

“It’s Like Having a Second Instructor”: A Descriptive Qualitative Study on Nursing Students’ Perceptions of Human-AI Collaboration in Generative Learning Analytics

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Abstract

Background: Generative AI (GenAI) is increasingly used in nursing education, yet most studies evaluate its functional utility, with limited attention to students' authentic experiences, emotional interactions, and role perceptions in human-AI collaboration from a generative learning analytics perspective.

Aim: This study aimed to investigate nursing students' experiences of collaborating with AI when using generative learning analytics tools for clinical reasoning learning.

Research design: A descriptive qualitative design was adopted.

Participants and research context: Semi-structured in-depth interviews were conducted with 15 undergraduate nursing students from a provincial medical university's nursing college in China between May and July 2026, using purposive sampling. Interview data were analyzed using conventional content analysis.

Ethical considerations: The study was approved by the Ethics Review Committee of Harbin Medical University.

Findings: Four themes were identified: (1) Students initially experienced novelty when first engaging with AI, yet rationally positioned AI as a "teaching assistant" rather than a substitute for human instructors, with senior students demonstrating quicker adaptation; (2) AI enhanced personalized learning and student initiative, although its feedback lacked affective responsiveness, leading to varied student evaluations; (3) The irreplaceable role of teachers' humanistic care and clinical experience was underscored, while AI facilitated more targeted teacher-student interactions, and students expressed expectations for teachers to become "AI literacy mentors"; (4) Students voiced concerns over data privacy, trusted AI's factual judgments, but relied on teacher confirmation for situational judgments and ethical decision-making, aspiring to a collaborative model wherein "AI handles data, teachers tend to the human dimension, and students retain decision-making authority."

Conclusions: Undergraduate nursing students acknowledged the auxiliary value of AI, yet remained dependent on teachers for affective judgments and ethical decisions. Nursing education should leverage the technological strengths of AI while simultaneously enhancing teachers' AI literacy, establishing ethical frameworks, and strengthening AI's affective responsiveness.

Clinical trial number Not applicable.

1. Introduction

Clinical reasoning is essential for nursing students and safe, high-quality care¹. Nursing education faces a dual mission: preserving humanistic care and clinical judgment while embracing technology to enhance learning and workplace readiness². Accrediting bodies mandate systematic clinical analysis

and decision-making skills³. Yet cultivating clinical reasoning within limited curricula remains challenging due to persistent gaps between classroom instruction and practice⁴.

Advances in generative AI (GenAI) offer new opportunities. Large language models like ChatGPT have entered higher education, reshaping pedagogy⁵. In nursing, GenAI supports clinical reasoning training through scenario simulation, case logic generation, and personalized feedback⁶. AI platforms have demonstrated feasibility in improving error analysis and reflective thinking⁷. Students report positive attitudes toward AI-assisted learning⁵.

However, current AI applications remain largely instrumental, treating GenAI as an information provider in command-response formats⁸. This approach neglects the cognitive-affective interplay in learning and underutilizes AI's potential for deep knowledge co-construction⁹. Students are positive yet cautious: they value efficiency but worry about accuracy, ethics, and cognitive over-reliance¹⁰. This prompts a key question: should we use AI as a tool or partner?

Generative learning analytics (GLA) offers a way forward by embedding GenAI across data collection, analysis, and feedback—enabling dynamic, personalized interventions that shift from retrospective measurement to generative cognitive companionship^{11,12}. Within this framework, AI becomes a collaborative partner for dialogue and co-construction¹³. This "iterative human-AI collaboration" model involves recursive exchanges: students query, AI responds, students revise, and deeper inquiry follows.

Social Cognitive Theory (SCT)¹⁴ underpins this study. SCT posits that learning occurs through the dynamic interplay of personal factors (e.g., cognition, affect), environmental influences, and behavior—a process termed triadic reciprocal determinism. We extend the environmental factor to include intelligent agents, conceptualizing AI as an active informational environment that reciprocally shapes cognition and behavior through feedback. This framing enables examination of how AI analytics influence self-efficacy and outcome expectations in clinical reasoning¹⁵. Crucially, we treat SCT not as a post-hoc labeling device but as an analytical lens that is applied iteratively throughout data interpretation, informing the derivation of themes and the conceptualization of emergent patterns.

The urgency of this inquiry is heightened by nursing's inherent tension between technological efficiency and humanistic caring. Unlike fields where AI's utility is primary, nursing must also cultivate empathy, ethical reasoning, and interpersonal sensitivity. When GLA intervenes in clinical reasoning—traditionally rooted in tacit knowledge and mentorship, the risk of dehumanizing learning represents a genuine pedagogical concern. Understanding how students navigate this tension is essential to preserving professional identity.

Emerging research shows undergraduates view GenAI as a "double-edged sword": efficiency gains balanced against ethical risks¹⁶. Some use GenAI as a "surrogate supervisor" for thesis work, hinting at a "quasi-mentorship" dynamic¹⁷. However, few studies explore the affective, cognitive, and relational

dimensions of GLA-facilitated human-AI collaboration¹⁸. Existing work mostly evaluates AI's functional utility, with less attention to students' social relationships with AI as a collaborative agent¹⁹. Trust, reliance, affective bonds, and cognitive shifts remain underexplored. When AI enters this human-centered field as partner rather than tool, questions of professional identity and clinical judgment agency demand qualitative investigation²⁰.

This study therefore examines nursing undergraduates' authentic experiences using GenAI for clinical reasoning. Guided by Social Cognitive Theory and descriptive qualitative design, we ask: (1) How do nursing undergraduates perceive GLA-generated data-driven feedback, and how does this shape their learning engagement and behavioral responses? (2) What cognitive-emotional experiences arise during iterative human–AI dialogue, and how do students balance AI recommendations against their own judgment? (3) How do students conceptualize the triadic relationship among AI (data analyst), teachers (humanistic mentor), and themselves (decision-maker) in the GLA-enhanced environment?

2. Methods

2.1 Design

This study adopts a descriptive qualitative research design. A descriptive qualitative approach aims to present participants' subjective experiences and perceptions directly, with minimal theoretical interpretation, and is well suited for exploring individuals' authentic perceptions, attitudes, and understandings of a given phenomenon. Within nursing education, descriptive qualitative research is considered particularly appropriate for uncovering the authentic experiences of educational participants, as it preserves the original meanings conveyed by participants, remains closely aligned with actual educational contexts, and can directly yield actionable insights for practice. Given that the core focus of this study is to explore nursing undergraduates' perceptions and experiences regarding human-AI collaborative relationships within generative learning analytics, with the aim of generating theoretically informed insights rather than constructing grounded theory or providing an ontological interpretation of the phenomenon, descriptive qualitative research constitutes the most suitable methodological choice. Throughout the research process, the Consolidated Criteria for Reporting Qualitative Studies (COREQ) were adhered to, ensuring procedural rigor and transparency²¹. A completed COREQ checklist is provided as supplementary material, detailing the reporting of each of the 32 items across the three domains: research team and reflexivity, study design, and analysis and findings.

2.2 Participants

Participants were recruited through purposive sampling. The inclusion criteria were as follows: (1) full-time undergraduate students enrolled in nursing programs; (2) having used generative artificial intelligence tools (including but not limited to large language model platforms such as ChatGPT, ERNIE Bot, Kimi, and Zhipu Qingyan) in learning activities related to clinical reasoning, case analysis, or nursing skills training; (3) using such tools at least once per week for a duration of no less than four weeks; and

(4) providing informed consent and voluntarily agreeing to participate in the study. The exclusion criteria were: (1) prior participation in similar qualitative studies on AI in nursing education; and (2) self-reported cognitive or psychological conditions that could impair the ability to provide informed consent or participate in in-depth interviews.

Thematic saturation was pursued in this study, to ensure methodological rigor and depth, the following strategies were employed. First, purposive sampling deliberately accounted for heterogeneity in key demographic and learning-related characteristics among nursing undergraduates, including academic year (from freshman to senior year), gender, prior experience with AI, and academic performance levels, while also considering whether participants had prior exposure to assistive technologies in online learning or clinical practicum settings. Second, an iterative research approach was adopted, wherein data collection and analysis proceeded simultaneously. Third, a reflexive stance was maintained throughout the research process. All formal interviews were conducted using a pre-developed, pilot-tested semi-structured interview guide. Saturation was determined when: (a) three consecutive interviews yielded no new initial codes, (b) the three coders independently confirmed that no new themes emerged, and (c) the research team reached consensus through discussion that further interviews were unlikely to add novel insights. Accordingly, a total of 15 interviews were included in the final analysis.

2.3 Research setting

The study was conducted at the School of Nursing of a provincial medical university in China. The school offers a four-year undergraduate nursing program, with approximately 500 nursing students enrolled per academic year. The school is equipped with comprehensive basic teaching facilities, including a nursing skills experimental teaching center and virtual simulation training rooms. During the study period, no unified guidelines or training programs regarding the use of generative artificial intelligence had been established by the school, and students' utilization of such tools in their learning activities relied primarily on their own choices and judgments. This situation afforded a favorable opportunity for capturing students' authentic experiences in a natural, unmanipulated state. All interviews were conducted in private, undisturbed conversation rooms within the school, ensuring that participants could express their genuine feelings in a safe and confidential environment free from external interference or faculty presence. The interview schedules were arranged according to each participant's own availability.

2.4 Data collection

Data were collected through semi-structured in-depth interviews. The interview guide was designed based on the triadic reciprocal determinism of SCT. Specifically, Question 1 captured students' cognitive representations of AI as an environmental factor (personal cognition $\leftarrow$ environment), using the metaphor of a "second mentor" to explore trust and role expectations. Questions 2 and 4 examined how specific behaviors of AI use affected self-efficacy and learning autonomy (behavior $\rightarrow$ personal factors). Question 3 directly explored the regulatory process of personal cognition (trust judgments) in response to environmental feedback (AI suggestions) (personal cognition $\leftrightarrow$ environment). Questions 5 and 6

addressed affective responses (privacy concerns) elicited by environmental factors (data monitoring), and how personal emotional states (anxiety/frustration) interacted with environmental responses through behavior (environment ↔ personal factors ↔ behavior). Question 7 invited students to reflect on how environmental design could be optimized to support positive cycles among personal factors and behaviors. The interview guide was reviewed and revised by three nursing education experts with qualitative research experience prior to formal use. Subsequently, pilot interviews were conducted with three nursing undergraduates who were not included in the formal study; based on the pilot results, the wording, question order, and probing strategies were finalized. The interview guide is presented in Table 1.

Table 1
Outline of the interview.

1.If you were to describe the role of the AI teaching assistant in your learning in one sentence or using a metaphor, what would you say, and why? (Probe: Some have referred to it as a “second mentor.” Do you agree? What do you consider to be the most significant similarities and differences between it and a human instructor?)
2.Please recall a specific example in which you felt that AI genuinely helped you—for instance, by making learning more efficient, helping you understand difficult points, or improving your assignments. What happened in that situation?
3.When AI provides you with learning suggestions—such as pointing out errors, recommending resources, or guiding case analysis—do you usually fully trust them, partially trust them, or distrust them? Please illustrate with an example.
4.After using AI, do you perceive that your learning autonomy—that is, your ability to decide what and how to learn—has increased, decreased, or remained unchanged? Why?
5.Have you ever been concerned about your learning data—such as video viewing duration, error records, or assignment content—being recorded and analyzed by AI? Why?
6.When you experience anxiety, frustration, or fatigue during learning, have you ever expressed these feelings to AI? How did its response make you feel?
7.If you were to propose two most important suggestions for improving this AI system, what would they be?

Interviews were conducted by research team members with experience in qualitative interviewing. All interviewers held doctoral degrees in nursing or related fields and had completed a two-day workshop on qualitative interviewing techniques, including probe usage, active listening, and managing power dynamics. None of the interviewers had prior teaching or supervisory relationships with the participants, which helped mitigate the inhibiting effects of power differentials. At the start of each interview, interviewers explicitly stated that participation was voluntary, that there were no right or wrong answers, and that they were interested in honest accounts of both positive and negative experiences. Prior to each interview, the interviewer explained the research background, objectives, privacy protection measures, and the principle of voluntary withdrawal; participants signed informed consent forms after fully understanding the information. Participants were informed that the interviewer had no role in their

academic assessment, and that their responses would not affect their grades or clinical placements. Interviews were conducted face-to-face between May and July 2026. Participants had used GenAI tools for clinical reasoning learning for durations ranging from 6 to 32 weeks (mean: 14.2 weeks) prior to the interviews. Each interview lasted approximately 45–60 minutes. All interviews were digitally audio-recorded, and the interviewer simultaneously took field notes during the process, with particular attention paid to participants' nonverbal information, emotional responses, and reflective observations. Verbatim transcription of the recordings was completed by the researcher within 24 hours after each interview, generating raw textual data. Interviews continued until data saturation was reached—defined as no new themes emerging from three consecutive interviews.

2.5 Trustworthiness of the Study

This study adhered to the trustworthiness framework proposed by Lincoln and Guba²², ensuring methodological rigor across four dimensions. Credibility was achieved through data source triangulation (interview transcripts, field notes, and team discussions) and member checking, with original statements presented as anonymous quotations and preliminary themes returned to participants for confirmation. Transferability was addressed by providing detailed descriptions of participant characteristics, educational backgrounds, technology exposure, and interview contexts, thereby enabling readers to assess the applicability of the findings. Dependability was ensured by establishing a complete audit trail, including transcripts, coding schemes, theme development processes, discussion records, and reflexive journals; a second author independently coded 20% of the transcripts, achieving an inter-coder agreement of 87%, with discrepancies resolved through team discussion. Confirmability was established through regular team cross-examination of coding and thematic interpretations, coupled with reflexive journaling that documented attitudes and experiences with AI and proactively examined potential biases, ensuring that findings were grounded in the data. Specifically, each interviewer completed a reflexive journal entry within 24 hours after each interview, recording initial impressions, emotional reactions, and assumptions about participants' responses. These journals were discussed at weekly team meetings to surface and bracket potential biases, and were referenced during data analysis to distinguish participant voices from researcher interpretations.

2.6 Role of the researcher and reflexivity

The research team was composed of four members, all of whom were teaching and research faculty in the field of nursing education. The first author, holding a doctoral degree in nursing, had systematically received training in qualitative methods and maintained an open yet neutral stance toward generative AI; no teacher–student or administrative relationship existed with the participants, so as to reduce the inhibitory effect of power differentials. The remaining authors, each with years of research experience in qualitative inquiry, participated throughout the entire process of study design, data analysis, and theme development, providing methodological supervision. The researchers actively attended to potential subjectivity throughout the qualitative process. As a whole, the team adopted a stance of “cautious acceptance” toward AI, acknowledging its potential value while remaining vigilant about its limitations and risks. This stance was consciously identified and labeled throughout the research process, and its

potential biasing effects were minimized through cross-checking among team members. Particular attention was paid to the value-laden implications of the metaphor “AI as mentor,” so as to prevent researchers’ own positions from unconsciously influencing interview directions or theme refinement. To this end, reflexive journals were completed after each interview and team discussion, documenting personal presuppositions and judgments, which were then recognized and adjusted in subsequent steps.

2.7 Data analysis

Interview transcripts were imported into NVivo 14.0 for data management and analyzed using conventional content analysis. The analysis proceeded through the following steps: (1) Data familiarization: two researchers independently and repeatedly read the transcripts to gain a holistic understanding of the entire text; (2) Open coding: meaning units relevant to the research questions were extracted line-by-line based on participants’ original expressions, with initial codes assigned as closely as possible to the participants’ verbatim accounts; (3) Category formation: initial codes were grouped according to semantic relationships to form more abstract categories; (4) Theme extraction: core themes and subthemes embedded in the data were identified through further abstraction and synthesis; (5) Definition and naming: extracted themes and subthemes were clearly defined and formally named, ensuring that each theme had a distinct central meaning without significant overlap; and (6) Cross-validation: a third researcher who had not participated in the initial coding reviewed and confirmed the entire coding framework. Throughout the analysis, the SCT framework was applied iteratively—not as a predetermined coding scheme, but as a sensitizing device to inform the interpretation of emerging patterns and to structure the discussion around the triadic interactions among environment, personal factors, and behavior. The coding process remained grounded in participants’ verbatim expressions; SCT concepts were introduced at the stage of theme interpretation rather than during initial open coding, thereby preserving the inductive integrity of the analysis. The data analysis process was iterative, with constant reference back to the raw transcripts to ensure that all categories and themes were grounded in the data. The research team held weekly data analysis meetings to discuss and resolve coding discrepancies until consensus was reached. To ensure that the analysis did not become artificially homogeneous, we actively searched for and coded disconfirming cases—instances where participants expressed views that deviated from the dominant patterns. These negative cases were retained and are reported alongside the main themes to provide a more balanced and nuanced account.

2.8 Ethical considerations

Ethical approval

for the study was obtained from the Ethics Review Committee of Harbin Medical University (approval number: HMUDQ2026051611) prior to data collection. Written and verbal informed consent was obtained from all participants after they were provided with detailed information about the study. Participation was entirely voluntary, and participants were informed of their right to withdraw at any stage. Data confidentiality and security were maintained throughout the research process.

3. Results

3.1. Characteristics of participants

A total of 15 participants were interviewed in this study, of whom 8 (53.33%) were female and 7 (46.67%) were male. The grade distribution was relatively balanced, with 3, 4, 5, and 3 participants from the freshman, sophomore, junior, and senior years, respectively. Regarding weekly AI usage frequency, freshmen reported once per week; sophomores, 1–2 times per week; juniors, predominantly 2–4 times per week; and seniors, all at least 4 times per week. In terms of academic performance, 3 participants (all seniors) ranked in the top 10%, 2 (juniors) in the top 20%, 3 (juniors) in the upper 30%, 4 (sophomores) in the middle 40%-60%, and 3 (freshmen) in the lower middle 60%-70%. Regarding prior experience with online learning or clinical assistive technologies, 8 participants (53.3%), predominantly upper-year students, reported relevant experience (e.g., virtual simulation training, online case repositories, electronic records in clinical internships), while 7 participants (46.7%), all freshmen and sophomores, reported no such experience. Detailed participant characteristics are presented in Table 2.

Table 2
Descriptive characteristics of the participants.

ID	Gender	Year/Level	Weekly AI Usage Frequency	Academic Performance Level (Class Ranking / Self-Assessment)	Experience with Online Learning / Clinical Assistive Technologies
S01	Female	Junior	2–3 times/week	Upper-middle (top 30%)	Yes (virtual simulation training)
S02	Male	Sophomore	1–2 times/week	Middle (40%–60%)	No
S03	Male	Senior	≥ 4 times/week	Excellent (top 10%)	Yes (online case repository)
S04	Female	Freshman	1 time/week	Lower-middle (60%–70%)	No
S05	Male	Junior	2–3 times/week	Upper-middle (top 30%)	Yes (electronic records in clinical internship)
S06	Female	Sophomore	1–2 times/week	Middle (40%–60%)	No
S07	Male	Junior	3–4 times/week	Good (top 20%)	Yes (online learning platform)
S08	Female	Senior	≥ 4 times/week	Excellent (top 10%)	Yes (virtual simulation + clinical assistive)
S09	Female	Sophomore	1–2 times/week	Middle (40%–60%)	No
S10	Male	Freshman	1 time/week	Lower-middle (60%–70%)	No
S11	Female	Junior	3–4 times/week	Good (top 20%)	Yes (nursing skills app)
S12	Male	Senior	≥ 4 times/week	Excellent (top 10%)	Yes (clinical decision support system)
S13	Female	Sophomore	1–2 times/week	Middle (40%–60%)	No
S14	Male	Junior	2–3 times/week	Upper-middle (top 30%)	Yes (online case discussion)
S15	Female	Freshman	1 time/week	Lower-middle (60%–70%)	No

3.2. Qualitative results

This study explored nursing undergraduates' perceptions of human-AI collaboration in generative learning analytics. Four overarching themes and twelve subthemes were identified, reflecting the

dynamic interplay of environmental factors (AI tools), personal factors (students' cognition and affect), and behavioral responses as conceptualized by SCT. The overarching themes encompassed the following: initial experiences and acceptance of human-AI collaboration; perceived shifts in learning processes and outcomes; reconceptualization of the teacher's role in human-AI collaboration; and perspectives on ethics, trust, and future cooperation. Within each theme, we also present divergent views from participants who expressed opinions that deviated from the dominant pattern, thereby ensuring that the analysis reflects the full range of student experiences rather than artificially homogenizing the data. The detailed thematic structure is presented in Fig. 1.

Theme 1: Initial Experiences and Acceptance of Human–AI Collaboration

As a novel technosocial environmental factor, AI triggered positive affective responses (personal factor) among students through its immediate feedback and targeted analysis. Concurrently, students' positioning of the AI role (assistive versus substitutive) reflected their self-regulatory mechanisms actively construing this new environmental affordance.

Subtheme 1.1: Positive Affective Experiences during Initial Encounters

This subtheme aligns with SCT's assumption regarding the direct elicitation of personal affect by environmental factors, suggesting that novel technological tools, as environmental stimuli, can rapidly evoke positive emotional responses in learners, thereby establishing an affective foundation for subsequent behavioral engagement. Most students reported feelings of novelty, surprise, and perceived utility when first using AI learning analytics tools. Such positive experiences typically arose from the AI's capacity to rapidly identify learning weaknesses and provide more detailed feedback than standard answer keys, thereby addressing students' latent needs for immediate and personalized guidance. One student (S03) shared: "The first time I used an AI-generated learning analytics report in my post-class review, it directly pinpointed the knowledge points I was weak in—it felt like having a teacher specifically monitoring my learning progress." Another student (S07) recalled: "Our instructor recommended using AI to analyze our errors in a mock test, and the feedback it gave was more detailed than the standard answer key—I was really surprised." Another student (S01) mentioned: "The first time I used AI to help analyze my nursing case assignment, it flagged each assessment step I had missed, one by one. At that moment, I felt this tool was amazing—it could uncover issues I hadn't even noticed myself." Another student (S14) also expressed: "When I first tried using AI for case analysis, it followed up with step-by-step questions based on my answers, guiding me to think about differential diagnoses that I had previously overlooked." Notably, not all initial encounters were uniformly positive. One participant (S15) recounted: "I was actually quite intimidated the first time I opened the AI feedback—it listed so many things I had done wrong that I felt a bit defeated. It took me a while to realize it was trying to help rather than judge me." This contrasting experience highlights that the affective impact of initial AI exposure may vary considerably across individuals.

Subtheme 1.2: Rational Positioning of the AI Role

This subtheme reflects the process of active interpretation and construction of environmental information by personal cognition, as conceptualized in SCT. Rather than passively accepting the metaphor of AI as a "mentor," students explicitly defined AI as a supportive "teaching assistant" rather than a substitutive "mentor," drawing upon their own learning experiences and awareness of technological limitations. Such rational positioning contributes to avoiding over-dependence and promotes healthy boundaries in human–AI collaboration. For instance, one student (S11) explained: "AI helps me organize my learning data, but it does not directly give me the answers; it is more like a teaching assistant that guides me to think for myself." Another student (S02) expressed a similar view: "AI provides references, not standard answers. Ultimately, I still have to understand and judge by myself. I think it is an assistant that helps me identify and fill gaps, not a real teacher." However, some students also expressed caution; as one participant (S05) noted: "Sometimes I worry about relying on it too much, after all, it cannot understand my emotions and learning habits the way a teacher does." A dissenting voice came from S12, a senior student, who remarked: "I actually find the 'assistant' label a bit limiting. In many ways, AI has become more of a thought partner for me—I bounce ideas off it and it pushes back with counterarguments. It is not just an assistant; it is a dialogue partner." This minority view, expressed primarily by senior students with extensive AI experience, suggests that the AI role perception may evolve over time, from assistant toward a more peer-like collaborative relationship.

Subtheme 1.3: Individual Differences in Acceptance Levels

This subtheme corroborates the moderating role of personal factors—such as prior experience, year level, and digital literacy—on the pace of environmental adaptation, as posited by SCT. Upper-year students, equipped with more mature learning strategies and greater technological familiarity, exhibited more rapid adoption of AI tools, whereas junior students required a longer adaptation period to comprehend the analytical charts and recommendations generated by AI. This disparity suggests that educators should consider tiered support strategies when promoting AI tools. One upper-year student (S09) stated: "I got used to it quickly because the learning analytics provided by AI were very intuitive." Another senior student (S12) added: "I am already very familiar with digital devices; I could grasp the key points of the AI reports at a glance, with virtually no learning curve." In contrast, a junior student (S02) remarked: "At first, I found it somewhat complicated and needed time to understand the charts and suggestions, but after getting used to it, I found it very useful." Another lower-year student (S10) admitted: "When I first opened the AI feedback, it took me a few minutes to figure out what those bar charts and percentages meant, but after a few more uses, it became fine."

Theme 2: Perceived Shifts in Learning Processes and Outcomes

This theme comprised three subthemes: enhancement of personalized learning, improvement in learning initiative, and differentiated evaluations of AI feedback quality. These findings are closely related to the dynamic mutual shaping of behavioral and personal factors within SCT. The personalized learning pathways provided by AI (environmental support) enhanced students' self-efficacy (personal factor), which in turn prompted them to adopt more proactive learning behaviors (behavioral change).

Meanwhile, students' differentiated evaluations of feedback quality reflected their expectations regarding the affective responsiveness of the technology, highlighting the screening function of personal cognition in response to environmental feedback.

Subtheme 2.1: Enhancement of Personalized Learning

This subtheme is consistent with the role of environmental support in enhancing learners' self-efficacy, as posited by SCT. The personalized learning pathways generated by AI, based on individual error records and review progress—enabled students to perceive a precise alignment between learning tasks and their actual competence levels, thereby reinforcing the belief that "I can learn well." Students generally considered such personalized design to be more efficient than uniform whole-class exercises and effective in bridging theoretical knowledge with clinical cases. One student (S06) noted: "AI generates a tailored learning path based on my mistakes and review time, which is far more efficient than doing the same exercises as the whole class." Another student (S12) added: "It can even recommend relevant nursing cases, helping me connect theory to clinical practice—it feels like it is customized just for me." Another participant (S01) shared: "Every time I finish a set of questions, AI analyzes which chapters I am weak in and automatically pushes corresponding knowledge explanations and practice questions—it feels like having a personal tutor." Another student (S14) also mentioned: "Previously, when reviewing medical-surgical nursing, I addressed everything indiscriminately. Now, AI targets my weak areas from the last test and only pushes content I need to reinforce, saving me a substantial amount of time." However, S13 offered a note of caution: "Sometimes I feel that AI's recommendations are too narrow, it keeps pushing me similar types of questions on my weak points, but I wonder if I am missing out on broader learning by focusing only on what it identifies. A teacher would consider the overall curriculum balance, whereas AI seems to optimize locally rather than globally." This comment suggests that while AI personalization is valued, some students question its algorithmic optimization logic and desire greater curricular breadth.

Subtheme 2.2: Improvement in Learning Initiative

This subtheme embodies the positive reciprocal cycle between behavioral and personal factors posited by SCT: the progress curve analysis provided by AI (environmental feedback) enhanced students' intrinsic learning motivation (personal factor), which in turn prompted them to adopt proactive learning behaviors such as voluntarily posing questions and independently addressing weaknesses (behavioral change). These behaviors further consolidated their sense of mastery over learning. One student (S05) described: "Upon viewing the progress curve generated by AI, I felt more motivated to address my weak areas without waiting for the instructor to prompt me." Another student (S08) shared: "I found myself starting to ask questions proactively, because AI could quickly help me locate relevant materials, making my learning feel more under control."

Subtheme 2.3: Differentiated Evaluations of AI Feedback Quality

This subtheme reflects the screening and appraisal mechanism of personal cognition in response to environmental feedback, as conceptualized in SCT. Most students acknowledged the immediacy and objectivity of AI feedback, considering it to avoid deviation from the topic that sometimes occurs in peer discussions, reflecting their need for efficient and unbiased information. However, some students noted that AI feedback lacked affective tone, such as encouragement or criticism—revealing the current technological environment's insufficiency in meeting learners' emotional support needs. One student (S10) commented: "AI feedback is very fast and objective, without digressing like some classmates' discussions tend to do." Another student (S13) pointed out: "AI feedback is sometimes too standardized, lacking the encouraging or critical tone of a teacher, which feels somewhat cold." Another student (S02) expressed: "I particularly appreciate AI's instant error correction; I know where I went wrong immediately after finishing a question, without having to wait until the next day for the teacher's grading." Another participant (S04) added: "The feedback from AI is very neutral, without personal bias that some classmates might have when evaluating assignments; I feel reassured about that." However, one student (S08) conveyed a different sentiment: "Sometimes I spend a lot of time writing a care plan, and AI merely lists a few deficiencies mechanically, without even a word like you've done well, I feel a bit disappointed." S11 offered a more pragmatic perspective: "I don't expect encouragement from AI—that is not its job. If I want emotional support, I go to my teachers or classmates. I prefer AI to be factual and honest, even if that means critical. The warmth can come from other sources." This view, while in the minority, suggests that students' expectations of AI feedback are not uniformly affective; some adopt a task-partitioning approach that assigns emotional functions exclusively to human agents.

Theme 3:Reconceptualization of the Teacher's Role in Human–AI Collaboration

This theme comprised three subthemes: the irreplaceability of the teacher's role, positive changes in teacher-student interaction patterns, and new expectations regarding teacher competencies. These findings resonate with the interplay between environmental factors and social support systems within SCT. As a novel technological environment, AI did not undermine the value of teachers as a core source of social support; rather, it further highlighted their functions of humanistic care and the transmission of clinical expertise. Concurrently, students' expectations regarding teachers' AI literacy reflected their deeper needs for the optimal configuration of environment-behavior dynamics.

Subtheme 3.1:The Irreplaceability of the Teacher's Role

This subtheme underscores the unique value of social support sources (teachers) as a critical environmental factor within SCT. Although AI is capable of efficiently processing data, teachers' abilities to leverage AI-generated analytics for targeted classroom instruction, share authentic clinical experiences, and provide individualized emotional care remain irreplaceable by current technology. This irreplaceability, in turn, made students more appreciative of interpersonal interactions with their teachers. One student (S01) stated: "AI can analyze data, but our teacher uses that data to specifically address the questions we commonly get wrong in class and shares clinical experiences—something AI cannot do." Another student (S14) added:"When I saw that the AI report showed I kept making mistakes

on a particular knowledge point, the teacher proactively approached me after class to help analyze the reasons. That feeling of being cared for is very important." One student (S15) also remarked: "Once, the AI system alerted that I scored low on an operational procedure. Initially, I thought I just needed more practice. But in class, the teacher specifically retrieved that simulation recording and, drawing on a real case he encountered in the emergency department years ago, walked us through my errors step by step. That feeling of 'someone truly has you in their thoughts' is something AI can never provide."

Subtheme 3.2: Positive Changes in Teacher–Student Interaction Patterns

This subtheme illustrates the mechanism by which the environment (AI tools) optimizes personal experiences through behavioral change, as posited by SCT. The objective learning data provided by AI enabled students to transition from "hesitating to ask questions or not knowing what to ask to "asking with evidence and posing more in-depth questions." Simultaneously, teachers were able to design more profound classroom discussions grounded in the data. This change did not weaken teacher-student relationships; rather, it rendered interactions more focused and efficient. One student (S05) remarked: "I used to rarely approach teachers proactively, but now with AI data, I can ask more targeted questions and engage in deeper discussions." Another student (S07) noted: "Our teacher now asks us to compare AI analyses with our own reflections, which makes class discussions much more dynamic." Another participant (S09) shared: "I used to be afraid to raise my hand in class, worrying that my questions might be too trivial. Now that the AI report shows which types of questions I frequently get wrong, I feel confident to approach the teacher with the data, and the teacher even provides targeted explanations based on the whole class's data—I no longer feel embarrassed about asking questions." Another student (S12) added: "AI helps me clarify what I don't know, and the teacher helps me understand why I don't know it. Once, based on the three knowledge points with the highest error rates from AI statistics, the teacher organized a debate-style discussion where everyone was eager to speak—this kind of interaction had never happened before."

Subtheme 3.3: New Expectations Regarding Teacher Competencies

This subtheme reflects individuals' reciprocal expectations of the environment within SCT: students recognized the reliability risks inherent in AI-generated information and thus expected teachers to assume a new role as AI literacy mentors, capable of guiding them in discerning the authenticity, limitations, and ethical boundaries of AI outputs. This expectation points to specific directions for teacher professional development, namely, expanding from knowledge transmitters to critical guides in technology use. One student (S02) candidly stated: "I hope teachers not only know how to use AI tools but also teach us how to discern whether the information provided by AI is reliable." Another student (S09) pointed out: "If teachers do not understand how AI works at all, it becomes difficult for us to receive effective guidance from them." Another participant (S03) remarked: "Once, AI provided a response that looked highly professional, but the teacher immediately identified the logical fallacies and outdated data in it and taught us how to cross-validate. We hope all teachers possess this ability." Another student (S10) added: "Teachers should proactively discuss the boundaries of AI use with us—for

instance, when to rely on AI and when to rely on our own judgment—rather than assuming we already know how to use it.” Another student (S11) expressed: “I hope teachers can analyze common error types and sources of bias in AI during class, so that we do not blindly trust AI outputs. Teachers are far more reliable in playing this role than us figuring it out on our own.”

Theme 4: Perspectives on Ethics, Trust, and Future Collaboration

This theme comprised three subthemes: concerns regarding data privacy and security, differentiated levels of trust in AI recommendations, and expectations for an ideal collaborative model in the future. These findings resonate with the constraining influence of environmental factors on personal affect and behavioral choices within SCT. Data privacy risks, as potential threats in the environment, triggered concerns among students (personal affect), which in turn influenced their trust judgments regarding AI (personal cognition). Meanwhile, students' ideal division of labor—AI responsible for data and teachers responsible for the human touch—reflected their conscious pursuit of a triadic balance among environment, behavior, and personal factors.

Subtheme 4.1: Concerns Regarding Data Privacy and Security

This subtheme reveals the negative impact of environmental uncertainty on learners' affective security, as conceptualized in SCT. Students generally expressed unease regarding the continuous analysis and potential leakage of their learning behavior data—including video viewing duration, error records, and assignment content. Such concerns arose not only from uncertainty about technological security but also from psychological discomfort associated with being “monitored” in their learning process. The absence of clear data governance regulations further exacerbated this distrust. One student (S11) emphasized: “All the data generated from our use of the learning platform is analyzed by AI, and I am very concerned about whether this data might be leaked or misused.” Another student (S05) questioned: “The school claims confidentiality, but who actually manages this data? Are there clear rules?” Another participant (S13) expressed: “Every time I see the system prompt ‘this learning session has been recorded,’ I feel like I am being watched. I understand it is for personalized recommendations, but it still makes me uncomfortable—especially not knowing how long this data will be stored and who will have access to it.” Another student (S07) added: “We cannot even find out what data of ours is stored or how to delete it. What if the school or the platform sells the data to third parties? I hope the teachers or the school can provide a transparent commitment, rather than just asking us to rest assured.” Interestingly, a minority of students expressed comparatively less concern. S12, a senior, remarked: “I am not too worried about privacy, my browsing data is already tracked everywhere online. If AI wants to know I spent two hours on cardiac nursing, so be it. I get better recommendations in return, so it is a fair trade.” This contrasting perspective suggests that privacy concern is not universal but may be moderated by prior exposure to digital surveillance and individual risk tolerance.

Subtheme 4.2: Differentiated Levels of Trust in AI Recommendations

Students generally acknowledged the reliability of AI in deterministic tasks, such as factual knowledge and data summarization—and therefore chose to “trust first.” However, in tasks involving contextual judgment, ethical decision-making, or conflicts with authoritative textbook content, they tended to treat AI recommendations as references and ultimately defer to teachers or textbooks for confirmation. This stratified trust strategy, which we conceptualize as conditional algorithmic deference, reflects students’ prudent critical thinking. One student (S03) stated: “I tend to trust AI’s analysis first because it is based on large amounts of data, but I will still seek confirmation from my teacher in the end.” Another student (S06) shared: “Once, the learning materials recommended by AI differed from the textbook, and I placed more trust in the textbook and the teacher.” Another participant (S08) remarked: “I generally accept AI-calculated answers first because it rarely makes calculation errors. However, when it comes to clinical case judgments, such as whether a particular symptom should be prioritized, I will definitely consult my teacher, as AI does not understand specific contexts.” Another student (S13) added: “I trust AI for handling ‘right-or-wrong’ questions, but when a question involves ethical dilemmas or empathy-based judgments, I treat AI suggestions as references and ultimately rely on my teacher’s analysis.” One student (S09) also expressed: “Once, AI and the textbook provided different interpretations of the same concept. I hesitated, but later the teacher pointed out the traditional disciplinary definition that AI had overlooked. Since then, I have formed a habit: I first trust AI for efficiency, then verify it with textbooks and teachers.” A contrasting pattern was observed in S04, who stated: “I actually trust AI more than my teacher for certain things, for example, when learning pharmacology, AI can instantly pull up the latest research, whereas my teacher’s knowledge from five years ago might be outdated. I cross-check AI with current guidelines rather than defaulting to the teacher.” This minority view indicates that the stratified trust pattern is not monolithic; for some students, AI’s perceived currency and comprehensiveness can supersede teacher authority in specific knowledge domains.

Subtheme 4.3: Expectations for an Ideal Collaborative Model in the Future

This subtheme demonstrates students’ conscious conceptualization of a triadic balance among environment (AI and teachers), personal factors (learners), as posited by SCT. Students clearly articulated that AI should assume structured, repetitive tasks, such as data analysis, progress tracking, and initial feedback—while teachers should focus on emotional support, in-depth explanation, and value guidance, with learners retaining ultimate decision-making authority. This division of labor “one responsible for data, the other for the human touch” harnesses the efficiency advantages of technology while safeguarding the humanistic core of nursing education. One student (S12) summarized: “The ideal scenario is for AI to handle data analysis, progress tracking, and initial feedback, while the teacher provides emotional support, in-depth explanations, and value guidance. It is like having two coaches, one in charge of data, the other in charge of the human heart.” Another student (S04) envisioned: “I hope that in the future, AI can more intelligently identify my learning difficulties and coordinate with teachers to provide assistance, rather than conflicting with each other.” Another participant (S13) stated: “Ultimately, I make the final decision myself. AI gives me analysis, teachers give me advice, but how I use this information and which nursing plan I choose—I need to decide that myself. When each of the three roles fulfills its own function, things do not get chaotic.”

4. Discussion

This study employed a descriptive qualitative research design to systematically explore nursing undergraduates' perceptions and experiences of human-AI collaborative teaching models within a large language model-driven generative learning analytics environment. Through in-depth interviews with 15 nursing undergraduates, we identified four core themes. Rather than simply re-describing findings already reported in the existing literature, we aim to contribute an original analytical interpretation by applying SCT's triadic reciprocal determinism to illuminate the underlying mechanisms of students' trust calibration and role negotiation. To structure the discussion theoretically, we organize the following sections around SCT's triadic framework, examining: (a) how AI as an environmental factor shaped students' personal cognitive and affective factors; (b) how these personal factors in turn drove behavioral changes in learning; and (c) how the feedback loop between behavior and environment generated expectations for future collaboration and ethical safeguards. We then explicitly differentiate our theoretical contribution from prior descriptive accounts.

4.1 AI as an Environmental Stimulus: Eliciting Affective Responses and Cognitive Appraisal

From the SCT perspective, the initial encounter with GLA tools exemplifies how a novel environmental factor directly elicits personal affective responses. Students' feelings of novelty and perceived utility—captured in Subtheme 1.1—reflect the immediate value of AI technology in addressing deficiencies of traditional teaching, such as delayed feedback and limited grading capacity. Students perceived AI-generated learning analytics reports as a form of "targeted monitoring," considering their feedback to be more detailed than standard answer keys, a finding highly consistent with the study by Yuan et al., which identified "personalized learning assistance" and "efficiency and cognitive expansion" as core advantages of generative AI in nursing students' perceptions²³. A systematic review by Alrazeeni et al. similarly confirmed that the provision of immediate, unbiased feedback through automated assessment tools constitutes one of the primary pathways through which AI transforms nursing education²⁴.

However, students' positioning of the AI role was not characterized by simple technological fetishism; rather, it manifested prudent rational judgment. Most students regarded AI as a "teaching assistant" or "facilitator" rather than a "substitute," clearly distinguishing between AI's instrumental attributes and the irreplaceability of human teachers. This positioning closely aligns with the "hybrid human-AI learning" theory proposed by El Arab, which posits that AI should serve as a "cognitive collaborator" rather than a cognitive substitute, preserving learners' role as active decision-makers while providing targeted scaffolding²⁵. Notably, some students expressed concerns about over-reliance on AI, suggesting that AI could not understand emotions and learning habits in the way human teachers could. This cautious attitude corroborates the concerns regarding GenAI's "limited emotional understanding" expressed by students in the qualitative study by Shen et al²⁶.

The observed seniority-related differences in AI adoption rates can be interpreted through SCT's concept of prior experience as a source of self-efficacy. Upper-year students' prior exposure to clinical internship settings, where they have encountered electronic health records and decision-support systems, provided them with enactive mastery experiences that enhanced their technological self-efficacy, thereby accelerating their adaptation to new AI tools. Conversely, lower-year students, lacking such contextual anchors, may struggle to translate AI-generated abstract analytics into clinically meaningful learning actions. This disparity suggests that nursing educators should consider grade-level differences and learning stage characteristics when introducing AI tools, and provide tiered training and support. A systematic review by Zhao et al. also indicated that nursing student populations exhibit significant variations in AI awareness, attitudes, and skills, necessitating targeted educational interventions²⁷.

4.2 From Personal Cognition to Behavioral Change: Personalized Learning and Self-Efficacy Enhancement

The perceived shifts in AI-assisted learning, enhancement of personalized learning, improvement in learning initiative, and differentiated evaluations of feedback quality, can be understood through SCT's mechanism of self-efficacy enhancement. The personalized learning pathways and adaptive resource recommendations generated by AI served as environmental support that strengthened students' beliefs in their capability to master clinical reasoning tasks.

Regarding personalized learning, students generally considered that the personalized learning pathways and adaptive resource recommendations generated by AI significantly improved learning efficiency, particularly in effectively bridging theoretical knowledge with clinical cases. This finding aligns with the conclusion drawn in the systematic review by Alrazeeni et al., which noted that personalized learning systems tailor content on demand, suggesting that generative learning analytics possess unique advantages in realizing individualized instruction²⁴. Notably, our findings extend this evidence by showing that personalization in nursing education—unlike in more abstract disciplines—operates through the specific mechanism of "theory-case bridging," wherein AI helps students recognize the relevance of foundational knowledge to clinical scenarios—a cognitive leap that traditional whole-class instruction often fails to scaffold.

The enhancement of learning initiative observed in this study can be interpreted through SCT's self-efficacy mechanism. The AI-generated progress curves served as enactive mastery experiences, providing students with direct evidence of their learning trajectory, which in turn elevated their efficacy beliefs and prompted proactive help-seeking behaviors. A study by Wang et al., grounded in self-determination theory, similarly found a significant positive correlation between supportive learning environments and autonomous learning capacity, suggesting that appropriate use of AI tools can promote learning autonomy by enhancing intrinsic learning motivation²⁸.

However, students' evaluations of AI feedback quality were differentiated. While the majority acknowledged the immediacy and objectivity of AI feedback, some students pointed out that AI

feedback was overly standardized and lacked the affective tone, such as encouragement or criticism—characteristic of human teachers. This criticism reveals a structural deficiency of current generative AI in nursing education applications—namely, the absence of affective responsiveness. From the SCT perspective, this deficiency represents an environmental limitation that fails to meet learners' emotional support needs, potentially weakening the positive feedback loop between environmental reinforcement and personal motivation. The study by Shen et al. similarly found that students explicitly expressed concerns regarding GenAI's limitations in emotional recognition²⁶. For nursing education, this issue is particularly salient, as the nursing profession itself takes humanistic care as its core value. Consequently, nursing education must harness the advantages of AI while safeguarding the humanistic core of the profession, a tension that requires deliberate pedagogical design rather than uncritical technological adoption.

4.3 Teacher as Social Support: The Irreplaceable Human Element in the SCT Triad

Within the SCT framework, teachers constitute a critical source of social support within the environmental dimension, one that is qualitatively different from technological tools. Students' recognition of teachers' irreplaceability (Subtheme 3.1) and their changing expectations of teacher competencies (Subtheme 3.3) both underscore that AI, as a technological environment, does not substitute for human social support but rather reconfigures its function.

Students generally believe that although AI performs well in data analysis, teachers' core status and humanistic care are still irreplaceable. Specifically, teachers can use class data provided by AI to deliver targeted explanations in class, share clinical experience, and offer emotional care when students encounter difficulties, functions that AI cannot fulfill. This finding resonates with SCT's emphasis on vicarious experience and social persuasion as key sources of self-efficacy: a teacher's clinical storytelling and personalized encouragement carry motivational weight that algorithmic feedback, by definition, cannot replicate. This finding echoes the research of Blomquist et al.: while 77% of teachers mention AI in their courses, a considerable proportion of students remain uncertain about the permissible scope of AI use, which highlights the more prominent roles of teachers as norm-setters and guides in the AI era²⁹.

The integration of AI has brought positive changes to the mode of teacher-student interaction. Consistent with SCT's assumption that environmental tools can optimize behavioral patterns, the learning data generated by AI enabled students to raise more targeted questions to teachers, and classroom discussions became more dynamic through the comparison between AI analysis and personal reflection. This indicates that AI does not weaken teacher-student interaction; instead, it makes interactions more focused and in-depth by providing objective learning evidence. Notably, this positive transformation is not automatic but depends on teachers' pedagogical mediation, a finding that underscores the active role of human agents in translating environmental affordances into meaningful learning experiences.

At the same time, students have put forward new expectations for teachers' competencies, they expect teachers to not only master AI tools but also teach students to identify the reliability of AI-generated information. From the SCT perspective, this expectation signals students' awareness that the environmental information provided by AI requires cognitive mediation by a trusted social agent. Students are not asking teachers to simply fact-check AI outputs; they are asking for metacognitive scaffolding, that is, teachers should equip students with transferable critical appraisal skills applicable beyond any single AI tool. This qualitative shift from content transmission to competence cultivation fundamentally redefines the teacher's role as an AI literacy mentor rather than a conventional knowledge transmitter. Such expectations reflect students' urgent demand for critical thinking guidance in the AI era. A scoping review conducted by Hardie et al. also emphasizes that clear policies and guidelines are required to ensure the ethical use of GenAI resources, and teachers act as key players in policy implementation and ethics education³⁰. Therefore, nursing educators are undergoing a role shift from traditional knowledge transmitters to AI literacy mentors, and this transformation places new requirements on teacher development programs.

4.4 Ethical Prudence and the Ideal Triadic Balance: Trust, Privacy, and Division of Labor

Students' trust in AI exhibited a stratified pattern that reflects SCT's concept of personal cognition actively appraising environmental information rather than passively accepting it. Most students trusted AI's accuracy in judging factual knowledge, yet held reservations about tasks requiring situational judgment and ethical decision-making. They tended to take AI suggestions as references and ultimately relied on teachers for validation. This stratified trust strategy, what we term conditional algorithmic deference—is distinct from either blind trust or blanket skepticism. It suggests that students are developing an emerging cognitive heuristic: trust AI for well-structured, verifiable tasks; defer to human authority for ill-structured, value-laden judgments. This finding extends prior work by demonstrating that trust in AI is not unidimensional but is contingent upon the nature of the learning task. This finding aligns with the study by Sajja et al.: students acknowledge the convenience of using AI tools, while persistent concerns remain regarding academic integrity and appropriate usage boundaries. Such divergent trust suggests that the design of AI systems should be enhanced in terms of algorithm transparency and confidence labeling, allowing students to clearly distinguish the reliability of AI recommendations³¹.

Data privacy constitutes a core ethical concern shared by most students, a concern that SCT would conceptualize as a negative affective response to environmental uncertainty. Students expressed discomfort over continuous analysis and potential leakage of their learning behavioral data, and questioned the transparency and clarity of rules governing data management. This concern is highly consistent with the conclusions on privacy worries put forward by Luque et al., who identify data privacy and security risks as one of the central challenges facing LLM applications³². The affective dimension of this concern is noteworthy: students reported feeling "watched" rather than merely concerned about data breach, suggesting that the psychological impact of surveillance-style analytics may be as significant as the objective security risks. This distinction has important implications for system design. Accordingly,

educational institutions should establish a consent-informed and revocable mechanism for data utilization, and clearly inform students of the scope of data collection, anonymization methods and data deletion rights at the initial stage of courses.

Students have formed a distinct vision of the anticipated human-AI collaboration model for the future, a vision that aligns remarkably well with the optimal triadic balance posited by SCT: AI (environment) takes charge of data analysis, progress tracking and preliminary feedback; teachers (social environment) provide emotional support, in-depth explanations and value guidance; and students (personal factors) retain the final decision-making power. This ideal division of labor is highly consistent with the propositions advocated by current human-AI collaboration theories, reflecting students' profound understanding of balancing technological assistance and humanistic care. A critical insight from our data, however, is that students' vision of this ideal model operates on a "role clarity" condition, they explicitly worry that when AI overpowers prompts or when teachers lack AI literacy, the boundaries blur and the model fails. This suggests that the success of human-AI collaboration in nursing education depends not only on technological capabilities but also on explicit role negotiation and continuous boundary management. Research by Alnawafleh et al. points out that insufficient institutional readiness acts as a major barrier to realizing this ideal model, as numerous nursing programs lack standardized curricula and infrastructural support³³. Therefore, systematic reforms across multiple dimensions including policies, curricula and teaching staff are still required in nursing education, ranging from individual willingness to systematic capacity building.

5. Strengths and limitations

The adoption of a descriptive qualitative research design, framed by social cognitive theory and focused on the authentic human-AI collaborative experiences of nursing undergraduates, enabled the illumination of humanistic and contextual elements that are frequently overlooked by quantitative studies in technology applications, thereby providing a rich interpretive perspective for the implementation of generative learning analytics in nursing education. Nevertheless, several limitations of this study warrant consideration: the sample was confined to 15 nursing undergraduates recruited from a single university, which limited the transferability of the findings; the cross-sectional design failed to capture the longitudinal evolution of students' perceptions and attitudes over the course of AI system use; and the exclusive focus on the student perspective, without incorporating the views of teachers and AI system designers, rendered a comprehensive understanding of the multidimensional nature of human-AI collaboration difficult to achieve. Future research may further advance this field through multi-center designs, longitudinal follow-ups, and mixed-methods approaches that integrate multiple stakeholder perspectives.

6. Implications for Nursing Education and Practice

The findings of this study suggest that, when introducing generative learning analytics tools, nursing education institutions should explicitly position AI as a "supportive teaching assistant" rather than a

“teacher substitute,” leveraging AI’s efficiency advantages in structured tasks such as factual knowledge feedback, error analysis, and learning progress tracking, while maintaining teacher dominance in scenarios centered on humanistic care, including clinical judgment, ethical decision-making, and emotional support.

AI ethics modules should be embedded in curriculum design to assist students in developing prudent trust in AI outputs and the capacity for critical evaluation. Concurrently, nursing faculty are required to systematically enhance their AI literacy, encompassing the ability to assess the reliability of AI-generated content, recognize algorithmic biases, and guide students in the appropriate use of AI tools. At the practice level, AI-generated learning analytics reports may be introduced into nursing clinical teaching and simulation training, serving as objective evidence for teacher–student interaction and reflective discussion, thereby facilitating the effective integration of theoretical knowledge and clinical practice. Educational administrators should establish transparent data use mechanisms that ensure “informed consent and the right of withdrawal,” and formulate institution-wide guidelines for AI use, so that technological applications not only enhance learning efficacy but also safeguard the humanistic core values of the nursing profession. The diversity of student responses to privacy concerns—ranging from high anxiety to pragmatic acceptance—suggests that a one-size-fits-all privacy policy may be insufficient; institutions should consider offering opt-in levels of data sharing, allowing students to choose their preferred balance between personalization and privacy.

7. Conclusion

Through a descriptive qualitative design, this study revealed the experiences of nursing undergraduates in human-AI collaboration within generative learning analytics. Students perceived AI as a “supportive teaching assistant,” acknowledging its efficiency and personalization in factual tasks, yet remained cautious about tasks involving emotional judgment and ethical decision-making, consistently upholding teachers as the ultimate authority. The study introduces the constructs of conditional algorithmic deference and teacher anchoring effect as original theoretical contributions that differentiate the findings from prior descriptive accounts. AI enhanced learning initiative and teacher-student interaction, but the lack of affective responsiveness in AI feedback, data privacy risks, and insufficient institutional readiness constituted core barriers. The study emphasized that nursing education should adhere to the division of labor principle “AI takes charge of data, teachers take charge of the heart, and students retain decision-making power”, by enhancing teachers’ AI literacy, establishing a transparent ethical framework, and promoting affective responsiveness enhancement in domain-specific large language models. Only by balancing technological empowerment and humanistic safeguarding can generative learning analytics truly become a “second mentor” rather than a “monitor” in nursing education.

Declarations

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contribution

Hong Su, conception and design of the study, drafting the article and approval of the version to be published; Yuke Zhang, contributed to data collection; Yuyan Cheng, contributed to data collection; Yuqiu Zhou, interpretation of data, drafting the article and approval of the version to be published. All authors have read and approved the final version of the manuscript.

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Data availability

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Figures

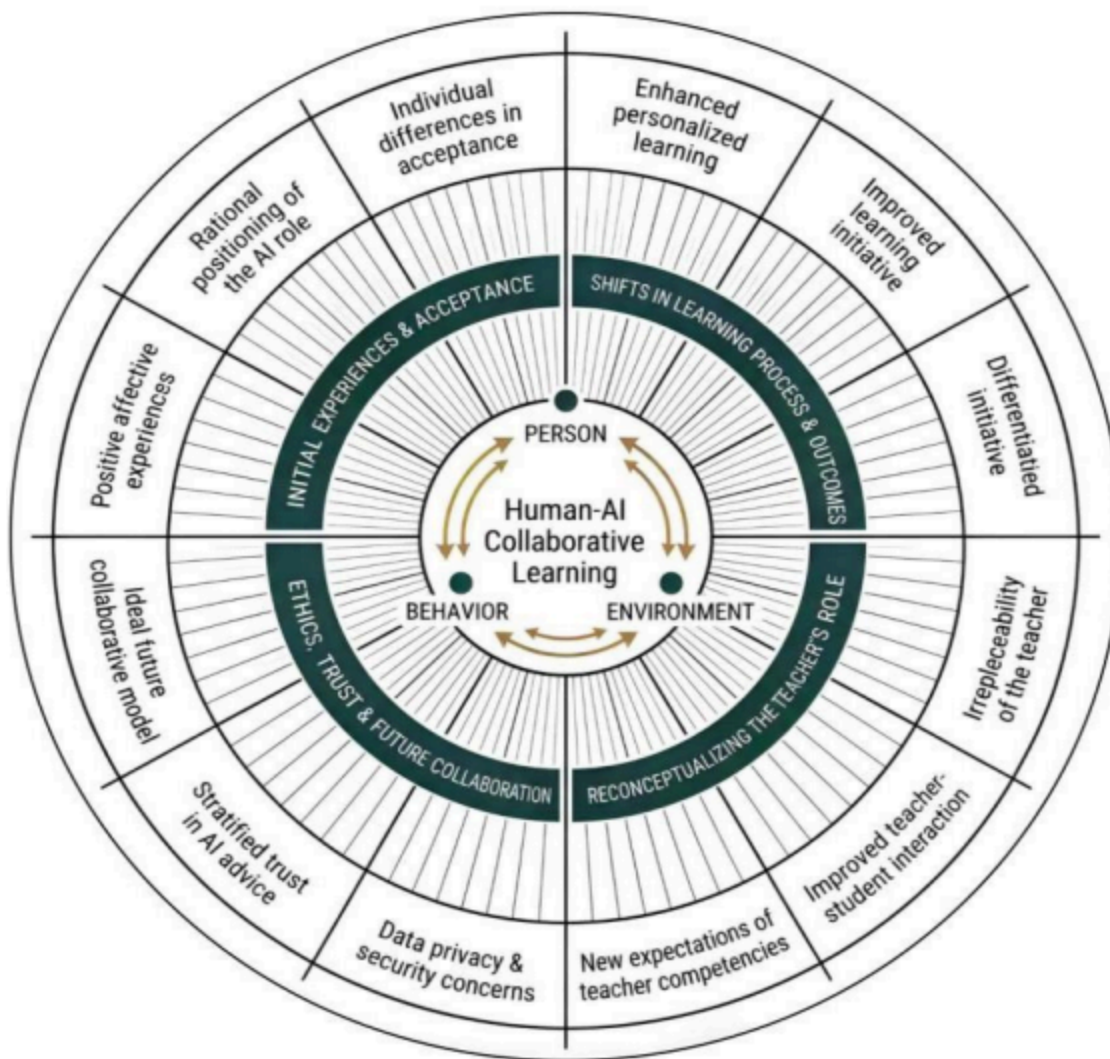


Figure 1

Themes and Sub-themes of Nursing Undergraduates' Perceptions of Human–AI Collaboration in Generative Learning Analytics