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Dimensional Structure of Student Perceptions in AI-Supported Avatar Learning Environments

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Abstract
As artificial intelligence (AI) is being integrated into various learning environments, more research is needed to examine how students structurally organise their perceptions when using such technology. This explorative study investigated the dimensional structure and reliability of student perceptions of an AI-assisted instructional avatar among a cohort of postgraduate students. A cross-sectional survey was administered using Google Forms, yielding 65 responses following engagement with the avatar instructional sessions. Exploratory factor analysis using principal axis factoring with oblimin rotation yielded a two-factor solution comprising perceived learning support (PLS) and cognitive engagement (CE). These findings provide structural evidence for improving an understanding of how students organise their perceptions when receiving technology-supported instruction and shed new light on how students experience AI-assisted avatars. The findings also offer insights into the design and evaluation of technology-based learning environments and inform the effective integration of avatars as pedagogical tools.

Keywords: avatars, artificial intelligence, education, student perceptions, exploratory factor analysis.

1. Introduction

Artificial intelligence (AI) is becoming increasingly visible in higher education (Abdallah et al., 2025), with universities adopting AI-driven tools to support teaching, learning, and assessment practices (Abdallah et al., 2025; Stöhr et al., 2024). Recent developments have led to the emergence of conversational agents and AI avatars that interact with students in more natural and responsive ways, moving beyond one-dimensional digital resources towards systems that actively support learning processes (Fink et al., 2024). AI-based instructional systems are commonly positioned as learning support agents, offering personalised explanations, timely feedback, and ongoing guidance that may complement or extend traditional teaching approaches (ElSayad & Mamdouh, 2025). Studies on educational conversational agents and AI-mediated instruction indicate that the effectiveness of AI-supported learning environments depends not only on technical functionality but also on how students experience and interpret their interactions with these systems (Al-Mamary & Alshammari, 2026; Botelho et al., 2025).

Research exploring AI avatars proposes that features such as social presence, responsiveness, and perceived human likeness shape student engagement and trust (Raave et al., 2026; Tan et al., 2025). More broadly, the adoption, application, and educational value of AI-supported learning technologies are strongly influenced by student perceptions (Al-Mamary & Alshammari, 2026). How students perceive instructional support affects their motivation and willingness to incorporate these systems into their learning practices (Alrajhi, 2024; ElSayad & Mamdouh, 2025). Positive student perceptions are associated with increased trust, sustained interaction, and meaningful cognitive engagement, whereas negative perceptions may limit the potential benefits (Bahçekapılı, 2023; Pereira et al., 2023). Despite this, existing research has largely focused on adoption drivers, performance expectancy, and behavioural intention, with comparatively limited attention on how students structure and organise their experiences of interacting with AI-driven instructional agents (Al-Mamary & Alshammari, 2026; Muneer et al., 2026). Although constructs such as usefulness, trust, enjoyment, and engagement are frequently examined, they are often treated as separate variables in technology acceptance frameworks. Comparatively little attention has been given to how these perceptions collectively constitute a coherent student experience (Fošner, 2024).

Despite the growing use of avatar-supported learning in education, there remains conceptual ambiguity regarding how students structure their perceptions of these tools. As most research treats constructs such as trust and usefulness as isolated variables, it remains unclear whether AI avatar-supported learning is perceived as a unified experience or as comprising distinct but related dimensions such as instructional support and engagement with learning tasks (Scaffidi Abbate et al., 2025; Zhang et al., 2025). This uncertainty regarding the underlying structure of student perceptions constitutes the problem addressed in this study. Given this conceptual ambiguity, exploratory approaches are appropriate for examining student perceptions in AI avatar-based instructional contexts.

Exploratory analyses allow latent perceptual dimensions to emerge from student data, providing insight into how instructional, affective, and interactional elements are organised within specific settings (Ferguson et al., 2025; Tang & Austin, 2009). Research further demonstrates that student perceptions are multifaceted and shaped by both cognitive and social factors, including engagement quality and interactional features (Howlader et al., 2025; Muneer et al., 2026; Tang & Austin, 2009). Therefore, identifying the underlying structure of student perceptions provides a stronger conceptual foundation for understanding AI-supported avatar instruction and offers a more precise evaluation of AI learning environments. When examining perception structures, it is also necessary to assess the reliability of any constructs derived from student data (Vázquez-Parra et al., 2024). Ensuring reliability confirms that identified dimensions represent stable and internally consistent aspects of the student experience (Vázquez-Parra et al., 2024). In addition to structural and reliability considerations, descriptive insights remain practically valuable, as students may recognise both benefits and concerns when engaging with AI-supported learning environments (Campillo-Ferrer et al., 2025; Miranda, 2025).

Taking the preceding discussion into account, the purpose of this study was to examine the factor structure underlying students' perceptions of AI-assisted avatar instruction and to evaluate the internal consistency of the identified dimensions. By shedding light on the dimensional structure and reliability of student perceptions, the study contributes exploratory evidence concerning student perceptions of AI-supported avatar instruction. The study ultimately identifies two related but distinct dimensions: perceived learning support (PLS) and cognitive engagement (CE).

2. Methodology

Characteristics of the Research Instrument

An extensive literature review was initially conducted to determine the scope of AI and student learning, covering areas such as AI in education, pedagogical agents, and self-regulated learning. From the initial readings, questions were adapted in line with the purpose of the research, which pertained to student perceptions of learning with an AI-assisted avatar. Ten items were included, adapted from extant literature, as shown in Table 1. To ensure validity, no new questions were developed; rather, the underlying constructs were established in the literature and applied to questions on research proposal development. The questions were measured using a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The items were further labelled to reflect the essence of each question, as shown in Table 1, and covered aspects ranging from perceived instructional support to overall learning experience. Given that items were adapted from existing instruments, construct validity was assessed through exploratory factor analysis (EFA) to examine the underlying structure of student perceptions in the sample. In addition, the internal consistency of the measurement instrument was assessed using Cronbach's alpha.

Table 1: Questionnaire items

Item	Label	Adapted from
1. The AI avatar was effective in teaching research proposal development	Perceived instructional effectiveness	Tan (2024)
2. The AI avatar helped me understand the structure and components of a research proposal	Structural knowledge acquisition	Tan (2024)
3. The AI avatar made the content more engaging compared to traditional teaching methods	Student engagement	Netland et al. (2025)
4. I feel confident in applying what I learned from the AI avatar to my research proposal	Task self-efficacy	Lin et al. (2020)
5. The AI avatar provided explanations or content in a way that was clear and easy to understand	Instructional clarity	Netland et al. (2025)
6. Learning from the AI avatar encouraged me to take more responsibility for my learning process	Student autonomy	Mohebbi (2025)

7. The AI avatar helped me stay accountable for completing tasks and meeting deadlines in the module	Adherence to schedule	Bellhäuser et al. (2023)
8. The AI avatar contributed to my ability to critically reflect on and improve my research proposal	Critical reflection support	Mohebbi (2025)
9. The AI avatar motivated me to engage more deeply with the module content	Intrinsic motivation	Lin et al. (2020)
10. Overall, I believe the AI avatar enhanced my learning experience in this module	Overall learning experience	Netland et al. (2025)

Participants and Data Collection

A cross-sectional survey was administered among postgraduate students enrolled at a South African university. The implementation occurred within the "Applied Research: Internal Auditing" module. Google Forms was used to collect data towards the end of the first half of 2025 and was administered to students following their engagement with five mandatory AI-supported avatar instructional sessions. The link to the survey was made available on the learning management system Moodle for easy access by participants. All students registered for the module were eligible to participate in the study. Of the 73 registered students, 65 responses were received, representing an 89% response rate. Any incomplete or invalid responses were to be excluded prior to analysis; none were identified.

The students received instructional support from an AI-assisted avatar regarding the mechanics of research proposal development. The AI instructional videos were facilitated using Animaker, a cloud-based SaaS platform for creating animated videos. Pedagogically, the avatar delivered video-based lectures featuring audio narration and synchronised physical gestures to enhance social presence. The avatar delivered standardised instructional material to all students. The material was developed by transcribing traditional lecture slides developed by the lecturer, refined using ChatGPT to ensure a conversational, student-friendly tone. Additional examples were generated to further support learning. Thereafter, the instructional scripts were vetted by the lecturer for accuracy and completeness of the content in line with the learning outcomes of the module. To prevent passive consumption, the videos also incorporated embedded interactive checkpoints based on the content covered that required student input before the lecture could proceed.

Statistical Analysis

IBM SPSS statistical package, Version 30 was used to conduct statistical analysis. Exploratory factor analysis was conducted using principal axis factoring with the oblimin rotation method. This approach was selected based on the anticipated correlations between factors. The Kaiser–Meyer–Olkin and Bartlett tests were administered to determine the adequacy of the model. Factors were retained based on eigenvalues greater than 1, supplemented by inspection of the scree plot. Items were retained if their primary loadings were greater than .40 on a single factor. Items with substantial cross-loadings were examined, but no items met the criteria for removal.

Scale scores were computed by calculating the mean of participants' item responses for each factor. Subsequent analysis was based on the newly created scales after EFA. The internal consistency of the scales was established by calculating Cronbach's alpha coefficients. Basic descriptive statistics were computed for the factor-derived scales, including means and standard deviations.

Ethical Considerations

Ethical approval for this study was obtained via the School of Accounting Research Ethics Committee. All participants received a cover letter and information about the study before participating. Participation was voluntary, and all responses were anonymous, thus protecting the identities of the students. Participants were also informed that they could withdraw from the study at any point without offering any explanation. The data were stored securely via password protection and used only for research purposes. Informed consent was obtained from all participants before engaging in the study.

3. Results

Participant Profiles

A total of 65 participants engaged in the study. Participants reported varying levels of prior AI use, as shown in Figure 1. Specifically, 57% of participants indicated that they used AI tools occasionally, 35% used AI tools frequently, with only 8% indicating that they never used AI tools. Figure 2 illustrates the level of digital comfort among the sample. The results reveal that 61.5% had medium comfort, 32.3% had high comfort, with only 6.2% indicating low comfort when using digital tools. This variation in AI use and digital comfort represents a heterogeneous sample, appropriate for exploratory analysis.

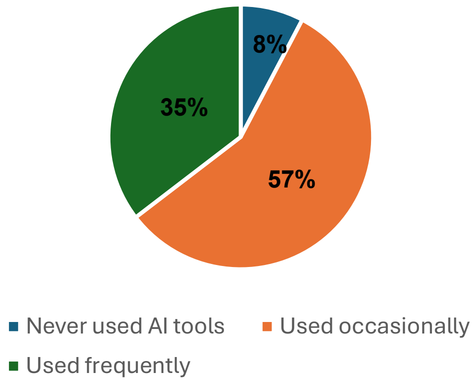

Figure 1: AI tool usage

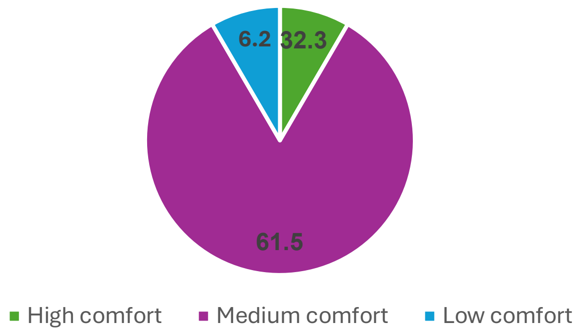

Figure 2: Digital comfort

Exploratory Factor Analysis

Exploratory factor analysis was conducted on the 10 items included in the questionnaire, assessing student perceptions of learning from an AI avatar. Prior to extraction, the suitability of the data for factor analysis was assessed. The Kaiser–Meyer–Olkin measure of sampling adequacy was .875, indicating strong sampling adequacy. Bartlett's test of sphericity was significant, with $\chi^2(45) = 337.22$, $p < .001$, confirming that the correlation matrix was appropriate for factor analysis.

Having confirmed the suitability of the data, factors were extracted using principal axis factoring with oblimin rotation because the constructs were expected to be correlated, given that the items were conceptually related. Notably, the oblique rotation revealed a moderate positive correlation between the two factors ($r = .661$). From the results, a two-factor solution was supported after examining eigenvalues greater than 1, including inspection of the scree plot. The pattern matrix, presented in Table 2, indicates an interpretable structure, with all items retained due to strong loadings (≥ .43) on the primary factor and minimal cross-loadings. The first factor comprised six items, reflecting knowledge acquisition, self-efficacy, instructional effectiveness, instructional clarity, learning experience, and learning engagement, pointing to a dimension reflecting PLS. The loadings ranged from .46 to .88, showing a strong association with the underlying construct. The second factor comprised four items, reflecting adherence to schedule, student autonomy, critical reflection, and intrinsic motivation, pointing to a dimension reflecting CE. The loadings for Factor 2 ranged from .43 to .81, supporting the coherence of this factor. These factors accounted for 56.31% of the total variance, with PLS explaining 50.52% of the variance and CE explaining 5.79% of the variance, and were retained based on an eigenvalue exceeding 1.

Table 2: Pattern matrix showing factor loadings for a two-factor solution

Label	**Perceived learning support**	**Cognitive engagement**
Structural knowledge acquisition	.88	
Task self-efficacy	.77	
Perceived instructional effectiveness	.67	
Instructional clarity	.61	
Overall learning experience	.52	
Student engagement	.46	
Adherence to schedule		.81
Student autonomy		.71
Critical reflection support		.57
Intrinsic motivation		.43

The clustering of these items into two distinct factors provides pedagogical insights for AI-supported learning environments. For the first factor, PLS, the strong association between items such as "structural knowledge acquisition" and "task self-efficacy” demonstrates that students do not separate the instructional clarity of the AI from their own personal competence. This suggests that when avatars deliver well-structured content, it directly fuels the students’ internal confidence and self-belief in their ability to apply their knowledge. Conversely, the groupings of items within the second factor, CE, specifically “adherence to schedule”, “student autonomy”, and “critical reflection support”, reveal that students also experience the avatar as a regulatory tool. Educationally, this signifies that students do not view the avatar as a passive video lecture, but as an active agent that encourages them to take ownership of their learning by keeping them accountable to module deadlines and by stimulating deeper intellectual involvement with the module’s content.

Reliability Analysis

The reliability of each factor-derived scale was subsequently assessed by considering internal consistency using Cronbach’s alpha. For the first factor, PLS, a score of .887 indicated very good reliability. The second factor, CE, also showed good reliability, with a score of .799. Thus, scores for both factors exceeded the recommended thresholds of $\alpha \geq .7$ for acceptable internal consistency (Hussey et al., 2025).

Descriptive Statistics

After conducting the EFA and internal consistency tests, descriptive statistics were computed, particularly the mean and standard deviation values for the two-factor-derived scales. As shown in Table 3, participants reported generally positive levels of PLS (M = 3.78, SD = 0.73), suggesting general agreement among participants that the AI avatar instruction supported learning. Furthermore, participants also reported positive levels for CE (M = 3.68, SD = 0.75), suggesting that the AI avatar supported active intellectual engagement.

Table 3: Descriptive statistics

Factor	N	Items	Mean	Std. deviation
Perceived learning support	65	6	3.78	0.73
Cognitive engagement	65	4	3.68	0.75

4. Discussion

The results from the EFA identified two related but distinct dimensions, namely PLS and CE, thereby refining the understanding of how students’ perceptions of AI avatar-supported instruction are structured. These two dimensions align with multimodal pedagogy and active learning (Moosa, 2025). In particular, the factor PLS reflects the necessity of clear, multimodal content delivery to make structural knowledge accessible (Drago & Wagner, 2004), whereas CE mirrors the active learning paradigm, demonstrating that effective digital education must move beyond passive consumption to ensure active “learning-by-doing” and hands-on intellectual application (Freeman et al, 2014). The originality of this study lies in its departure from technology acceptance frameworks that dominate in education literature (Al-Mamary & Alshammari, 2026). Instead of restricting student experiences to isolated, predetermined variables such as usefulness or trust (Fošner, 2024; Muneer et al., 2026), the exploratory methodology in this study allowed the authentic structure of student perceptions to surface organically. The dimensions identified clarify the conceptual ambiguity in the literature by showing that students process avatar learning environments as an instructional scaffold and a driver of autonomy. The finding related to the PLS dimension is consistent with prior studies emphasising the importance of clarity, responsiveness, and instructional guidance in AI-supported learning environments (Alrajhi, 2024; ElSayad & Mamdouh, 2025). At the same time, the identification of a CE dimension is consistent with extant literature, which links positive student perceptions to sustained and meaningful engagement in AI-mediated environments (Bahçekapılı, 2023; Pereira et al., 2023). Thus, the two dimensions identified signal that the responses of the students clustered around themes reflecting instructional support and CE.

The reliability tests indicate that each dimension demonstrates satisfactory internal consistency. These results suggest that item loadings on each factor formed coherent perceptual groupings within this sample, offering preliminary support for the stability of the identified dimensions. Notwithstanding these results, further validation of the identified dimensions in diverse samples is warranted. In addition, the results from the descriptive statistics show moderately high levels of PLS and CE, suggesting that students exposed to the avatar had overall positive experiences. This aligns with arguments that effective AI-based instructional systems depend on how students interpret and experience their interactions with such technologies (Al-Mamary & Alshammari, 2026; Botelho et al., 2025).

5. Conclusion

This study identified two related but distinct perceptual dimensions – perceived learning support (PLS) and cognitive engagement (CE) – in students' experiences of AI avatar-supported instruction. The study's contribution lies in advancing understanding in a contemporary and evolving area of research by identifying two perceptual dimensions, providing exploratory structural evidence for improving the understanding of AI avatar-supported instruction. Practically, these findings urge educators to move beyond simply using avatars for one-way information delivery. Instructional designers must purposefully blend clear visual and auditory support with active learning triggers such as embedded quizzes or critical reflection prompts to maximise student outcomes. In essence, effective AI-assisted avatar design cannot rely on technological novelty alone, as it requires pragmatic pedagogical balance where technology acts as a sophisticated tool for both clear instructional delivery and structured, active student engagement. These findings provide a valuable foundation. Nevertheless, as the study is limited to a specific South African postgraduate cohort, future research across diverse settings is warranted to confirm and extend these findings.

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