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Human-Centered Learning Analytics for ERD Education: A Needs Analysis of Dashboard Requirements

Hasna Nabhan Arasy [1,*], Eki Nugraha [1], Rasim [1]

[1] Universitas Pendidikan Indonesia, Indonesia
[*] Corresponding author: Hasna Nabhan Arasy, Universitas Pendidikan Indonesia, Indonesia
hasnanabhan23@upi.edu

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Abstract
Learning to construct Entity Relationship Diagrams (ERDs) is challenging for secondary vocational students, because it requires both conceptual understanding and formal diagramming skills. This cross-sectional study identified learner needs and translated them into requirements for a human-centered learning analytics dashboard. A quantitative survey was administered to 25 Grade 10 Software and Game Development students. Descriptive results showed a stronger understanding of entities ($M = 3.84$, $SD = 0.62$) and attributes ($M = 3.80$, $SD = 0.65$) than of formal ERD symbols ($M = 3.40$, $SD = 0.76$), which was categorized as moderate. Cardinality confusion ($M = 3.56$, $SD = 0.77$) co-occurred with self-reported fear of design errors ($M = 3.48$, $SD = 0.71$) without establishing causality. The dashboard feature requirements received the highest construct score ($M = 4.08$, $SD = 0.62$), and real-time error confirmation and dialogic hints had the highest item means (both $M = 4.16$). These findings highlight the requirements for automated diagnostics, scaffolded hints, competency visualization, and constructive feedback. The main contribution is a Design Translation Framework that links learner problems, empirical scores, priorities, functional requirements, and pedagogical rationales. The study specifies design requirements; it does not test platform effectiveness.

Keywords: actionable feedback; entity relationship diagram; human-centered design; learning analytics; vocational education

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INTRODUCTION

Conceptual data modelling is an essential skill in database and software engineering education, as it necessitates the translation of real-world requirements into formal representations of entities, attributes, relationships, and constraints. Entity Relationship Diagrams (ERDs) are extensively employed for this purpose. However, novice learners often find the construction of ERDs cognitively challenging because of the need for abstraction, interpretation of domain semantics, and the concurrent application of modelling rules. Empirical research indicates specific challenges in defining relationships and cardinalities (Rosenthal et al., 2023). According to Cognitive Load Theory, these challenges may occur when the interaction of multiple elements surpasses the working-memory capacity of learners (Paas & van Merriënboer, 2020).

Learning Analytics Dashboards (LADs) can aid learners by offering feedback based on data, tracking progress, and providing visual displays of learning outcomes. Nonetheless, their educational effectiveness depends on whether the information facilitates significant learning choices. Historically, many LADs have focused more on descriptive metrics than on providing actionable insights (Susnjak et al., 2022). Further reviews highlight that feedback is most beneficial when prompt, understandable, and actionable (Banihashem et al., 2022). Studies on dashboards designed for learners also point out discrepancies between the intended goals and foundational educational principles (Valle et al., 2021a). Although recent studies suggest a trend towards dashboards that are more aligned with educational principles, the primary functions remain monitoring and awareness (Paulsen & Lindsay, 2024).

This study is situated within the realm of human-centered Learning analytics (HCLA), which prioritizes educational objectives and the requirements of stakeholders over mere data availability. Recent studies on HCLA underscore the role of learners as proactive contributors to the creation and understanding of analytics systems (Alfredo et al., 2024; Buckingham Shum et al., 2024). This viewpoint is further supported by Cognitive Load Theory and the concept of feedback literacy. Cognitive Load Theory underscores the necessity for organized assistance in intricate ERD tasks, while feedback literacy pertains to learners' ability to comprehend and utilize feedback effectively (Carless & Boud, 2018; Woitt et al., 2025). These viewpoints are also consistent with learning analytics research that connects learning behavior, instructional design, and self-regulated learning (Fan et al., 2021).

Crucially, providing additional information or more complex visualizations does not necessarily improve learning outcomes. The way feedback is presented in dashboard interventions can lead to varying cognitive and emotional reactions, and certain types of motivational support may even heighten student anxiety (Valle et al., 2021b). Students also have different perceptions of which dashboard information is beneficial (Rets et al., 2021). Recent findings suggest that feedback derived from analytics can boost perceived usefulness, encourage reflection, and promote self-regulation, although its success is influenced by learners' ability to understand feedback (Weidlich et al., 2025). Consequently, feedback should be viewed as a process that facilitates understanding and subsequent action rather than merely conveying performance metrics (Jensen et al., 2021).

Another limitation pertains to the educational environment. Research on learning analytics is more advanced in higher education than in primary and secondary education, where learner traits and teaching frameworks vary (Paolucci et al., 2024). While recent investigations have started to explore human-centered dashboard design in K–12 education and context-aware personalization in STEM learning (Bin Qushem et al., 2025; Wiley et al., 2024), the available evidence is still relatively sparse. Historically, large-scale dashboard studies have predominantly concentrated on university contexts (Broos et al., 2020). As a result, there is limited understanding of how the cognitive and emotional challenges faced by secondary vocational students in ERD learning shape the requirements of learner-facing dashboards.

The scientific gap arises not only from the limited availability of Learning Analytics Dashboards (LADs) specifically designed for ERD instruction, but also from the lack of empirical linkage between domain-specific learning challenges and dashboard requirements. Rosenthal et al. (2023) highlight persistent learner difficulties in conceptual modelling, particularly in interpreting cardinality, translating abstract cases, and representing relationships through formal notation. Simultaneously, LAD research demonstrates how analytics can support monitoring, reflection, and timely feedback during the learning process (Alfredo et al. 2024). However, these two research streams have rarely been integrated during the requirement-analysis stage. Consequently, a human-centered approach is needed to establish clear traceability between empirical learner evidence and subsequent design decisions, particularly for addressing challenges related to cardinality reasoning, abstract case transformation, symbolic representation, and learning anxiety (Alfredo et al., 2024; Rosenthal et al., 2023).

This research explores the conceptual grasp of secondary vocational students, their challenges with ERD modelling, learning-related anxiety, and their preferences for analytics-based assistance. These insights were utilized to outline and prioritize the functional needs of the LogicERD Academy Learning Analytics Dashboard. The primary contribution of this study is the conversion of real learner challenges into specific dashboard requirements, moving beyond generic analytics metrics. This conversion is structured using a Design Translation Framework, which connects learner issues, empirical data, priority rankings, suggested features, and educational considerations. Thus, the framework offers a more context-aware foundation for creating analytics support for learners in secondary vocational database education. As the research was confined to the requirement-analysis phase, further exploration through implementation and experimental assessment is necessary to understand the impact of the dashboard on learning outcomes, cognitive load, and anxiety.

METHOD

This study used a descriptive cross-sectional needs analysis design within a human-centered design (HCD) framework. The purpose was to convert reported learner needs into functional Learning Analytics Dashboard (LAD) specifications; the design was not intended to test an intervention or establish causal relationships. The study was conducted at SMK Al Falah Bandung with a purposive sample of 25 Grade 10 Software and Game Development students (Class X PPLG 3). Students were eligible if they had completed the foundational database theory and participated in ERD exercises. Students who did not complete the core modules were excluded. Purposive sampling was appropriate for this exploratory, context-bound requirements study because participants needed direct experience with the target-learning task (Campbell et al., 2020). The sample supports initial requirement elicitation but does not permit statistical generalization.

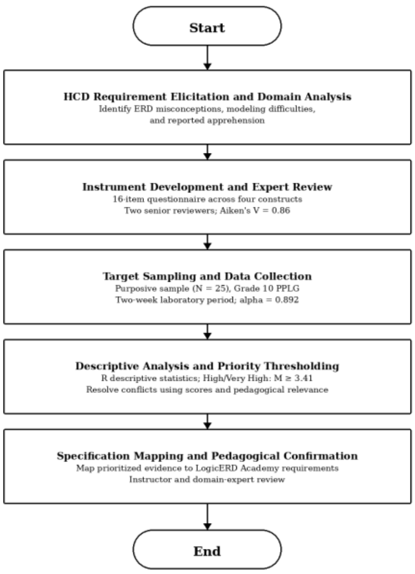

Figure 1. Research workflow for human-centered learning analytics dashboard requirement engineering

Data were collected in April 2026 during a two-week laboratory period using a 16-item five-point Likert questionnaire covering four constructs. Two senior computer science education lecturers with expertise in database instruction and educational technology reviewed each item for relevance and clarity. Their comments were reconciled by the research team, and item wording was revised before administration; the resulting content validity coefficient was

Aiken's V = 0.86. The internal consistency was high (Cronbach's alpha = 0.892). Descriptive statistics were computed in R. Scores in the High and Very High intervals ($M \geq 3.41$) were considered during feature prioritization, while the final priority tier also reflected the corresponding feature-preference score and pedagogical relevance. Course instructors and domain experts then reviewed the proposed specifications, and comments were discussed and incorporated until agreement was reached on the final mapping.

This study employed a five-stage methodological process, as illustrated in Figure 1. The first stage involved domain needs elicitation to identify ERD misconceptions, modelling difficulties, and reported apprehension. The questionnaire was subsequently developed and reviewed by two senior lecturers before it was administered to a purposively selected sample. A descriptive analysis was then conducted to determine the relative prominence of learner needs and preferences. In the final two stages, the empirical findings were translated into the proposed functional requirements and subsequently reviewed for pedagogical relevance. Therefore, this workflow represents the methodological process used to derive the requirements, and the resulting requirements are presented in the Results section.

RESULTS AND DISCUSSION

Results

Based on the results of the ERD learning needs analysis presented in Table 1, students generally demonstrated a good level of understanding of fundamental Entity Relationship Diagram (ERD) concepts, with the overall score for the “Understanding of ERD Concepts” construct reaching M = 3.70 (SD = 0.68), which was categorized as High. Students showed a stronger understanding of basic ERD components, particularly in understanding entities and their functions (M = 3.84, SD = 0.62) and identifying appropriate attributes for each entity (M = 3.80, SD = 0.65). These findings indicate that the students were relatively capable of recognizing the main objects in the database system and identifying the characteristics associated with each object. However, understanding of formal ERD symbols obtained the lowest score (M = 3.40, SD = 0.76) and was categorized as moderate, suggesting that students had better conceptual knowledge of ERD components than their ability to represent those concepts using formal graphical notation.

In addition to conceptual understanding, the results revealed that the students still experienced difficulties during the ERD modeling process. The “Modeling Obstacles and Anxiety” construct achieved a mean score of M = 3.63 (SD = 0.71), categorized as High, indicating that students faced challenges when applying ERD concepts to practical modeling tasks. These difficulties were reflected in several areas, including confusion about relationship cardinality (M = 3.56, SD = 0.77), difficulty in converting real-world cases into ERD diagrams (M = 3.72, SD = 0.68), and the perception that ERD materials were too abstract to visualize (M = 3.76, SD = 0.72). Students also reported concern about making mistakes when designing an ERD (M = 3.48, SD = 0.71), indicating the need for learning support mechanisms that can provide guidance and feedback throughout the modeling process.

Regarding learning support preferences, the “Interest in Visualization Tools” construct obtained a score of M = 3.79 (SD = 0.66), categorized as High, indicating that students showed strong interest in visual-based support to facilitate ERD learning. The highest-rated need within this construct was the ability to visualize mastered and unmastered topics (M = 3.92, SD = 0.64), suggesting that students required information about their learning progress and areas that required further improvement. Students also expressed interest in applications that provided clear learning statistics (M = 3.88, SD = 0.60) and preferred achievement-oriented information rather than only numerical grades (M = 3.76, SD = 0.66). These findings indicate that students preferred more meaningful representations of their learning progress and competency development.

Furthermore, the "Dashboard Feature Requirements" construct received the highest score among all constructs, with M = 4.08 (SD = 0.62) and was categorized as High. This result indicates that students had strong expectations for learning dashboard features that could provide direct assistance during ERD construction. The most prioritized features were real-time error confirmation and dialogic hints, both of which received the highest mean score of M = 4.16, followed by concrete improvement suggestions with M = 4.08.

Overall, the findings from Table 1 indicate that although students possessed adequate foundational knowledge of ERD concepts, particularly regarding entities and attributes, they still encountered challenges in applying these concepts to diagram construction, interpreting relationships among entities, and correcting modeling errors. Therefore, needs analysis provides evidence for designing a human-centered learning dashboard that incorporates automated feedback, step-by-step guidance, competency visualization, and constructive improvement recommendations. These findings serve as the basis for defining dashboard requirements rather than demonstrating the effectiveness of an implemented system.

Table 1. Results of the student needs analysis for erd learning

Construct/Sub-indicator	Mean	SD	Category	Rank
Understanding of ERD concepts	**3.70**	**0.68**	**High**	**-**
Understanding entities and their functions	3.84	0.62	High	3
Identifying appropriate attributes for each entity	3.80	0.65	High	4
Understanding relationships among database entities	3.76	0.72	High	5
Understanding formal ERD symbols	3.40	0.76	Moderate	12
Modeling obstacles and anxiety	**3.63**	**0.71**	**High**	**-**
Confusion about relationship cardinality	3.56	0.77	High	10
Difficulty converting real-world cases into diagrams	3.72	0.68	High	8
ERD material is too abstract to visualize	3.76	0.72	High	5
Fear of making mistakes when designing an ERD	3.48	0.71	High	11
Interest in visualization tools	**3.79**	**0.66**	**High**	**-**
Greater enthusiasm for learning through visualizations	3.60	0.71	High	9
Interest in applications that display clear statistics	3.88	0.60	High	2
Preference for achievement data over numerical grades	3.76	0.66	High	5
Need to visualize mastered and unmastered topics	3.92	0.64	High	1
Dashboard feature requirements	**4.08**	**0.62**	**High**	**-**

Table 2 presents the Requirement Mapping Matrix for the Design Translation Framework, which describes how learner problems were translated into proposed dashboard requirements through the sequence of learner problems, empirical scores, priority decisions, functional requirements, and pedagogical rationale. The first mapping addresses cardinality confusion and difficulties in understanding formal ERD symbols. Students reported difficulties with cardinality (M = 3.56, SD = 0.77) and formal symbols (M = 3.40, SD = 0.76; moderate). These findings resulted in a critical priority for real-time error confirmation (M = 4.16), accompanied by a complementary requirement for symbol support. Accordingly, the proposed function consists of an automated diagnostic feedback system integrated with a contextual symbol guide. This function was intended to provide immediate explanations, clarify the meaning and use of ERD symbols, and support students in producing accurate diagram maps.

The second mapping addresses the challenge of translating real-world scenarios into diagrams and the difficulty of visualizing abstract ERD concepts. These issues were evident in the scores for case conversion (M = 3.72, SD = 0.68) and abstraction (M = 3.76, SD = 0.72). This requirement was deemed critical for dialogic hints (M = 4.16), leading to the development of a dialogic hint-scaffolding module to assist students with complex modeling tasks. The third mapping relates to fear of design mistakes and self-reported learning anxiety (M = 3.48, SD = 0.71). It was classified as a supporting priority based on students' preference for improvement suggestions (M = 4.08). The proposed requirement involves providing constructive, actionable feedback messages to offer supportive guidance instead of punitive error notifications.

The fourth mapping highlights a preference for visual representations of achievement information over numerical grades. The importance of visualizing both mastered and developing topics was rated at M = 3.92 (SD = 0.64), resulting in a supporting priority and the creation of interactive competency visualizations to aid reflection and self-regulation. As shown in Table 2, learner evidence was converted into four suggested dashboard functions: automated diagnostic feedback, dialogic hint scaffolding, constructive actionable feedback, and competency visualization. These functions are based on evidence-based design requirements, and have not yet been implemented or evaluated as learning outcomes.

Table 2. Requirement mapping matrix for the design translation framework

Learner Problem	Empirical Score	Priority Decision	Functional Requirement	Pedagogical Rationale
Cardinality confusion and difficulty with formal ERD symbols	Cardinality: M = 3.56, SD = 0.77; symbols: M = 3.40, SD = 0.76 (Moderate)	Critical for error confirmation (preference M = 4.16); Complementary for symbol support	Automated diagnostic feedback with a contextual symbol guide	Provide immediate formative explanations and support accurate diagram mapping.
Difficulty converting real-world cases and visualizing abstract ERD material	Cases: M = 3.72, SD = 0.68; abstraction: M = 3.76, SD = 0.72	Critical for dialogic hints (preference M = 4.16)	Dialogic hint-scaffolding module	Break complex modeling tasks into guided, reflective steps.
Fear of design errors and self-reported learning anxiety	M = 3.48, SD = 0.71	Supporting (improvement suggestions M = 4.08)	Constructive, actionable feedback messages	Replace punitive alerts with guidance intended to support confidence and feedback.
Preference for visual achievement information over numerical grades	Mastery view: M = 3.92, SD = 0.64; achievement data: M = 3.76, SD = 0.66	Supporting (3.70-4.09)	Interactive competency visualization	Mastered and developing topics to support reflection and self-regulation.

The analysis of requirement mapping resulted in four suggested dashboard features, each catering to different learner requirements: automated diagnostic feedback, dialogic hint scaffolding, constructive actionable feedback, and competency visualization. Figure 2 provides a summary of the analytical findings from the Results section, illustrating the conversion of survey data and decision rules into the proposed dashboard requirements. The concluding box outlines the intended types of pedagogical support, rather than the outcomes shown by the current study, as the LogicERD Academy has not yet been implemented or evaluated.

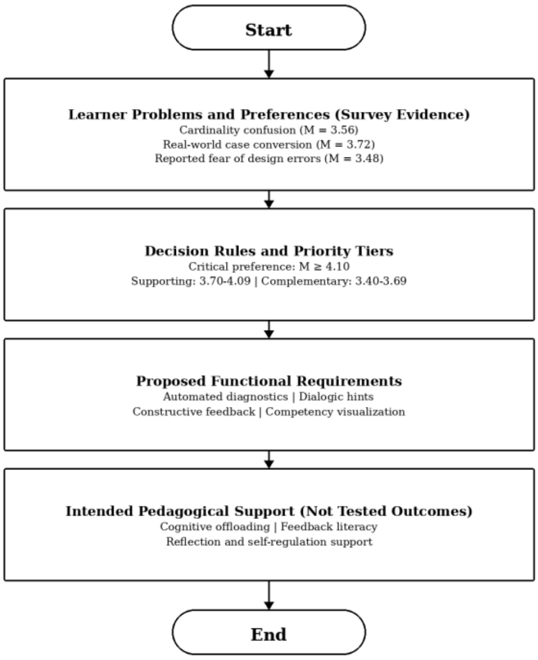

Figure 2. Design translation framework from learner evidence to dashboard requirements

Discussion

According to this study, secondary vocational students demonstrated a more robust grasp of ERD components, particularly entities and attributes. However, they faced more difficulties when it came to using this knowledge to create formal diagrams. Additionally, students placed high value on dashboard features that offered instant error feedback, interactive guidance, and visualization of skill progression. These results fulfil the research goal by identifying evidence-based needs for a human-centered learning analytics dashboard rather than showcasing the success of a system already in place.

The findings indicate a distinction between declarative knowledge and operational modeling competence. Although students may recognize ERD concepts, constructing accurate models requires the simultaneous coordination of semantic interpretation, relationship constraints, cardinality, and graphical representation. This pattern supports Cognitive Load Theory, suggesting that structured scaffolding and contextual feedback may help manage the complexity of ERD modeling tasks (Paas & van Merriënboer, 2020). The findings also reinforce feedback literacy perspectives, which emphasize that analytics information becomes educationally meaningful when learners can interpret and act upon feedback rather than simply receiving performance indicators (Carless & Boud, 2018; Jensen et al., 2021; Woitt et al., 2025).

These findings are consistent with previous learning analytics research highlighting the importance of actionable feedback, reflection support, and self-regulated learning (Banihashem et al., 2022; Fan et al., 2021; Paulsen & Lindsay, 2024). This study extends the existing evidence in two important ways. First, it focuses on secondary vocational learners in a specific knowledge domain, namely ERD education, where learning difficulties involve conceptual abstraction and modeling processes. Second, unlike studies evaluating existing dashboards, this study addresses the requirement-analysis stage by establishing a traceable connection between learner difficulties and dashboard specifications (Alfredo et al., 2024; Buckingham Shum et al., 2024).

An important finding was the difference between the students' relatively moderate difficulty with formal ERD symbols and their strong preference for real-time support. This suggests that the primary challenge may not be isolated knowledge deficiency, but rather the integration of multiple knowledge elements during authentic modeling activities. While this interpretation is theoretically aligned with cognitive load perspectives, future research using behavioral data, learning traces, and performance-based assessments is required to confirm this mechanism.

The main scientific contribution of this study is the Design Translation Framework, which provides a systematic approach for translating learner evidence into pedagogically justified dashboard requirements. Unlike conventional dashboard development approaches, which often begin with available data or technical functions, this framework establishes traceability among learning problems, empirical evidence, priority decisions, functional features, and pedagogical purposes. Thus, this study contributes to human-centered learning analytics by demonstrating a context-sensitive requirement engineering process for educational technology design (Alfredo et al., 2024).

These findings have practical implications for instructional design and educational technology development. Teachers can use the identified learning difficulties to strengthen ERD instruction through scaffolding and formative feedback, whereas developers can use the requirement mapping process to design learner-facing analytics features with explicit pedagogical objectives. However, these implications should be interpreted as design guidance rather than evidence of improved learning outcomes.

Several limitations of this study should be considered when interpreting these findings. The purposive sample from a single vocational institution limits transferability to other educational contexts, and the cross-sectional self-report design reflects students' perceived difficulties, rather than objectively measuring cognitive processes or learning behaviors. Furthermore, because the proposed dashboard has not yet been implemented or evaluated, its effects on learning achievement, self-regulation, and feedback literacy are yet to be established. Future studies should validate the framework through prototype implementation, usability evaluation, integration of learning analytics data, and longitudinal or quasi-experimental research designs.

CONCLUSION

This study enhances human-centered learning analytics during the pre-implementation phase by converting domain-specific learner data into traceable dashboard specifications for secondary vocational ERD education. The primary contribution is the Design Translation Framework, which links learner challenges, descriptive scores, priority rules, functional requirements, and pedagogical justifications prior to development. Unlike studies focused on performance visualization or existing dashboards, this study provides requirements process informed by evidence specifically tailored to the conceptual, procedural, and reported emotional needs of vocational learners. While it aids in design decisions, it does not assess platform effectiveness. The study's small, single-institution, cross-sectional sample restricts claims, necessitating future longitudinal validation.

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