Generative AI Confidence Modeling in Nursing Education Based on Interpretable Machine Learning: An Analytical Framework for Structured Questionnaire Data

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***Abstract*: With the rapid penetration of Generative Artificial Intelligence (GenAI) into education and healthcare practice, learners' "confidence in using" these tools is gradually becoming a key variable influencing effective application, sustained adoption, and risk control. Existing research largely remains at the level of descriptive statistics or qualitative discussions, lacking quantitative modeling methods that can simultaneously characterize the combined effects of "training experience—familiarity—confidence in using" and have a reproducible process. Therefore, this paper proposes an interpretable machine learning analysis framework for nursing education scenarios. Variables such as training exposure, GenAI familiarity, tool usage, learning experience, and self-rated confidence are collected based on an online questionnaire; after data cleaning and privacy protection, feature engineering is used to unify key variables into modelable inputs, and "confidence" is predicted and explained through both regression and classification paths. This paper emphasizes using transparent and interpretable models as a strong baseline, and combines cross-validation and visualization analysis to output actionable educational recommendations, providing data-driven evidence for curriculum design, tiered training, and capacity building.**

***Keywords:* Generative Artificial Intelligence; AI Literacy; Nursing Education; Questionnaire Data Analysis; Learning Analytics; Explainable Machine Learning.**

I. INTRODUCTION

Generative Artificial Intelligence (GenAI), represented by large language models, is reshaping educational activities such as learning support, writing assistance, data analysis, and simulation training, and is gradually entering the teaching and practice of medical and nursing professions [1]–[3]. However, the improvement of technology availability does not necessarily translate into effective and responsible use by learners in real tasks. Numerous studies have pointed out that an individual's self-efficacy and confidence in the use of technology will significantly affect their willingness to adopt, depth of use, and persistence [4], [5]. In nursing education, learners need to master tool skills as well as understand their limitations, biases, and ethical risks, which makes "AI literacy" and "confidence modeling" important research topics [6].

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From a theoretical perspective, the Technology Adoption Model (TAM) emphasizes the influence of perceived usefulness and ease of use on the intention to use [4]; the Unified Theory (UTAUT) further incorporates factors such as social influence and support conditions [5]. From a psychological perspective, self-efficacy theory believes that an individual's judgment of their own ability to complete a task will affect their behavioral choices, intensity of investment, and persistence [7].

In the context of GenAI, training experience and familiarity may simultaneously shape learners' confidence, but the two are not linearly consistent: some learners may still show high confidence (potential over-reliance) even without systematic training, and may remain cautious even after receiving training. Descriptive statistics alone are insufficient to reveal this multi-factor interaction.

In recent years, the field of educational data mining and learning analytics has proposed a reproducible research path that combines structured data with machine learning to predict learning performance, learning risks, and behavioral patterns [8]–[10]. Meanwhile, for high-impact decision-making scenarios, researchers emphasize the importance of model interpretability and propose interpretation methods such as LIME and SHAP to enhance transparency and usability [11], [12]. Based on this, this paper proposes an interpretable modeling process for nursing education questionnaire data, focusing on the quantitative modeling and educational implications of "training-familiarity-confidence".

II. LITERATURE REVIEW

A. AI Literacy and Technology Adoption in Education

AI literacy is generally regarded as an extension of digital literacy in the AI era, encompassing the understanding of AI concepts, capability boundaries, risks and ethics, as well as the ability to critically use AI tools in specific contexts [6]. In the fields of education and medical education, research and policy initiatives generally call for the inclusion of AI literacy in the curriculum system and the construction of operational capability frameworks for different disciplines[6],[13]. From the perspective of technology adoption, TAM and UTAUT are widely used to explain the process of learners/practitioners' acceptance of new technologies, emphasizing factors such as perceived usefulness, ease of use, social impact and support conditions[4],[5].

B. Questionnaire Data Analysis and Predictive Modeling

Questionnaire research has long been used to characterize attitudes and intentions, but relying solely on correlation or mean comparisons often makes it difficult to reveal complex relationships between variables. A review of educational data mining work points out that predictive modeling based on machine learning can better handle multivariate and multi-type data, and improve reproducibility through rigorous validation [8]. Learning analytics research emphasizes the standardization of data processing, feature engineering, and evaluation processes to support educational decision-making [9], [10].

C. Confidence Modeling and Self-Efficacy Research

Self-efficacy and confidence are considered important psychological variables affecting learning and technology use. Bandura's self-efficacy theory provides a classic framework for understanding an individual's behavioral choices and persistence when facing new tasks [7]. In nursing and health professional education, training opportunities, cognitive readiness, and organizational support regarding AI/GenAI affect learners' attitudes and usage intentions, and related reviews also emphasize the importance of systematic training [2], [3], [14].

D. Interpretable Machine Learning in Educational Data

Educational scenarios belong to high-impact decision-making fields, and model interpretability is particularly crucial for credible adoption. LIME interprets black-box models through local linear approximation [11], and SHAP provides a unified feature contribution interpretation framework based on Shapley values [12]. In addition, using interpretable linear/regularized models as a strong baseline is also a common practice for transforming analysis results into actionable recommendations [15].

E. Summary and Research Gaps

In summary, existing research provides a theoretical foundation for AI literacy and technology adoption, and methodological support for machine learning analysis of questionnaire data. However, in the context of GenAI in nursing education, there is still a lack of a reproducible process that simultaneously integrates training experience and familiarity, and outputs actionable educational recommendations through interpretable modeling. The framework proposed in this paper aims to fill this gap.

III. METHODOLOGY

This section presents the proposed end-to-end methodology, including data collection, cleaning and privacy protection, feature engineering, model design, training, and evaluation. The overall process is shown in Figure 1:

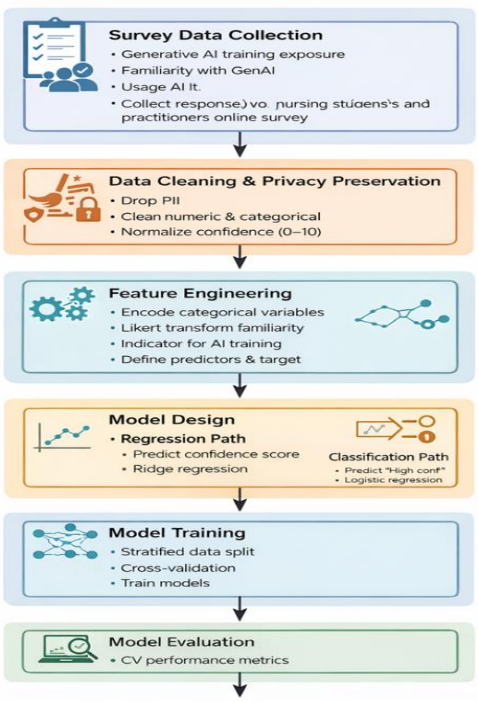

Figure 1: Overview of the proposed methodology for predicting confidence in generative AI usage based on training exposure and familiarity levels.

a) Data Collection and Variable Design

We collected information from nursing students and practitioners based on an online questionnaire, including their training exposure to GenAI (whether they had received relevant training), familiarity level (e.g., basic/intermediate/advanced), experience using AI tools/simulations, and self-rated confidence (0–10) in using GenAI in nursing practice. To reduce the risk of sensitive information, personally identifiable information (PIIs) such as name, email, and contact information were removed before being included in the modeling.

b) Data Cleaning and Privacy Protection

To address common issues with questionnaire data (missing data, non-standard text, outliers), we performed the following: (1) deletion of PII fields; (2) standardization of category text (e.g., "Yes/No"); (3) forced conversion of numerical fields and handling of missing data; and (4) normalization of confidence scores to the 0–10 range. 3.3 Feature Engineering

Category variables (learning stage, training, familiarity, tool use, etc.) are One-Hot encoded; Likert/rank variables retain ordinal information (mapped to 1–3 or 1–5 if necessary); numerical variables (such as years, performance rating) are imputed with medians. The target variable is self-rated confidence (continuous regression), and "high confidence/low confidence" threshold labels can be constructed for binary classification.

c) Model Design and Training

To ensure interpretability and small sample stability, we use a regularized linear model as a strong baseline: Ridge regression is used for regression tasks, and Logistic regression (L2 regularization) is used for classification tasks. Data partitioning uses stratified sampling and performance is reported under K-fold cross-validation to reduce randomness and improve robustness [16].

d) Evaluation Indicators and Statistical Visualization

MAE, RMSE, and R^2 are reported for regression tasks; Accuracy, F1, and AUC are reported for classification tasks. Key group statistics (such as familiarity × training) and 95% confidence interval visualization are also provided for educational intervention design. 4. Experimental Setup

This study used structured questionnaire data collected by the authors. To avoid disclosing personal information, this section only reports the aggregate statistics and modeling process. The model was implemented in Python, and the scikit-learn pipeline was used for preprocessing, training, and evaluation.

IV. RESULTS

This section presents descriptive statistics and grouping visualizations, and provides a table of key performance indicators for predictive modeling.

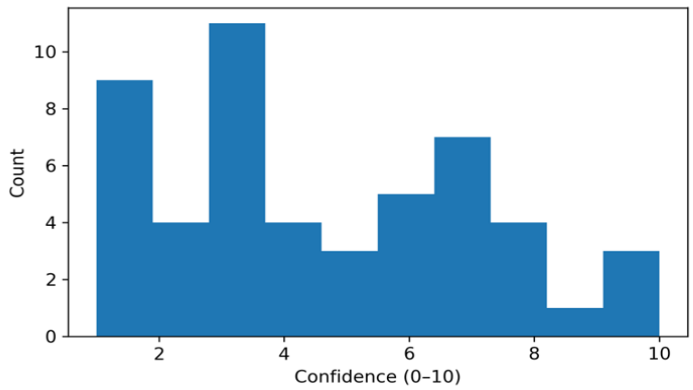

Figure 2. Distribution of self-rated confidence of nursing learners in using GenAI in nursing practice (0–10).

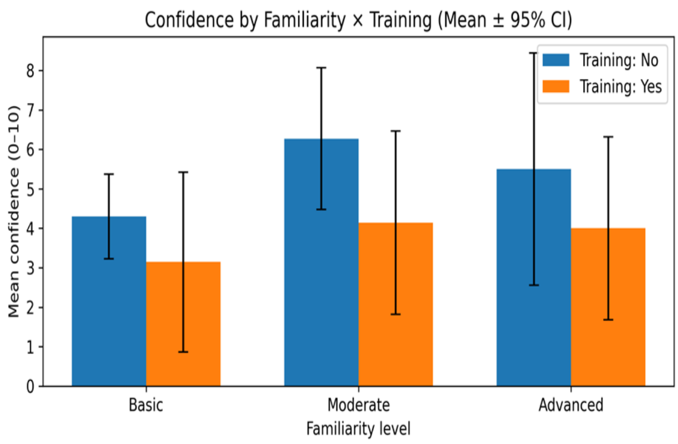

Figure 3. Mean confidence (±95% confidence interval) for training or not at different levels of familiarity.

Main Tables (from automated statistical output)

The following tables were directly exported by the data processing script (Publication_Tables.xlsx) for selective citation during paper formatting. To control length, only the core tables (sample features, key variable distributions, and model performance) should be retained during submission.

Table1A: Demographics Numeric

Unnamed 0	Variable	N	Mean	SD	Median
0	Age (filled by)	49	25.265	6.103	23
1	Experience-years (filled by)	41	4.524	3.409	3

Table1B: Frequency Level of Study

Level of Study	Count	Percent
Undergraduate (BSN)	41	68.33
Graduate (MSN)	08	13.33
Certification (CNA)	06	10.0
Others	05	8.34

Table1C: Frequency Training on GenAI

Training on GenAI	Count	Percent
No	31	51.7
Yes	21	35.0
Unaware	8	13.3

Table1D: Frequency Familiarity with GenAI

Familiarity with GenAI	Count	Percent
Basic	28	46.7
Moderate	18	30.0
Advanced	8	13.3
Unaware	6	10.0

Table1E: Frequency of using AI tools

Used AI tools	Count	Percent
Yes	35	58.3
No	17	28.3
Unaware	8	13.3

Table1F: Frequency Encountered Challenges

Encountered challenges	Count	Percent
Maybe	20	33.3
Yes	18	30.0
No	11	18.3
Other	8	13.3
Unaware	3	5.0

Table2A: Confidence byTraining

Have you received any training or education on generative AI?	N	Mean	Median	SD
No	30	5.1	5.5	2.657
Yes	19	3.737	3.0	2.864

Table2B: Confidence by Familiarity

How familiar are you with generative AI and its applications in nursing education?	N	Mean	Median	SD
Advanced	8	4.375	4.0	2.264
Basic	25	3.92	3.0	2.465
Moderate	18	5.444	5.5	3.166

Table3A: Regression Performance

Unnamed	Metric	Value
0	Holdout MAE	1.739
1	Holdout RMSE	2.0016
2	Holdout R2	0.5133
3	CV MAE (mean)	2.3293
4	CV MAE (std)	0.5251
5	CV R2 (mean)	-0.2778
6	CV R2 (std)	0.6924

Table3B: Classification Performa

Unnamed	Metric	Value
0	AUC	0.7143
1	Accuracy	0.8182
2	F1	0.6667
3	High-confidence rate (overall)	0.3922

Table3C: Odds Ratios Top20

Unnamed	Feature	Coefficient	Odds Ratio
8	What is your current level of study?_Graduate (MSN)	0.9816	2.6688
7	What is your current level of study?_Certification (CNA)	-0.7831	0.457
12	Have you encountered any challenges or difficulties while using generative AI in your nursing education?_Maybe	0.5679	1.7645
1	How effective do you think generative AI is in enhancing your learning experience?	0.5623	1.7547
6	How familiar are you with generative AI and its applications in nursing education?_Moderate	0.4061	1.5009
13	Have you encountered any challenges or difficulties while using generative AI in your nursing education?_No	-0.3472	0.7067
4	How familiar are you with generative AI and its applications in nursing education?_Advanced	-0.3422	0.7102
0	2. How many years of nursing experience do you have (if applicable)?	-0.2898	0.7484
2	Have you received any training or education on generative AI?_No	0.2527	1.2875
3	Have you received any training or education on generative AI?_Yes	-0.2513	0.7778
9	What is your current level of	-0.1972	0.821

	study?_Undergraduate (BSN)		
15	Have you encountered any challenges or difficulties while using generative AI in your nursing education?_Yes	-0.1754	0.8391
11	Have you used any AI-powered tools or simulations in your nursing education?_Yes	0.1053	1.111
10	Have you used any AI-powered tools or simulations in your nursing education?_No	-0.104	0.9013
5	How familiar are you with generative AI and its applications in nursing education?_Basic	-0.0625	0.9394
14	Have you encountered any challenges or difficulties while using generative AI in your nursing education?_Unaware	-0.0439	0.957

V. DISCUSSION

Implications for Training and Instructional Design

Based on group statistical and modeling analysis, we recommend that future training and learning support focus on the following areas:

1. Differentiated training (from "basic familiarity" to "advanced familiarity")

Provide differentiated learning paths for different starting points to avoid inefficiency or frustration caused by a "one-size-fits-all" curriculum.

2. Task-driven, contextualized practice

Design assessable tasks around nursing scenarios (medical record summarization, nursing plans, health education material writing, simulated case reasoning), emphasizing a closed loop of "prompt words—verification—revision."

3. Credibility and ethics module

Incorporate content on data privacy, bias and illusion identification, citation and academic integrity, etc., to form operational usage guidelines and risk lists.

4. Collaborative participation of teachers and clinical mentors

Establish a demonstration case library through a "teaching-clinical" collaborative approach to enhance learners' ability to transfer GenAI to real nursing tasks.

5. Continuous assessment and feedback

Integrate AI literacy and usage confidence into the learning analysis system to form periodic assessments and individualized feedback to support continuous improvement.

VI. CONCLUSION

This paper proposes an interpretable machine learning framework based on structured questionnaire data for modeling and analyzing learners' confidence in using generative AI in nursing education. The framework provides an integrated process from data governance to modeling and evaluation, and can output actionable recommendations for training and curriculum design.

Limitations and Future Work

First, the sample size and geographical/institutional coverage of the questionnaire may limit extrapolation; second, confidence is a self-rated indicator and may be affected by social expectation bias. In the future, longitudinal tracking, task-based objective assessment and richer interpretation methods (such as SHAP/LIME) can be combined to enhance the robustness of the conclusions [11], [12]. In addition, the trade-off between tree models and linear models in predictive performance and interpretability can be further compared, and intervention experiments can be carried out in different nursing courses/clinical training modules.

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