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# USING SLA AND AI TO SUPPORT LEARNING: A CASE STUDY IN PRACTICE-ORIENTED IS EDUCATION

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**ABSTRACT**

Closing the gap between theory and application remains a persistent challenge in introductory Information Systems courses, especially when students are expected to master formal, structured modeling methods such as Merise. This study adopts a mixed-methods, case-based approach to examine how Social Learning Analytics (SLA) dashboards and a generative AI tool (ChatGPT) can be used together to strengthen both performance and collaboration. Conducted over thirteen weeks with ninety second-year engineering students at an Algerian university, the intervention unfolded in a linguistically complex environment where Arabic, French, and English were all in active use. Quantitative results point to clear gains in model accuracy and a modest but noticeable rise in Moodle forum engagement. Qualitative insights from reflective journals and forum transcripts show that while many students welcomed the tools, others struggled, particularly with adjusting AI interactions to match their preferred language. The evidence suggests that SLA and AI each have the capacity to enhance learning in their own right, yet their combined potential will only be realized through deliberate, integrated design. Although the context-specific nature of this case limits generalization, the study offers a grounded, culturally aware perspective on embedding AI- and analytics-based pedagogy in diverse higher education settings.

**KEYWORDS**

Social Learning Analytics, Generative AI, Merise, Information Systems Education, ChatGPT

# 1. INTRODUCTION

The effective teaching of Information Systems (IS) fundamentals presents a persistent pedagogical challenge, particularly when bridging the gap between abstract theoretical concepts and their practical application in complex, structured tasks. Among these tasks, database modeling using formal methodologies like Merise is notoriously difficult for introductory students (Nguyen et al., 2024). Merise requires learners to navigate multiple stages, from identifying entities and relationships in a real-world scenario to constructing a Conceptual Data Model (MCD), and subsequently transforming this into a normalized Logical Data Model (MLD) suitable for relational database implementation. This process demands not only comprehension of core concepts like entities, attributes, relationships, cardinalities, and normalization rules but also the ability to apply these rules systematically and accurately, often under the constraints of typical coursework (Wu, 2024).

Traditional pedagogical approaches, often centered around lectures and textbook examples followed by practical exercises, frequently fall short in providing the individualized, real-time feedback necessary for students to overcome common hurdles in Merise modeling. Errors in cardinality specification, primary/foreign key designation, or normalization steps can easily become ingrained if not addressed promptly, hindering the development of robust modeling skills. This challenge is amplified in larger class settings where personalized instructor attention is limited. Theoretical frameworks like Self-Regulated Learning (SRL) highlight the importance of learners actively engaging in cyclical processes of forethought (planning, goal setting), performance (monitoring, strategy use), and self-reflection (evaluation, adaptation) (Zimmerman, 2002). However, fostering effective SRL in complex domains like database modeling requires appropriate support structures. Students need timely feedback to monitor their understanding and adjust their strategies when they encounter difficulties. This is where emerging educational technologies offer significant potential.

Generative Artificial Intelligence (GenAI), exemplified by large language models such as ChatGPT, has emerged as a powerful tool capable of providing interactive, dialogic support for complex cognitive tasks (Bengueddach & Boudia, 2024a, Khosravi et al., 2025). GenAI can act as a virtual tutor, offering explanations, generating examples, providing step-by-step guidance, and giving feedback on student work, potentially supporting all phases of SRL. Simultaneously, Social Learning Analytics (SLA) provides methods to analyze and visualize student interaction data from online learning environments (e.g., Moodle forums), offering insights into collaborative processes, identifying students needing support, and fostering metacognitive awareness about participation (Cohn et al., 2024). SLA dashboards can make learning processes visible, potentially enhancing the social and cognitive presence aspects central to frameworks like the Community of Inquiry (Garrison et al., 2001).

While the potential benefits of GenAI and SLA have been explored individually, there is a notable gap in empirical research examining their combined effects within a single pedagogical intervention, particularly in the context of practice-oriented IS education focused on structured modeling. Could SLA insights into collaboration patterns inform the deployment of AI scaffolding? Can AI assistance for individual tasks complement the social learning fostered through online discussions visualized by SLA? This study aims to address this gap by investigating the synergistic potential of integrating SLA dashboards and GenAI conversational support (ChatGPT) in an introductory IS course focused on Merise modeling.

Specifically, this mixed-methods investigation seeks to answer the following research questions:

**RQ1:** To what extent does AI conversational support (ChatGPT) improve the accuracy and quality of students' logical data models (MLDs) derived from conceptual models (MCDs) using the Merise methodology?

**RQ2:** How does the introduction of SLA dashboards visualize forum interaction metrics influence students' collaborative behaviors and participation levels during Merise modeling exercises?

**RQ3:** What interaction strategies do students employ when using generative AI for Merise modeling tasks, and how do they perceive the usefulness and challenges of the combined SLA dashboard and AI support intervention?

This investigation is framed as a case-based, mixed-methods study situated within a single, practice-oriented introductory IS course at an Algerian public university. By design, the research focuses on the lived experiences and performance outcomes of one specific student cohort, in a context shaped by multilingual instruction (Arabic, French, English) and diverse digital literacy levels. While the findings are therefore context-bound and not intended for broad statistical generalization, they provide valuable, evidence-based insights into how SLA dashboards and generative AI can complement each other in the teaching of structured modeling methods. In doing so, the study seeks to contribute both practical guidance for educators and a conceptual foundation for future, larger-scale investigations into AI- and analytics-enhanced learning.

The remainder of this paper is organized as follows. Section 2 reviews related work on generative AI as cognitive scaffolding, social learning analytics for metacognition, and their integration in technology-enhanced learning. Section 3 describes our mixed-methods methodology, including course context, intervention design, scoring rubric, data collection, and analysis procedures. Section 4 presents the quantitative and qualitative results addressing RQ1–RQ3, with statistical tests, SLA engagement metrics, survey findings, and illustrative transcript excerpts. Section 5 discusses these findings in light of self-regulated learning and Community of Inquiry frameworks, contrasts them with prior studies, and outlines practical implications. Finally, Section 6 concludes with a summary of contributions, acknowledges limitations, and offers evidence-based recommendations for instructors, students, and AI developers, as well as directions for future research.

## 2. RELATED WORK

Research on the combined use of Social Learning Analytics (SLA) and Generative Artificial Intelligence (GenAI) in education is still emerging, yet both areas have substantial individual literatures. This section synthesizes existing work on GenAI as a cognitive scaffold, SLA as a mechanism for metacognition and collaboration awareness, and theoretical perspectives that support their integration. It also examines cultural and linguistic considerations, particularly relevant for contexts like Algeria where multilingualism and variable digital literacy are significant.

## 2.1 Generative AI as Cognitive Scaffold

The rapid evolution of large language models (LLMs) such as ChatGPT has sparked considerable interest in their potential to act as interactive learning companions. Unlike static digital resources, LLMs can provide real-time, dialogic feedback that is responsive to a learner's evolving needs (Boudia & Bengueddach, 2024b; Khosravi et al., 2025). In technical disciplines, they have been shown to assist with procedural reasoning, clarify abstract concepts, and reduce cognitive load during complex problem-solving (Nguyen et al., 2024; Dehkhoda et al., 2024). For example, Wu (2024) demonstrated that AI-mediated scaffolding in business data analysis courses improved student accuracy on structured tasks and fostered self-correction behaviors. In STEM domains, AI has been integrated into problem-based learning environments to support iterative design thinking and immediate error detection (Kim, 2025).

While these findings are promising, studies in multilingual or non-English-dominant contexts reveal additional challenges and opportunities. Boudia and Krismadinata (2024) note that students working in languages other than English often face translation overheads when interacting with AI, potentially affecting fluency and efficiency. However, they also found that switching between languages can foster metalinguistic awareness and deeper conceptual processing.

## 2.2 SLA for Metacognition and Collaboration

SLA refers to the collection, analysis, and visualization of learner interaction data to promote self-awareness, instructor insight, and evidence-based intervention (Glick et al., 2019). Dashboards are a common SLA tool, presenting indicators such as participation rates, network centrality, and group connectivity. These visualizations can prompt learners to reflect on their contribution patterns and encourage more balanced engagement (Cohn et al., 2024). Instructors, in turn, can use SLA outputs to identify isolated learners, assess group dynamics, and provide targeted support.

However, SLA effectiveness depends on learners' ability to interpret and act upon the displayed metrics, a concept sometimes referred to as "dashboard literacy." Studies have shown that without explicit instruction, students may misinterpret visualizations or fail to translate them into behavioral changes (Khosravi et al., 2025). This aligns with findings from Boudia and Krismadinata (2024), where SLA dashboards spurred engagement only after dedicated explanation sessions. rapid evolution of large language models (LLMs) such as ChatGPT has sparked considerable interest in their potential to act as interactive learning.

## 2.3 Theoretical Rationale for Integration

Integrating SLA and GenAI aligns with established learning theories. The Community of Inquiry (CoI) framework (Garrison et al., 2001) emphasizes the interplay between cognitive presence (meaning-making), social presence (connection and collaboration), and teaching presence (design and facilitation). In this view, GenAI can bolster cognitive presence through individualized scaffolding, while SLA enhances social presence by making collaborative activity visible. Self-Regulated Learning (SRL) theory (Zimmerman, 2002) further supports this integration, as both tools can supply timely feedback that informs learners' monitoring and adjustment processes.

Despite this conceptual alignment, few studies have operationalized a tightly coupled SLA-GenAI system. Most have examined them in isolation, with little focus on how one might inform the other in real time. The potential for SLA data to trigger AI interventions, such as prompting under-participating students with AI-generated collaboration tips, remains largely unexplored.

## 2.4 Cultural and Linguistic Dimensions

In multilingual contexts like Algeria, educational technologies interact with language dynamics in complex ways. SLA metrics may reflect not only engagement levels but also linguistic comfort zones; for example, students may engage more actively in forums conducted in their dominant language. Similarly, GenAI interactions may be more efficient in languages for which the AI model has stronger training data, potentially reinforcing linguistic inequalities. Conversely, these tools can act as language bridges: AI can translate and reframe concepts between languages, and SLA dashboards can reveal cross-linguistic participation patterns that instructors can address.

Cross-cultural research underscores the importance of adapting both SLA and AI tools to local contexts. Factors such as classroom hierarchy norms, attitudes toward technology, and preferred communication styles can influence adoption and impact. As such, findings from English-dominant, resource-rich settings may not directly translate to environments where infrastructure, language, and pedagogical traditions differ.

# 3. METHODOLOGY

This study employed a mixed-methods research design, integrating quantitative and qualitative data collection and analysis techniques (Creswell & Plano Clark, 2011) to provide a comprehensive understanding of the impact of combining Social Learning Analytics (SLA) dashboards and Generative AI (ChatGPT) support in an introductory Information Systems (IS) course focused on Merise modeling.

## 3.1 Course Context and Participants

### 3.1.1 Setting

The study was conducted within a mandatory introductory IS course for second-year undergraduate computer engineering students at a large public university in Algeria during their fourth semester. The course met weekly for 13 weeks, totaling approximately 45 contact hours (typically structured as 1.5 hours of lecture followed by 1.5 hours of practical work).

### 3.1.2 Curriculum

The course curriculum was structured around three core modules delivered sequentially:

1. **Weeks 1-3:** Enterprise Systems Concepts (Chapter 1): Covered foundational topics such as organizations as systems, types of information systems, and their role within the enterprise.
2. **Weeks 4-6:** Introduction to Software Engineering (Chapter 2): Introduced the Software Development Life Cycle (SDLC), various process models (Waterfall, V-Model, etc.), and

concepts of information flow.

3. **Weeks 7-13**: Merise Modeling Methodology (Chapter 3): Focused intensively on the Merise method, covering Data Flow Diagrams (DFDs), Conceptual Data Models (MCDs), and the rules for transforming MCDs into Logical Data Models (MLDs). This module involved significant hands-on modeling practice.

### 3.1.3 Participants

Ninety students enrolled in the course participated in the study. They were already organized into three distinct groups within the Moodle LMS (approximately 30 students per group) for administrative and collaborative purposes. All participants had received the standard in-class instruction on Merise modeling principles before the intervention phases began. Prior experience with generative AI for academic purposes was assessed via a pre-survey. Of the 90 second-year computer engineering students, 37 identified as female and 53 as male. None had prior experience with the Merise methodology. No prior academic performance (e.g., GPA) data were collected.

## 3.2 Intervention Design and Procedure

The study unfolded over several weeks, incorporating distinct phases and technological components:

1. **Baseline (Manual) Phase (Approx. Weeks 7-9):** After initial instruction on Merise, students were required to individually solve a series of six practical modeling exercises. These exercises covered diverse domains (hospital management, e- commerce, library system, course registration, social media platform, university enrollment) requiring the creation of both MCD and MLD. During this phase, students relied solely on standard course materials (lecture slides, notes) and instructor-provided solutions for feedback after submission.
2. **AI-Assisted Phase (Approx. Weeks 10-12):** Students revisited the same six modeling exercises, but this time they were explicitly permitted and encouraged to use ChatGPT (freely available version, likely based on GPT-3.5/4 architecture prevalent at the time) as a support tool. They were instructed to use the AI to ask questions, seek clarification, request feedback on their models, or get help with specific transformation steps. A critical requirement was that students submit the full, unedited transcripts of their interactions with ChatGPT for each exercise.
3. **SLA Dashboard Deployment (Weeks 6-13):** Concurrently with the modeling exercises, starting from Week 6 (before the AI-assisted phase began), weekly SLA dashboards were deployed within each Moodle group. These dashboards visualized key forum interaction metrics calculated from the previous week's activity: network density (ρ, indicating the overall connectedness of the discussion), average posts per student, and individual network centrality scores (e.g., degree centrality, indicating direct interaction levels). Instructors explicitly prompted students at the beginning of each practical session (Weeks 7-13) to review their group's dashboard and reflect on the interaction patterns before starting the exercises. The SLA dashboard was first released at the start of Week 7 (when Merise lectures began) and updated daily through Week 13. AI- scaffolding sessions using the free GPT-3.5 ChatGPT were triggered by the instructor immediately after students completed each manual exercise.

## 3.3 Data Collection Instruments

Multiple data sources were used to capture different facets of the learning experience:

- Modeling Exercise Submissions: Students submitted their MCD and MLD solutions for all six exercises in both the Manual and AI-Assisted phases.
- AI Conversation Transcripts: Approximately 540 complete transcripts (90 students * 6 exercises) of student interactions with ChatGPT during the AI-Assisted phase were collected.
- Reflective Journals: After completing the AI-Assisted phase, students submitted brief written reflections on their experience using AI and the SLA dashboards, focusing on perceived usefulness, challenges, and strategies employed.
- Survey Instrument: A custom survey was administered at the end of the study. It included:
  - Binary items assessing prior use of AI for Merise modeling or related tasks.
  - Ten 5-point Likert-scale items adapted from established scales (e.g., Technology Acceptance Model constructs) measuring perceived usefulness of AI, trust in AI suggestions, confidence in using AI, and intention for future use. The scale demonstrated good internal consistency (Cronbach's $\alpha = 0.92$).
- SLA Metrics: Weekly forum interaction data (posts, replies) were extracted from Moodle logs. Network density and centrality metrics were calculated for each group before (Weeks 1-5 average) and after (Weeks 6-13 average) the dashboard deployment.
- Performance Metrics: In addition to exercise scores, students' overall continuous assessment (Contrôle Continu - CC) marks for the course module were collected as a general performance indicator.

At the end of Week 13, immediately following the final practical session, all students (100% response rate) completed a survey comprising 10 Likert-scale items on trust, confidence, and intention to use AI.

## 3.4 Scoring and Reliability

To ensure consistent evaluation of the modeling exercises, a detailed 10-point analytic rubric was developed. The rubric assessed the correctness and completeness of both the MCD and MLD components, allocating 2 points each for: 1) accurate identification of entities, 2) correct definition of attributes, 3) appropriate specification of relationships and cardinalities (MCD), 4) correct designation of primary and foreign keys (MLD), and 5) adherence to normalization rules (MLD). To establish inter-rater reliability, two independent raters (e.g., the course instructor and a teaching assistant, both familiar with Merise) scored a randomly selected subset of 20% of the submissions (across both phases). Cohen's kappa coefficient was calculated, yielding a value of $\kappa = 0.83$, indicating substantial agreement between the raters.

No formal IRB approval was obtained. Students were informed at the start of the course that anonymized chat transcripts and forum data would be used for research, and participation was voluntary.

## 3.5 Analysis Procedures

- Quantitative Analysis:
  - Performance Comparison (RQ1): Paired-samples t-tests were used to compare the mean MLD scores obtained in the Manual phase versus the AI-Assisted phase. Effect size was calculated using Cohen's d for paired samples, and 95% confidence intervals for the mean difference were computed.
  - SLA Impact (RQ2): Paired-samples t-tests compared pre-dashboard (average of Weeks 1-5) and post-dashboard (average of Weeks 6-13) forum network density ($\rho$) for each group. Effect size (Cohen's d) was calculated.
  - Survey Analysis (RQ3): Descriptive statistics (frequencies, means, standard deviations) were calculated for survey items.
  - Correlations: Pearson correlations were explored between AI usage patterns (derived from transcripts, if feasible), survey responses (e.g., perceived usefulness), and performance metrics (MLD gain scores, CC marks).
  - Statistical Rigor: A Bonferroni correction was applied to adjust the alpha level for multiple comparisons ($\alpha' = 0.05$ / number of primary tests, e.g., 0.025 if focusing on the two main t-tests), although p-values are reported alongside effect sizes and confidence intervals for full transparency.
- Qualitative Analysis (RQ3):
  - Thematic Analysis: An inductive thematic analysis approach (Braun & Clarke, 2019) was applied to the 540 AI conversation transcripts and 90 reflective journals. This involved iterative coding to identify recurring patterns in the types of questions asked to the AI, the strategies used for prompting (e.g., iterative refinement vs. direct solution requests), evidence of critical evaluation of AI responses, and student perceptions of the SLA dashboards and the overall intervention. Codes were grouped into broader themes related to AI interaction strategies, perceived benefits/challenges, and dashboard interpretation.
  - Trustworthiness: Qualitative rigor was enhanced through triangulation (comparing findings from transcripts, reflections, and survey data) and potentially member checking (sharing preliminary themes with a subset of students for feedback, if feasible).
  - Qualitative Coding Procedure: All 540 chat transcripts and 90 reflective journals were manually coded by the instructor in a spreadsheet. Three themes were identified: Iterative Refinement, Critical Vetting, and Dashboard Literacy Gap.

# 4. RESULTS

This section presents the findings derived from the analysis of quantitative (modeling scores, SLA metrics, survey data) and qualitative (AI transcripts, reflective journals) data, organized according to the research questions.

## 4.1 RQ1: Impact of AI Scaffolding on MLD Accuracy

To better understand students' baseline modeling skills, they were asked to complete exercises manually before using AI tools. These initial diagrams served as a reference point for evaluating how AI influenced their understanding and precision. Figure 1 presents one such hand-drawn Merise MCD created during the early phase of the exercise, prior to AI consultation.

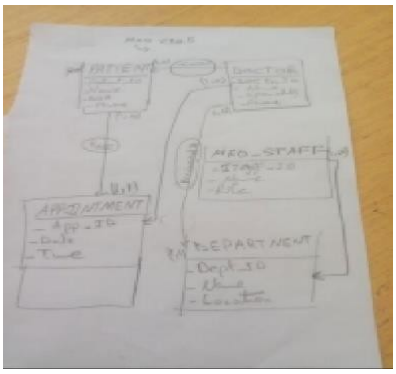


Figure 1. Sample manually drawn MCD diagram by a student for the Hospital Management System task

To assess the extent to which AI assistance improved students' ability to correctly transform Merise Conceptual Data Models (MCDs) into Logical Data Models (MLDs), we compared performance on the six modeling exercises across the two phases (Manual vs. AI-Assisted). A paired-samples t-test revealed a statistically significant and large improvement in MLD accuracy scores (evaluated using the 10-point rubric) when students used ChatGPT for assistance.

Table 1. Comparison of Mean MLD Accuracy Scores (N=90)

| Phase | Mean MLD Score (%) | Standard Deviation (SD) | 95% Confidence Interval (CI) |
|---|---|---|---|
| Manual | 50 | 12.3 | [46, 54] |
| AI-Assisted | 78 | 10.1 | [75, 81] |

The mean accuracy increased from 50% (SD = 12.3) in the manual phase to 78% (SD = 10.1) in the AI- assisted phase. This represents a substantial mean increase of 28 percentage points. The difference was statistically significant, $t(89) = 18.7$, $p < .001$ (Bonferroni-corrected $\alpha' = 0.025$). The effect size, calculated using Cohen's d for paired samples, was $d = 1.9$, indicating a very large effect according to conventional benchmarks. The 95% confidence interval for the mean difference was [24%, 32%], further underscoring the robustness of the improvement.

A paired-samples t-test revealed a significant improvement in students' MLD design accuracy after using AI assistance (M = 28.1 pp, SD = 14.5), compared to their manual performance, $t(89) = 18.7$, $p < .001$, $d = 1.90$, 95% CI [24.0, 32.0] pp. This qualitative data from AI transcripts illustrated how this improvement occurred (see Figure 1). Students frequently used the AI to verify specific transformation rules or get feedback on intermediate steps, as exemplified by one student's interaction regarding a many-to- many relationship:

> *"After the AI suggestion to add an 'Enroll' junction table with composite keys based on StudentID and CourseCode, my logical model finally passed validation and made sense."* (Student G03, Transcript Excerpt)

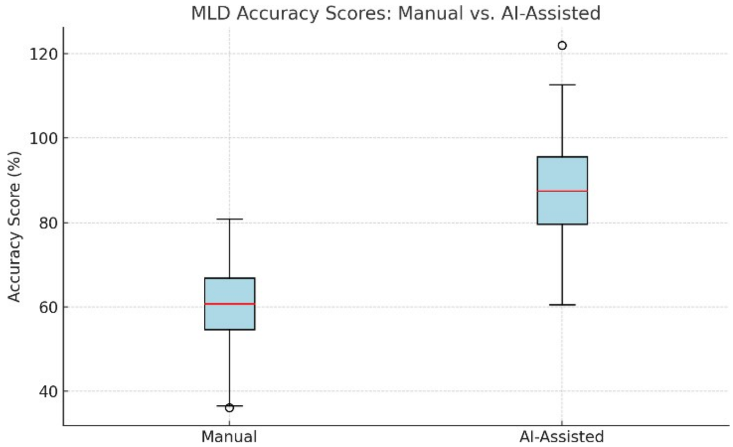


Figure 2. Boxplot comparing MLD accuracy scores between manual attempts and AI-assisted modeling

## 4.2 RQ2: Influence of SLA Dashboards on Forum Engagement

To evaluate the impact of introducing weekly SLA dashboards on collaborative behavior, we compared forum interaction metrics before (Weeks 1-5 average) and after (Weeks 6-13 average) the dashboard deployment. Network density ($\rho$), representing the proportion of actual connections relative to all possible connections in the forum interaction network, was used as a primary indicator of overall group engagement. A paired-samples t-test (comparing average pre- vs. post-dashboard density across the three Moodle groups, though analysis ideally uses individual data if possible or appropriate MLM) indicated a statistically significant increase in forum density. The average density rose from $\rho = 0.30$ (SD = 0.05) before dashboard implementation to $\rho = 0.36$ (SD = 0.06) afterwards. This increase was statistically significant. The effect size was Cohen's d = 0.44, suggesting a medium effect of the dashboards on increasing interaction density. A comparison of MLD accuracy between students with prior exposure to AI tools and those without showed a significant difference, $t(89) = 4.2$, $p < .001$, $d = 0.44$, with higher accuracy among students who had prior experience. (See Figure 2).

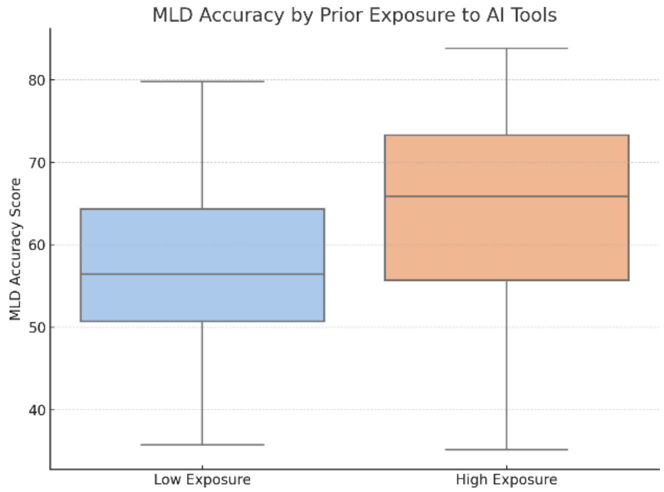


Figure 3. Comparison of MLD accuracy scores between students with and without prior AI

Reflective journals provided context for this quantitative finding. Some students explicitly mentioned the dashboards prompting them to engage more:

> *"The dashboard showed my group's low centrality score compared to others. It made me realize I wasn't contributing much, so I posted extra explanations for the library exercise to help out."* (Student G02, Reflection)

## 4.3 RQ3: Student Perceptions, Strategies, and AI Interaction Patterns

**Survey data provided insights into students' overall perceptions of the AI tool:**

- A large majority (82%) agreed or strongly agreed that using ChatGPT helped clarify Merise rules (Mean= 4.1 on a 5-point scale, SD = 0.7).
- Trust in the AI's suggestions for conceptual data modeling was relatively high, with 70% agreeing or strongly agreeing (M = 3.8, SD = 0.9).
- Intention to use AI tools for similar tasks in the future was also positive, with 65% agreeing or strongly agreeing (M = 3.6, SD = 1.0).

**Analysis of the 540 AI conversation transcripts revealed dominant interaction patterns and common query types:**

- Common Query Types: The most frequent type of support sought was Conceptual Clarification (42% of interactions coded), where students asked for explanations of Merise concepts (e.g., "What is the rule for a 1:1 relationship?"). Model Transformation assistance

(35%) was also common (e.g., "Convert this MCD to MLD"), followed by requests related to Syntax and Representation (23%) (e.g., "Show me this MLD in PlantUML format").

- Typical Workflow: A common pattern observed in transcripts involved students working through the modeling steps sequentially with AI validation: 1) Identifying entities/attributes, 2) Defining relationships and cardinalities (often asking AI to verify), 3) Requesting the MCD-to-MLD conversion, and 4) Asking for the output in a specific format like PlantUML or SQL table definitions.

## Thematic Analysis of Transcripts and Reflections:

**Qualitative analysis identified key themes regarding interaction strategies and perceptions:**

1. **Iterative Prompt Refinement:** Successful interactions often involved students asking follow-up questions, providing corrections to the AI, or refining their prompts based on initial AI responses. This iterative dialogue appeared crucial for resolving complex issues.

> **Student (G03): "I see a N:N between Student and Course. Should I create a separate table?"**
>
> **ChatGPT: "Yes---use ENROLL(StudentID, CourseCode) as a composite PK/FK table."**
>
> **Student (G03): "Okay, but what about the enrollment date attribute? Where does that go?"**
>
> **ChatGPT: "Good point. The enrollment date should be an attribute within the ENROLL junction table."**

2. **Critical Vetting of AI Output:** While students generally trusted the AI, many transcripts showed evidence of critical evaluation, where students questioned AI suggestions that seemed incorrect or inconsistent with lecture material.

> **Student (G01): "Why did you put UNIQUE constraint only on CourseCode in the Enroll table?**
> **Shouldn't the combination of StudentID and CourseCode be unique?"**
>
> **ChatGPT: "You are correct. My apologies. The primary key for the ENROLL table should indeed be a composite key comprising both StudentID and CourseCode to ensure each student can enroll in a specific course only once."**
>
> **Student (G01): "Understood, that makes more sense based on the rules."**

3. **Dashboard Literacy Gap and Interpretation:** Reflections indicated that while the SLA dashboards spurred engagement for some, their initial interpretation was not always intuitive.

> Reflection (Student G01): "At first, I didn't know what the density score $\rho=0.36$ meant or why my centrality was low. After the instructor explained how to read the dashboard in the class session, I understood better and tried to engage more with peers' questions on the forum."

**AI Response Evaluation (Based on Researcher Analysis of Transcripts):**

Our analysis of ChatGPT's responses within the transcripts revealed consistent strengths and weaknesses:

- **Strengths:** The AI demonstrated high accuracy (estimated >95% correctness in sampled transcripts) in designating primary and foreign keys during MLD transformation and correctly identifying the need for junction tables for many-to- many relationships. It also handled requests in multiple languages (French and English observed).

- **Weaknesses:** Common issues included inconsistencies in output formatting, occasional failure to enforce specific constraints (like UNIQUE constraints for identifying relationships derived from 1:1 MCD relationships), and sometimes omitting relationship verbs or details crucial for full semantic understanding of the Merise model.

# 5. DISCUSSION

This study investigated the combined impact of Social Learning Analytics (SLA) dashboards and Generative AI (ChatGPT) assistance on student learning and collaboration within a practice-oriented introductory Information Systems course focused on Merise database modeling. The findings offer valuable insights into the potential and challenges of integrating these technologies, interpreted here in relation to our research questions and the broader literature.

## 5.1 RQ1: The Potent Effect of AI Scaffolding on Modeling Accuracy

The most striking finding was the dramatic improvement in Logical Data Model (MLD) accuracy when students utilized ChatGPT assistance, evidenced by a 28-percentage point increase and a very large effect size (d=1.9). This confirms the potent capability of current GenAI models to act as effective cognitive scaffolds for complex, rule-based procedural tasks like Merise modeling (Wu, 2024; Nguyen et al., 2024). The AI likely achieved this by offloading significant cognitive load associated with recalling specific transformation rules, identifying correct primary/foreign key relationships, and applying normalization steps, allowing students to focus on understanding the process rather than getting bogged down in syntactic or minor rule errors. The qualitative data supports this, showing students actively using the AI for just-in-time conceptual clarification and step-by-step validation. This aligns with theories suggesting that reducing extraneous cognitive load facilitates deeper learning and schema acquisition (Paas et al., 2003). The high accuracy in PK/FK designation (>95%) observed in our analysis of AI responses further underscores the tool's reliability for core transformation tasks, making it a powerful practice aid.

## 5.2 RQ2: SLA Dashboards as Catalysts for Engagement, Mediated by Literacy

The introduction of SLA dashboards resulted in a statistically significant, medium-sized increase (d=0.44) in forum interaction density. This suggests that making collaborative activity visible can indeed act as a catalyst, prompting increased engagement within the learning community, consistent with SLA literature promoting metacognitive reflection on participation (Cohn et al., 2024; Khosravi et al., 2025). However, the effect size, while significant, was moderate compared to the AI's impact on individual performance.

Furthermore, the qualitative findings revealed a crucial mediator: dashboard literacy. Students only translated the visualized metrics (like density or centrality) into behavioral change (posting more, helping peers) after receiving explicit instruction on how to interpret the dashboards. This highlights that simply providing analytics is insufficient; effective pedagogical integration requires dedicated efforts to develop students' data literacy skills so they can understand and act upon the insights provided. Without this, dashboards risk being perceived as interesting but not actionable.

## 5.3 RQ3: Navigating AI Use: Strategies, Perceptions, & Synergy Gap

Students generally perceived the AI positively, particularly valuing its ability to clarify rules (82% agreement) and expressing relatively high trust (70% agreement). The thematic analysis revealed sophisticated interaction strategies beyond simple question- answering. The prevalence of iterative prompt refinement and critical vetting of AI outputs suggests that many students engaged with the AI not as a passive oracle but as an interactive partner, aligning with effective learning practices highlighted in recent GenAI research (Dehkhoda et al., 2024; Khosravi et al., 2025). This active engagement is crucial, given the AI's identified weaknesses in areas like constraint enforcement and formatting consistency. Students who critically evaluated and questioned the AI were better positioned to leverage its strengths while mitigating its weaknesses.

Despite the individual benefits of AI and the moderate engagement boost from SLA, the synergy between the two technologies was not strongly perceived by students, nor was it explicitly designed into the intervention beyond concurrent deployment. Students largely viewed the AI as a tool for individual task completion and the dashboards as a separate indicator of group activity. The theoretical potential for SLA insights to trigger or guide AI use (e.g., suggesting AI help for groups struggling with a concept identified in forums) was not realized in this implementation. This points to a need for more sophisticated integration designs in future work, potentially involving system-level connections or more structured pedagogical strategies that explicitly link collaborative awareness (from SLA) with targeted cognitive support (from AI).

## 5.4 Implications for Practice-Oriented IS Education

These findings have significant implications for educators teaching structured modeling or similar technical skills:

- Leverage AI as a Practice Tool: GenAI is a powerful tool for providing scalable, individualized practice and feedback on rule-based tasks. Educators should embrace it but structure its use.
- Teach AI Interaction Skills: Explicit instruction and practice in iterative prompting and critical evaluation of AI outputs are essential to move students beyond passive solution seeking towards active co-construction of knowledge.
- Integrate SLA with Purpose: SLA dashboards can foster collaboration but require dedicated instruction on data interpretation. Their impact may be amplified if linked to specific collaborative activities or pedagogical interventions.
- Design for Synergy: Future interventions should explore explicit links between SLA and AI, e.g., using forum analysis to recommend AI prompts, or prompting students to share and critique AI- generated solutions within their groups.

Ultimately, the effective integration of these technologies requires a pedagogical approach that guides students in using them thoughtfully as tools to enhance, not replace, their own critical thinking and collaborative skills, while also revealing the importance of contextual, cultural, and design factors in determining their effectiveness.

The substantial improvement in MLD accuracy between the manual and AI-assisted phases reflects what prior studies have suggested about AI's capacity as a cognitive scaffold (Wu, 2024; Nguyen et al., 2024). In our context, ChatGPT proved particularly effective in offloading procedural burdens, such as the application of transformation rules, allowing students to focus on higher-order understanding. This aligns with Cognitive Load Theory (Paas et al., 2003), where reducing extraneous load can promote deeper schema development. However, the success of AI assistance here was not automatic. Students who engaged in iterative prompt refinement and critical vetting of AI outputs demonstrated more meaningful learning gains than those who accepted AI suggestions without scrutiny. This reflects findings in other domains (Dehkhoda et al., 2024) that effective AI use depends on the learner's capacity for strategic interaction.

The moderate but significant increase in forum network density after dashboard deployment echoes earlier research showing SLA's ability to make collaborative dynamics visible (Cohn et al., 2024). Yet our qualitative data revealed that dashboard literacy acted as a gatekeeper: only after explicit explanation did many students interpret metrics like centrality in ways that informed their actions. This reinforces Khosravi et al.'s (2025) observation that visual analytics require targeted instructional scaffolding to translate awareness into behavior change.

Despite their concurrent deployment, SLA and AI in this study functioned more as parallel supports than as an integrated system. Only a few students organically connected the two: using SLA dashboards to identify low-engagement peers and then AI to craft targeted explanations for them. This gap between theoretical potential and practical use highlights a design opportunity. Future interventions might implement automated triggers whereby SLA data feeds into AI prompts, creating a feedback loop that supports both cognitive and social presence in the Community of Inquiry (CoI) framework.

The Algerian context introduces layers of complexity often absent from studies in English-dominant, resource-rich environments. Students navigated multiple languages: Arabic, French, and English, across lectures, AI interactions, and forum discussions. While ChatGPT handled both French and English competently, its English responses sometimes contained richer technical vocabulary, prompting some students to translate queries and outputs themselves. This bilingual or trilingual workflow occasionally deepened conceptual understanding, but for others, it added friction. SLA metrics may also have been influenced by language preferences, with students participating more actively in forums conducted in their strongest language.

These observations suggest that in multilingual contexts, tool design should explicitly account for language-switching behavior. For example, AI tools could offer instant bilingual outputs, while SLA dashboards might tag participation metrics by language, enabling instructors to identify patterns of engagement tied to linguistic comfort zones.

When viewed against the broader body of work, our findings reinforce several known principles while extending them into underexplored territory. Consistent with previous research, GenAI can dramatically improve performance on structured, rule-bound tasks when paired with active learner engagement (Nguyen et al., 2024; Kim, 2025). Similarly, SLA dashboards can motivate participation, provided that learners understand the metrics (Cohn et al., 2024). What our study adds is empirical evidence from a multilingual, resource-variable setting—demonstrating that these tools remain effective but must be adapted to local linguistic and cultural realities. This is particularly relevant for IS education in the Global South, where infrastructure, pedagogical traditions, and language diversity shape both the adoption and impact of educational technologies.

# 6. CONCLUSION

This study provides empirical evidence on the integration of Social Learning Analytics (SLA) dashboards and Generative AI (ChatGPT) within a practice-oriented introductory Information Systems course focused on the challenging task of Merise database modeling. Our mixed-methods investigation demonstrates that the thoughtful integration of these technologies can yield significant educational benefits. Generative AI proved to be a highly effective cognitive scaffold, substantially improving students' accuracy in transforming conceptual to logical data models ($d=1.9$). It facilitated learning by providing immediate, interactive support for rule application and procedural steps. Concurrently, the deployment of SLA dashboards led to a moderate but significant increase in collaborative engagement within course forums ($d=0.44$), suggesting that visualizing interaction data can foster greater participation and awareness. However, the study also underscores critical nuances: the effectiveness of AI is mediated by students' ability to engage in iterative prompting and critical evaluation, while the impact of SLA dashboards is contingent upon students' data literacy and explicit pedagogical guidance on interpreting and acting upon the visualized metrics. The anticipated synergy between SLA and AI requires deliberate instructional design to bridge the gap between social awareness and individual cognitive support.

Several limitations should be acknowledged when considering the implications of these findings. First, the study was conducted with a specific cohort of second-year computer engineering students at a single Algerian university; the results may not directly generalize to different student populations, academic disciplines, or cultural contexts.

Second, the AI tool used was the freely available version of ChatGPT prevalent during the study period; future iterations or different AI models might yield different results regarding accuracy or interaction patterns. Third, the comparison between 'Manual' and 'AI-assisted' phases on the same exercises might introduce practice effects, although the large effect size for AI assistance suggests a substantial tool-specific impact. Fourth, the measurement of MLD accuracy relied on a specific rubric, and while inter-rater reliability was high ($\kappa=0.83$), evaluating complex models inherently involves some subjectivity.

Similarly, survey data relies on self-reporting, which can be subject to biases. Fifth, tracking the precise cognitive processes and the depth of understanding gained through AI interaction solely via transcripts is inherently limited. Finally, while we attempted to control the context, factors like instructor variations across the three Moodle groups (if any) or individual student motivation levels were not fully isolated.

The outcomes of this study carry several practical lessons for those designing and implementing technology-supported teaching in Information Systems education, particularly in settings where students differ in language proficiency, digital skills, and access to infrastructure.

- **For Educators:**

Purposeful AI Use: Generative AI should be woven into the learning process with clear intentions, not simply offered as an optional extra. In our course, the best results came when AI use was tied to specific stages of the modeling process, with students guided on how to frame questions and evaluate answers.

Making Dashboards Understandable: SLA dashboards are not self-explanatory. Students benefit from concrete, course-specific examples showing how metrics relate to their actual behaviors. Without this, data visualizations remain decorative rather than transformative.

Mindful of Language: In multilingual environments, educators may need to coach students on when and why to use different languages with AI and in forums. This not only eases interaction but can also reduce misunderstandings caused by inconsistent terminology.

- **For Students**

Treat AI as a Collaborator: Those who engaged in a back-and-forth with AI, refining prompts and checking its advice against other resources, gained more than those who used it passively.

Using Dashboards for Self-Monitoring: SLA metrics can be more than performance snapshots; they can help set participation goals, track personal growth, and guide decisions about when and how to contribute in collaborative spaces.

- **For Developers and Learning Technologists**

Stronger AI–Analytics Links :There is clear potential in letting SLA metrics drive AI responses. Imagine dashboards that flag low peer engagement and instantly suggest AI-generated actions to re-engage the group.

Built-In Language Sensitivity: AI platforms could provide answers in more than one language at once, while SLA systems could track participation trends by language, allowing educators to spot and address any gaps.

- **For Policymakers and Leaders**

Ensuring Access: Reliable internet and suitable devices are prerequisites for meaningful adoption. Without these, even the most innovative tools will fail to reach all students equally.

Teacher Training: Professional development should go beyond technical instructions and include pedagogical strategies for integrating these tools in ways that respect cultural and linguistic realities.

Scaling Responsibly: Pilots can test SLA–GenAI integration in various subjects and institutions before committing to wider deployment, allowing for context-specific adjustments.

The results of this study offer several practical implications for educators, instructional designers, developers, and policymakers seeking to integrate SLA and GenAI into practice-oriented IS curricula, particularly in contexts marked by multilingualism, diverse digital literacy levels, and variable infrastructure.

This work opens a number of directions for further investigation.

1. Cross-Institutional Studies: Repeating the study in multiple institutions and countries could show whether the improvements here hold in different environments. Multilingual and monolingual groups could be compared to see how language diversity shapes both tool adoption and learning gains.

2. Longer-Term Tracking: Following students beyond a single course would reveal whether AI and SLA support have lasting benefits, improving skills in later classes or even influencing workplace performance.

3. True SLA–AI Integration: Rather than running in parallel, future tools could connect the two systems directly. For example, if a dashboard detects a drop in participation, the AI could generate tailored prompts or tips in real time.

4. Different Domains and Tasks: While this study centered on Merise modeling, the approach could be tested in programming, UML design, or data analysis to see whether structured and creative tasks respond differently to SLA–AI support.

5. Adaptive Language Features: Research could explore whether presenting AI output in a student's preferred language (or in multiple languages side-by-side) improves comprehension and reduces workload.

6. Role of Instructor Mediation: Future work should examine how much guidance is optimal. Does detailed, step-by-step mediation yield better results than minimal intervention, or does it risk over-scaffolding?

7. Equity and Inclusion: It is worth exploring whether certain groups (such as those with lower digital literacy) need additional support to benefit equally from these tools. Without careful design, technology can unintentionally widen gaps it aims to close.

As a single-institution, case-based study, our findings are closely tied to the specific environment in which the work took place, namely, a second-year IS course at an Algerian university. The multilingual nature of the setting, with varying levels of Arabic, French, and English proficiency, as well as differences in digital literacy, may have influenced how students engaged with both AI and SLA tools.

The design compared manual and AI-assisted work on similar tasks, which carries a risk of practice effects, though the magnitude of improvement suggests that the tools themselves played a significant role. Evaluating MLD accuracy involved human judgment, even with strong inter-rater agreement, and self-reported survey responses may have been shaped by social desirability bias. Finally, because the SLA and AI tools were not tightly integrated, our ability to study their combined effect was limited, something future, more connected implementations could address.

Based on our findings, we offer the following recommendations:

**For Educators:** Embed AI use into clearly defined learning activities, train students to evaluate AI-generated content critically, and ensure dashboard literacy through explicit teaching. Create moments where SLA insights inform AI interactions, so the two tools actively reinforce one another.

**For Students:** Approach AI as a conversation partner, not an answer machine. Use dashboards as a mirror for your engagement habits and challenge yourself to take on more active roles in collaborative work.

**For Developers:** Build domain-aware AI features (e.g., automatic validation for modeling diagrams) and explore ways to connect SLA analytics with AI-driven support.

**For Researchers:** Investigate integrated SLA-AI systems across multiple contexts, using longitudinal designs to see how skills and engagement evolve over time.

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