 197-203. https://doi.org/10.30476/JAMP.2021.90618.1419.

[20] Al Omari, O. *et al.* "Demographic Factors, Knowledge, Attitude and Perception and Their Association with Nursing Students' Intention to Use Artificial Intelligence (AI): A Multicentre Survey across 10 Arab Countries." *BMC Medical Education*, vol. 24, no. 1, 18 December 2024. https://doi.org/10.1186/s12909-024-06452-5.

[21] Alruwaili, A.N. *et al.* "Neonatal Nurses' Experiences with Generative AI in Clinical Decision-Making: A Qualitative Exploration in High-Risk NICUs." *BMC Nursing*, vol. 24, no. 1, 7 April 2025. https://doi.org/10.1186/s12912-025-03044-6.

[22] Salama, N. *et al.* "Knowledge, Attitudes and Practices toward AI Technology (ChatGPT) among Nursing Students at Palestinian Universities." *BMC Nursing*, vol. 24, no. 1, 11 March 2025. https://doi.org/10.1186/s12912-025-02913-4.

[23] Venkatesh, V. *et al.* "User Acceptance of Information Technology: Toward a Unified View." *MIS Quarterly*, vol. 27, no. 3, 2003, pp. 425-478. https://doi.org/10.2307/30036540.

[24] Tao, W. *et al.* "Utilization of, Perceptions on and Intention to Use AI Chatbots among Medical Students in China: National Cross-Sectional Study." *JMIR Medical Education*, vol. 10, no. 1, 28 October 2024. https://doi.org/10.2196/57132.

[25] Kwak, Y. *et al.* "Influence of AI Ethics Awareness, Attitude, Anxiety and Self-Efficacy on Nursing Students' Behavioral Intentions." *BMC Nursing*, vol. 21, no. 1, 30 September 2022. https://doi.org/10.1186/s12912-022-01048-0.

[26] Alenazi, L. and E. Alhalal. "Factors Affecting Artificial Intelligence Usage Intention among Nursing Students: Unified Theory of Acceptance and Use of Technology." *Nurse Education Today*, vol. 152, September 2025. https://doi.org/10.1016/j.nedt.2025.106780.

[27] Bouziane, A. and K. Bouziane. "Analysis of Artificial Intelligence Acceptance in Humanities and Social Sciences: The Case of Moroccan Universities." *Discover Education*, vol. 4, no. 1, 15 October 2025. https://doi.org/10.1007/s44217-025-00632-1.

[28] El Arab, R.A. *et al.* "Artificial Intelligence in Nursing: A Systematic Review of Attitudes, Literacy, Readiness and Adoption Intentions among Nursing Students and Practicing Nurses." *Frontiers in Digital Health*, vol. 7, 2025. https://doi.org/10.3389/fdgth.2025.1666005.

[29] Shinners, L. *et al.* "Exploring Healthcare Professionals' Perceptions of Artificial Intelligence: Validating a Questionnaire Using the e-Delphi Method." *Digital Health*, vol. 7, January 2021. https://doi.org/10.1177/20552076211003433.

[30] Shinners, L. *et al.* "Exploring Healthcare Professionals' Perceptions of Artificial Intelligence: Piloting the Shinners Artificial Intelligence Perception Tool." *Digital Health*, vol. 8, 7 February 2022. https://doi.org/10.1177/20552076221078110.

[31] Han, S. *et al.* "Nursing Students' Perceptions and Use of Generative Artificial Intelligence in Nursing Education." *Nursing Reports*, vol. 15, no. 2, 14 February 2025. https://doi.org/10.3390/nursrep15020068.

[32] Long, D. and B. Magerko. "What Is AI Literacy? Competencies and Design Considerations." *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, Association for Computing Machinery, 2020, pp. 1-16. https://doi.org/10.1145/3313831.3376727.

[33] Majidpanah, K. *et al.* "Iranian Nursing Students' Perspectives, Knowledge, Attitudes and Practice Regarding Artificial Intelligence (2024-2025)." *Journal of Nursing and Midwifery Sciences*, August 2025. https://doi.org/10.5812/jnms-165629.

[34] Von Elm, E. *et al.* "The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Statement: Guidelines for Reporting Observational Studies." *Bulletin of the World Health Organization*, vol. 85, no. 11, November 2007, pp. 867-872. https://doi.org/10.2471/BLT.07.045120.

[35] Cochran, W.G. *Sampling Techniques*. 3rd Ed., 1977. https://agris.fao.org/search/en/providers/122621/records/647396ad68b4c299a3fb6445.

[36] Nunnally, J.C. "An Overview of Psychological Measurement." *Clinical Diagnosis of Mental Disorders*, by Wolman, B.B. (Edt.), Springer US, 1978, pp. 97-146. https://doi.org/10.1007/978-1-4684-2490-4_4.

[37] Kuder, G.F. and M.W. Richardson. "The Theory of the Estimation of Test Reliability." *Psychometrika*, vol. 2, no. 3, September 1937, pp. 151-160. https://doi.org/10.1007/BF02288391.

[38] Cohen, J. *Set Correlation and Contingency Tables*. 1988. https://www.learntechlib.org/p/140719/.

[39] Hair, J.F. *et al.* "When to Use and How to Report the Results of PLS-SEM." *European Business Review*, vol. 31, no. 1, 14 January 2019, pp. 2-24. https://doi.org/10.1108/EBR-11-2018-0203.

[40] Podsakoff, P.M. *et al.* "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies." *Journal of Applied Psychology*, vol. 88, no. 5, 2003, pp. 879-903. https://doi.org/10.1037/0021-9010.88.5.879.

[41] Akca Sumengen, A. *et al.* "Nursing Students' Attitudes and Literacy toward Artificial Intelligence: A Cross-Sectional Study." *Teaching and Learning in Nursing*, November 2024. https://doi.org/10.1016/j.teln.2024.10.022 .

[42] Taskiran, N. "Effect of Artificial Intelligence Course in Nursing on Students' Medical Artificial Intelligence Readiness: A Comparative Quasi-Experimental Study." *Nursing Education*, May 2023. https://doi.org/10.1097/NNE.0000000000001446.

[43] Han, J. *et al.* "Perceptions and Readiness for Generative AI Implementation among Oncology Nurses: A Qualitative Study in a Specialized Cancer Hospital." *Asian Nursing Research*, 13 December 2025. https://doi.org/10.1016/j.anr.2025.11.004.

[44] Choe, J. and K. Woo. "Factors Associated with Intention to Use Generative Artificial Intelligence in Nursing Practice: A Cross-Sectional Study." *BMC Nursing*, vol. 24, no. 1, 24 October 2025. https://doi.org/10.1186/s12912-025-03985-y .

[45] Ng, D.T.K. *et al.* "AI Literacy: Definition, Teaching, Evaluation and Ethical Issues." *Proceedings of the Association for Information Science and Technology*, vol. 58, no. 1, 2021, pp. 504-509. https://doi.org/10.1002/pra2.487.

[46] Han, J.W. *et al.* "Development and Effects of a Chatbot Education Program for Self-Directed Learning in Nursing Students." *BMC Medical Education*, vol. 25, no. 1, 2 June 2025. https://doi.org/10.1186/s12909-025-07316-2.