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Designing embodied generative artificial intelligence in mixed reality for active learning in higher education

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ABSTRACT

Generative Artificial Intelligence (GenAI) technologies have introduced significant changes to higher education, but the role of Embodied GenAI Agents in Mixed Reality (MR) environments is still relatively unexplored. This study was carried out to develop an embodied GenAI system designed to facilitate active learning, self-regulated learning and enhance human-AI shared regulation in educational settings. The study also aimed to understand how adult learners engage with and perceive these anthropomorphic agents in an immersive MR setting, with a particular focus on their effects on active learning and cognitive load. Using an echeloned Design Science Research ([e]DSR) approach, we developed an MR learning experience incorporating an Embodied GenAI Agent. The application was demonstrated with 26 higher education learners through questionnaires and observational recordings. Our study contributes to the ongoing design and development of AI-based educational tools, with the potential to afford more active and agentic learning experiences.

KEYWORDS

Generative AI; mixed reality; higher education; active learning; Self-regulated learning

Introduction

The rapid development and adoption of generative artificial intelligence (GenAI) has introduced complex challenges and sparked extensive discussions in higher education (Giannakos et al., 2024; Nguyen, Hong, et al., 2024). Recent studies highlight significant concerns, including threats to academic integrity from the potential misuse of GenAI and ethical debates surrounding its influence on cognitive development due to the risk of over-reliance (Chen et al., 2024; Lee et al., 2024). While various detection tools for GenAI-produced content have been proposed, accurately identifying GenAI-generated content remains a technical challenge (Dalalah & Dalalah, 2023; Perkins et al., 2024). The fundamental architecture of GenAI, which mimics human language processing and corpus structures, complicates the effectiveness of these tools, as they struggle to distinguish between human and AI-generated content. Furthermore, as GenAI increasingly integrates into everyday life and professional settings, it is essential to shift from restrictive policies

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towards more constructive, adaptive strategies (OECD, 2023). Rather than imposing an outright ban, recent literature suggests that a more balanced approach including scientific investigation and evidence-based guidelines, responsible use policies, comprehensive educator support and stakeholder engagement could better leverage GenAI's potential in educational settings while managing associated risks (Fleischmann, 2024; Jauhiainen & Guerra, 2024; Kishore et al., 2023). The current literature reveals a significant gap, as it is largely dominated by opinion-based discussions and speculative analyses concerning the capabilities of generative AI and its potential applications in education. Most existing studies emphasise theoretical possibilities rather than offering evidence-based insights into the practical applications and real-world impacts of generative AI on learning.

Furthermore, while early research on human-AI collaboration in educational contexts has explored shared regulation of learning using text-based GenAI models (e.g. Nguyen, Hong, et al., 2024), the literature remains limited on embodied GenAI applications, particularly within mixed reality (MR) environments. These environments allow for immersive learning experiences by combining virtual and physical elements, presenting unique opportunities for adaptive, customised educational content. This study addresses this gap by investigating the potential of embodied GenAI in MR settings to enhance active learning and regulatory behaviours, offering a framework for integrating GenAI into educational practice. This study adopts the human-AI shared regulation model proposed by Järvelä et al. (2023) and Tuunanen et al. (2024)'s echeloned Design Science Research (^{e}DSR) methodology to design, develop and demonstrate an innovative embodied GenAI in mixed reality for higher education students. In particular, the research question for this study is as follows: How can an innovative embodied GenAI in mixed reality be designed to support self-regulatory behaviours and active learning in higher education?. Active learning, a pedagogical approach recognised for promoting critical engagement through collaborative and interactive activities, emphasises dynamic learner interaction with learning content. GenAI's capacity to generate realistic peer-like interactions and collaborative tasks opens new possibilities for enhancing active learning and regulatory behaviour.

Theoretical foundations

Active learning and self-regulated learning

Active learning has become a central focus in modern educational research, emphasising the role of learner engagement in improving academic outcomes (Bonwell & Eison, 1991; Chi & Wylie, 2014). Unlike traditional, passive methods where students primarily receive information, active learning approaches encourage students to engage dynamically with the material, often through collaborative or interactive tasks that promote critical thinking, analysis and application of knowledge (Freeman et al., 2014).

At the pedagogical level, active learning is often implemented through techniques like problem-based learning, collaborative tasks and hands-on projects. These strategies promote not only cognitive engagement but also social interaction, fostering a deeper understanding of content (Michael, 2006). However, research has noted that while active learning benefits students across educational settings, its impact can vary based on how

learners engage with these activities independently. Thus, active learning not only requires involvement but also demands that learners regulate their approach to maximise the benefits of these activities.

At this juncture, the concept of SRL becomes particularly relevant. While active learning emphasises the role of the educator in designing engaging activities, self-regulated learning shifts the focus to the learner's role in managing and directing their cognitive and metacognitive processes (Winne & Hadwin, 1998; Zimmerman, 2008). SRL is characterised by a cycle of forethought, performance and self-reflection, wherein learners set goals, monitor their progress and adjust strategies as needed to achieve optimal outcomes (Zimmerman, 2008). The interplay between active learning and SRL becomes apparent when considering the demands of active learning environments; as learners engage in active tasks, they must self-regulate to effectively navigate complex activities, evaluate their understanding and refine their approaches (Pintrich, 2000). This synergy implies that active learning alone may be insufficient without self-regulation skills, as the benefits of active engagement are often contingent on a learner's ability to monitor and control their learning processes. Active learning activities can act as a context in which students develop SRL competencies, with each feeding into the other to support comprehensive learning outcomes.

The emergence of generative artificial intelligence and its opportunities

The integration of GenAI into educational settings introduces new possibilities for fostering both active learning and SRL (Kong & Yang, 2024; Molenaar, 2022). GenAI's ability to create simulated peer interactions and collaborative tasks aligns well with active learning environments that prioritise social interaction. Through these GenAI-driven interactions, learners can experience a responsive environment that continuously adjusts to their progress, creating a tailored experience that encourages ongoing participation and thinking (Ng et al., 2024; Nguyen, Hong, et al., 2024). Research suggests that when learners interact with collaborative, AI-driven agents, they may develop cognitive and metacognitive skills that enhance their capacity for self-regulation in future group-based learning experiences (Edwards et al., 2024; Järvelä et al., 2023).

Embodied GenAI, an advanced form of generative technology, introduces physical or virtual agents (e.g. holograms, avatars, robots) that interact with learners through multimodal communications, such as voice, gestures and spatial cues (Lynn et al., 2023). This creates immersive, human-like experiences that promote active learning and self-regulated learning (SRL) by enabling learners to engage in interactive scenarios, receive immediate feedback and refine their understanding (Chheang et al., 2024; Lynn et al., 2023). The multisensory engagement fosters cognitive involvement and supports the development of self-regulatory skills through continuous reflection and adaptation.

Despite the promising applications of embodied GenAI in promoting active learning and SRL, significant research gaps remain. Up to date, there are still limited studies examining this phenomenon. Furthermore, existing research on embodied GenAI has primarily focused on applications within fully immersive virtual reality environments (Chheang et al., 2024) or through the use of physical robots (Obrenovic et al., 2024). However, there is a limited body of research exploring how embodied GenAI can be designed for MR environments, where virtual and physical elements are seamlessly integrated.

Human-AI Shared Regulation in Learning (HASRL) theoretical framework

To design and investigate the integration of embodied GenAI in MR for active learning, Järvelä et al. (2023)'s Human-AI Shared Regulation in Learning (HASRL) stands out as the most appropriate framework that captures the collaborative regulation processes between humans and AI systems. The HASRL model, as outlined by Järvelä et al. (2023), proposes a dynamic shared regulatory relationship wherein AI and human learners engage in shared regulatory activities towards the learning outcomes. Unlike traditional SRL frameworks, which focus on individual or collaborative human-regulated processes, HASRL emphasises the interplay between AI's responsive capabilities and the learner's regulatory actions. In this model, AI does not merely function as a tool but as an active regulatory agent, adapting its feedback and guidance to align with the learner's cognitive and emotional states.

The HASRL model aligns well with the potential of embodied GenAI to scaffold self-regulated learning (SRL) in an MR environment. Embodied GenAI systems – such as holographic agents with multimodal communication capabilities – can support SRL processes by actively participating in the regulation cycle, providing real-time feedback, prompting reflection and assisting learners in refining their strategies based on current performance. For instance, an embodied AI tutor can recognise when a learner is struggling with a particular concept and respond by adjusting its approach, offering encouragement, or suggesting alternative strategies. This aligns with HASRL's notion of 'responsive regulation', where the AI adapts its interventions to meet the learner's evolving needs, creating a flexible and supportive learning environment.

Echeloned Design Science Research (eDSR) methodology

This study employs the Echeloned Design Science Research ([e]DSR) methodology, a structured, iterative approach to designing, developing and evaluating embodied GenAI in mixed reality environments for active learning in higher education (Tuunanen et al., 2024). [e]DSR advances the traditional Design Science Research (DSR) (Hevner et al., 2004; Peffers et al., 2007) by emphasising a multi-layered, or 'echeloned', process of inquiry that integrates theoretical, empirical and evaluative stages to systematically refine and assess design artefacts.

[e]DSR offers significant advantages over traditional DSR by organising the research process into this structured, multi-layered approach that allows for systematic reporting of findings at each stage (Tuunanen et al., 2024). Building upon traditional DSR, which is often criticised for being time-consuming and resource-intensive due to the requirement of comprehensive evaluation only after completing a full cycle, [e]DSR is organised into distinct echelons. Each echelon focuses on progressively refining theoretical, empirical and practical aspects of the design artefact. This structure not only enables iterative assessment and improvements at various levels of complexity but also allows researchers to share insights and partial findings at each stage, thereby making ongoing contributions to the knowledge base and reducing the risk of extensive revisions late in the process. Beermann et al. (2024) offers an exemplar of this. Their study investigates how to disentangle the search process of validating the problem statement. By capturing and disseminating findings incrementally, [e]DSR provides continuous value to the research

community and practitioners, fostering transparency and adaptability. Thus, [e]DSR ensures that early theoretical insights inform design elements that are then tested and refined through controlled and real-world implementations, maximising resource efficiency and reducing time to actionable results. As such, [e]DSR enhances both the rigour and relevance of the research while making efficient use of resources and supporting practical, context-sensitive adjustments throughout the process. Recent studies have also utilised this structured yet adaptable methodology to design educational technology innovations that support human-AI collaboration (e.g. Edwards et al., 2024).

The [e]DSR aligns with this study's objective to develop an embodied GenAI system designed to facilitate active learning and enhance human-AI shared regulation in educational settings. Specifically, this study concentrates on the Demonstration echelon, which aims to validate the proof of concept for the instantiated artefact. To achieve this, we will first present the prototype to experts to gather initial feedback. Following this, we will conduct a formal experiment using the prototype to systematically validate and evaluate its effectiveness. The analysis of pre- and post-questionnaires enabled us to examine whether the intended affordances were effectively enacted, thereby providing evidence for the artefact's utility and efficacy.

For the demonstration of the prototype, the main validation criteria outlined by Tuunanen et al. (2024) were adopted. These criteria included (1) fit to the validated design of the artifact, ensuring coherency; (2) ease of use, assessing user-friendliness; (3) effectiveness, measuring how well the artifact fulfils its intended purpose; (4) efficiency, evaluating the artefact's performance in achieving goals with minimal effort; and (5) robustness, verifying the artefact's reliability and stability under various conditions.

Kai – an embodied generative artificial intelligence (GenAI) in MR for active learning

We designed and developed 'Kai' – an Embodied Generative Artificial Intelligence (GenAI) in a Mixed Reality environment aimed at promoting active learning on ethical considerations in using GenAI. Kai's development followed an iterative process, employing the Unity cross-platform engine with a mixed reality template, and utilising the InWorld API for character creation, which incorporates the GPT-3 model as the language engine (OpenAI, 2024).



Figure 1. Initial prototype with non-verbal interaction (left Image); and with verbal interaction (right).



Figure 2. Interactions with Kai – an embodied generative artificial intelligence (GenAI) in mixed reality for active learning.

The initial prototype, depicted in Figure 1, featured Kai with capabilities for both verbal and non-verbal interaction with learners. Following a demonstration and feedback session with four experts (three professors and one lecturer) from Learning Sciences, Computer Science, Business Ethics and Information Systems, the prototype was refined and enhanced. Kai's appearance and voice were adapted to reflect diverse racial characteristics, and the cognitive model was augmented with content focused on ethical considerations in GenAI, with case studies from the creative industries.

Additionally, interactive learning objects were developed in the same MR setting, creating an integrated environment to support a comprehensive learning experience. Figure 2 illustrates the fully operational Kai, engaging in interactive, embodied and contextually relevant dialogues within this MR environment, facilitating active learning on ethical implications associated with GenAI use.

The system environment consists of five main interface components (as annotated in Figure 3 below): (1) Kai, the embodied GenAI agent; (2) an instruction panel providing guidance on tasks; (3) a timer to track the session duration; (4) hint flashcards that users can flip for additional help; and (5) video panels displaying relevant visual content. Together, these components create an engaging and supportive learning experience.

Kai – the embodied GenAI agent

Kai, the embodied GenAI agent, is designed as an expert on ethics in GenAI, capable of engaging in real-time conversations with learners to facilitate discussions on this topic. Kai was engineered to not only provide clear and concise answers to learners' questions but also to pose relevant follow-up questions, fostering a natural and engaging discussion on the topic. This approach encourages deeper reflection and active participation, enhancing the overall learning experience. To support comprehension, a real-time transcript log is displayed above Kai, allowing learners to follow the dialogue more easily and quickly spot any potential misunderstandings.

In addition to verbal responses, Kai employs various gestures that align with the conversation's content, enhancing the interaction's depth. Previous studies have underscored the significant role of non-verbal interactions in learning processes (Purwati et al., 2019), especially in supporting learners' regulatory processes (Whitehead et al., 2024). Building on these findings, Kai incorporates hand gestures and body postures in response to the content of the conversation. Furthermore, Kai's eye gaze has been carefully

engineered to follow the learner's attention, maintaining eye contact throughout the discussion. This feature enhances the sense of engagement and presence, making interactions with Kai feel more personal and responsive.

The instruction panel

The instruction panel is positioned directly in front of the learner, providing a constant reference point throughout the learning session. Fixed in place and non-interactive, the panel serves as a stable, accessible guide, allowing learners to monitor their task goals at any moment. By remaining visible and unchanging, the instruction panel reinforces the objectives, helping learners stay focused and oriented within the learning environment without the need for additional interactions. This visual reinforcement allows learners to check their goals at any point, facilitating ongoing self-assessment and reflection, which are critical components of SRL (Hadwin & Winne, 2012). This design empowers learners to take an active role in regulating their own learning journey, promoting autonomy and persistence in goal-oriented tasks.

Timer panel

The timer panel provides learners with a continuous visual of the time allocated for each task. Positioned for easy viewing, the timer helps learners manage their time effectively, a crucial aspect of active and self-regulated learning (Dang et al., 2023). By displaying the countdown in real-time, the Timer panel encourages learners to monitor their pacing, make timely adjustments to their approach and stay focused on achieving their goals within the set timeframe. This time-awareness feature fosters learners' planning and time-management skills, enhancing their ability to regulate their efforts and complete tasks efficiently.

Hint flashcards

The Hint flashcards serve as guiding prompts, encouraging learners to explore various aspects of the topic on ethical considerations in using GenAI. Positioned at a distance in the learning environment, the flashcards require learners to engage physically by pointing at a specific card and using a two-finger pinch gesture to flip it. This interaction design fosters active participation, prompting learners to engage with questions that guide their understanding and critical thinking. The flashcards provide structured support, helping learners investigate ethical issues while promoting an interactive and hands-on approach to active learning.

Video panels

The Video panels, positioned on either side of the instruction panel, provide dynamic learning materials on the topic. These panels are fully interactive, allowing learners to control playback with simple hand gestures and offering additional flexibility to move and resize the panels within the environment. This hands-on interactivity enables learners to

personalise their viewing experience, adjusting the video size and placement for optimal focus and comfort. The video panels support an immersive, learner-centred exploration of the topic, enhancing learning engagement.

Demonstration of Kai

Participants and procedure

The demonstration of Kai involved an experiment with 26 higher education students (male/female = 8/18; 22 master's and 4 doctoral students) using the operational prototype on a Quest3 headset. The experiment was conducted through individual sessions, with each participant interacting with Kai separately. Participants were recruited via email and registered voluntarily through a booking system named Sona Systems (https://www.sona-systems.com/), where they could select their preferred time slots. Participants had the option to withdraw from the study at any time without providing an explanation, and any data collected up to that point in such cases was deleted.

The procedure starts with each consenting participant completing a pre-questionnaire to gather background information, their prior experiences with GenAI and Extended Reality applications (including Mixed Reality and Virtual Reality). The Partner Model Questionnaire (Doyle et al., 2025) was also administered before and after the interaction to evaluate participants' perceptions GenAI agent as speech interface. Participants then received a brief explanation of the task from the researcher before being guided to the designated setup area, where they were assisted in wearing the Quest3 headset. This area is positioned in front of two TP-LINK Tapo C225 video cameras, which, along with the Quest3's built-in first-person view camera, record the session in third-person views of participants' full-body movements.

Prior to the task, a wireless microphone was attached to participants to capture audio with minimal interference. The entire task, limited to 30 min to prevent headset discomfort, involved a structured flow: a 5-min orientation to the virtual environment and gestures, a 20-min interactive discussion with Kai on ethical AI topics and a concluding 5-min oral assessment.

During the task, no restrictions about moving head or body were announced to the participants to ensure natural interaction. The only instruction provided was to avoid stepping too far from the Quest3's pre-set boundary grid, which would display a virtual boundary without interfering with the experiment itself. Figure 3 illustrates a snapshot of the learners' interactions with Kai in the MR for active learning. Upon completing the task, participants also filled out a post-questionnaire.

Instruments

The questionnaire aimed to capture their assessment on the experiment including their engagement with Kai (Engagement and Interest (EI) – 6 items) (Jennett et al., 2008) and the learning materials, their perceptions of Kai as a conversation partner (16 items) (Doyle et al., 2025), as well as their perceived Cognitive load (Intrinsic Load (IL) – 3 items, Extraneous Load (EL) – 3 items and Germane Load (GL) – 3 items) (Andersen & Makransky, 2021) in the learning, and any technical challenges encountered. Table 1

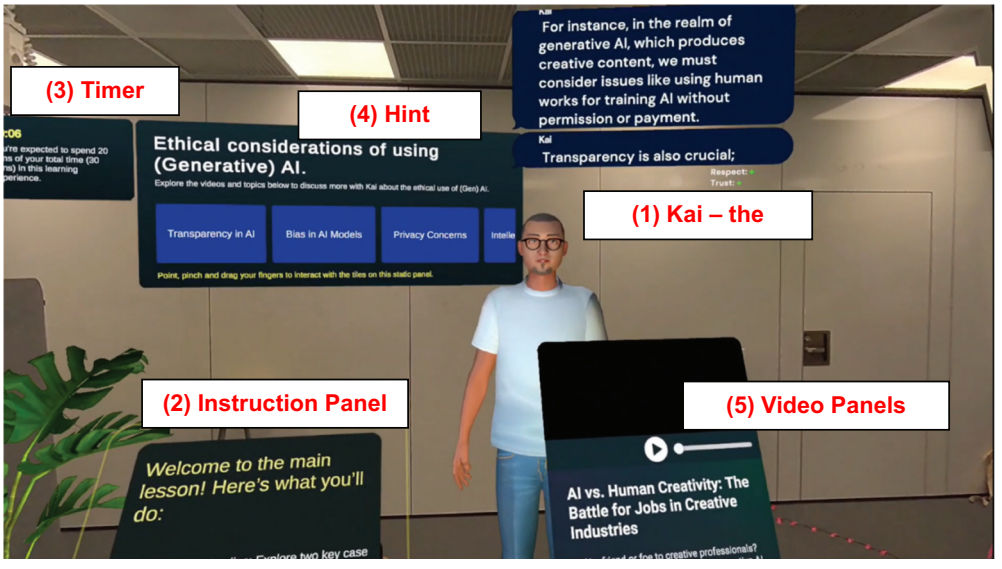

Figure 3. Kai – an embodied generative artificial intelligence (GenAI) in mixed reality for active learning.

Table 1. Descriptive analysis of measurements.

Variable	Mean	SD	Median	Min	Max
Pre-perceptions	4.04	0.91	3.94	2.44	6.19
Post-perceptions	4.72	0.86	4.75	2.88	6.62
Intrinsic Load (IL)	2.82	1.00	2.67	1.00	5.00
Extraneous Load (EL)	1.69	0.75	1.33	1.00	3.33
Germane Load (GL)	3.56	0.57	3.58	2.33	4.67
Engagement and Interest (EI)	4.04	0.72	4.00	2.33	5.00

reports the descriptive statistics of measurements. Additionally, learners' experience with AI/VR/XR interactions was assessed using a 5-point rating scale. The results indicated that learners were generally not very familiar with these technologies, with a mean score of 2 (SD = 0.75).

Findings and lessons learned

Participants' perceptions of the embodied MR Agent as a learning partner

A paired sample T-test was conducted to compare participants' perceptions towards learning with the embodied MR agent before and after our experiment. A Shapiro–Wilk test indicated that the differences between scores in the pre- and post-questionnaires were normally distributed (W = 0.95, p = .204). The paired-samples t-test (as reported in

Table 2. Paired-sample t-test of the partner model questionnaire (Doyle et al., 2025).

Measurements	N	Mean	SD	$t(25)$	df	p	95% CI
Pre-questionnaire	26	4.04	0.91	– 3.64	25	.001	– 1.08, – 0.30
Post-questionnaire	26	4.72	0.86				

Table 3. Cognitive load reported by participants in the experiment.

Cognitive Load Type	Mean	SD	χ2	df	*p*	Pairwise
Intrinsic Load (IL)	2.82	1.00	31.32	2	<.001***	IL > EL***
Extraneous Load (EL)	1.69	0.75				GL > IL*** (***: ***: significant at $p < .001$)
Germane Load (GL)	3.58	0.80				

Table 2) revealed a statistically significant increase from Pre-questionnaire ($M = 4.04$, SD = 0.91) to Post-questionnaire ($M = 4.72$, SD = 0.86), $t(25) = -3.64$, $p = .001$, with a mean difference of 0.69. This suggests that our MR agent provided participants with an authentic and human-like impression during the interaction. This fulfilled the first and third criteria of the evaluation at the demonstration echelon: alignment with the validated design of the artefact, ensuring coherence and effectiveness, assessing how well the artefact fulfils its intended purpose.

Cognitive load invested by participants during the experiment

A Friedman test was conducted to compare ratings across the three types of cognitive load: Intrinsic Load (IL), Extraneous Load (EL) and Germane Load (GL). Table 3 shows the results of cognitive load reported by participants in the experiment. The results indicated a statistically significant difference in cognitive load ratings, $\chi2(2) = 31.32$, $p < .001$. Post-hoc analyses using the Wilcoxon signed-rank test with Bonferroni correction revealed significant differences between IL and EL ($p < .001$) and between EL and GL ($p < .001$). However, the difference between IL and GL was not statistically significant ($p = .058$). It indicated that the design was efficient and did not cause unnecessary load that hindered learning. This satisfied both the second and fourth criteria of the evaluation at the demonstration echelon: ease of use, which assesses user-friendliness, and efficiency, which evaluates the embodied AI in mixed reality (MR) for its ability to achieve intended goals with minimal effort. This also partially addresses the fifth criterion, robustness, by verifying the artefact's reliability and stability under various conditions.

Associations between MR agent perceptions, cognitive load and engagement

To explore the associations between participants' perceptions of the embodied MR agent and measures of cognitive load and engagement, Pearson's correlations were conducted to examine the relationships between participants' perceptions of the embodied MR agent and measures of cognitive load (IL, EL and GL) as well as Engagement and Interest (EI). Table 4 reports the results for correlations between perceptions of the embodied MR agent and other factors.

Results revealed a marginal correlation between perceptions about the MR agent and Germane load, $r = 0.39$, $p = .05$. However, there was no significant correlation between perceptions and Intrinsic Load, $r = -0.06$, $p = .76$, or between perceptions and Extraneous Load, $r = -0.32$, $p = .11$. Regarding Engagement and Interest: A significant positive

Table 4. Correlations between perceptions of the embodied MR agent and other factors.

	IL	EL	GL	EI
Post-questionnaire	− .06	− .32	.39*	.55***

*: significant at $p < .05$, ***: significant at $p < .001$.

correlation was found between perceptions and EI ($r = 0.55$, $p = .004$), suggesting that participants who perceived the MR agent more anthropomorphic and the conversation more natural also reported higher levels of engagement. This further reinforced the validation of effectiveness, evaluating how well the artefact achieves its intended purpose.

Discussion and conclusion

In this study, we explored the design and development of a GenAI-enhanced MR environment, integrating an embodied GenAI agent, Kai, to foster active learning within higher education. Previous studies indicate that GenAI and MR offer promising opportunities to create innovative learning experiences and new solutions for promoting regulatory behaviour, enhancing student engagement and learning outcomes (Farrokhnia et al., 2024; Giannakos et al., 2024; Nguyen, Kremantzis, et al., 2024). However, there is still limited empirical research on how these advanced technologies can be effectively designed and implemented within educational contexts (Molenaar, 2022). Our findings highlight the feasibility of implementing such advanced technologies in educational contexts, offering insights into how GenAI and MR can be meaningfully incorporated into learning settings to engage students in these innovative learning environments.

Our analysis revealed that the embodied GenAI agent was perceived by participants as authentic and human-like, which positively influenced their engagement. Although participants were not very familiar with learning using this technology, they responded positively to the embodied agent. The findings suggest that despite limited prior experience, learners were receptive to the agent's presence and interaction, highlighting its potential to support the learning process without adding an extra cognitive burden for technology familiarisation (Mayer & Fiorella, 2021). This finding is further reinforced by participants' reported cognitive load during the learning session. The design efficiently supported learning by avoiding extraneous cognitive load, thereby sustaining the educational focus of the experience. Notably, participants who perceived the GenAI as more anthropomorphic and engaging reported higher levels of immersion and willingness to engage actively with the content, indicating that these qualities may be instrumental in fostering sustained student interaction and learning in AI-driven environments. This study also sheds light on another life-like application of embodied learning, where learners can actively engage with immersive environments, interact with digital agents or peers and acquire knowledge through hands-on experiences (Lyu & Deng, 2024).

The capability of GenAI to enable human-like interaction invites further investigation into its impact on learning processes, especially concerning human-AI collaboration and shared regulatory practices (Nguyen, Hong, et al., 2024). Current research highlights the need to better understand how collaborative and regulatory mechanisms unfold in these GenAI-integrated learning environments (Cukurova, 2024; Giannakos et al., 2024; Järvelä et al., 2023; Molenaar, 2022). Our study contributes to this area by illustrating a novel context of human-AI collaborative learning where both physical and virtual elements are seamlessly blended. This unique setup emphasises the potential of embodied GenAI agents not only as information providers but as active learning partners that adapt to student needs, enhancing the overall learning experience. This study has significant implications

for stakeholders in higher education, including educators, instructional designers and policymakers. Educators could leverage embodied GenAI to create immersive learning environments that actively engage students, instructional designers can utilise the findings to develop GenAI-integrated platforms that facilitate natural, human-like interactions and policymakers might consider the importance of supporting such innovations to equip students with essential digital and AI literacy skills. These implications feature the need for continuous research and investment in technologies that advance educational practices in response to evolving digital landscapes.

This study has some limitations. First, although the sample size of 26 participants is reasonable given the advanced technology used and the need for individual data collection sessions, future research could benefit from larger-scale evaluations. A broader sample would enable more robust assessment of the design's effectiveness and efficiency, while also identifying potential risks associated with scaling the approach. Moreover, our data relied solely on self-report questionnaires, which may introduce bias. Future studies should incorporate multiple data sources to triangulate findings and enhance validity. Additionally, a field study in authentic ecological settings would be valuable for evaluating the artefact's practical application and effectiveness within real-world learning environments.

Despite these limitations, our prototype demonstration serves as a solid proof-of-concept for integrating embodied GenAI in MR for educational purposes. This aligns with the demonstration echelon in educational eDSR, providing a foundation for subsequent iterations that could place a greater focus on the evaluation echelon, moving towards more extensive testing and validation. Future research could explore the learning processes of students interacting with the GenAI agent in greater detail to establish evidence-based guidelines for effective GenAI implementation in higher education. By closely examining these interactions, future studies could enhance understanding of how GenAI can optimally support student learning and engagement, thereby informing best practices for its integration across various educational contexts.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author, Dr Andy Nguyen (andy.nguyen@oulu.fi). The data are not publicly available due to privacy/ethical restrictions.

This research complied with the research integrity and ethics guidelines provided by the Ethics Committee of Human Sciences of the University of Oulu and European General Data Protection Regulation (GDPR). Informed consent was collected by all the participants.

References

Andersen, M. S., & Makransky, G. (2021). The validation and further development of a multidimensional cognitive load scale for virtual environments. *Journal of Computer Assisted Learning*, *37*(1), 183–196. https://doi.org/10.1111/jcal.12478

Beermann, V., Rieder, A., Uebernickel, F., & Vom Brocke, J. (2024). Disentangling the problem space: A validated problem statement for sustainability support systems. In M. Mandviwalla, M. Söllner, & T. Tuunanen (Eds.), *Design science research for a resilient future* (pp. 3–17). Springer Nature. https://doi.org/10.1007/978-3-031-61175-9_1

Bonwell, C. C., & Eison, J. A. (1991). Active learning: Creating excitement in the classroom. 1991 ASHE-ERIC higher education reports. *ERIC Clearinghouse on higher education*. The George Washington University. 20036-1183 ($17 https://eric.ed.gov/?id=ED336049

Chen, B., Lewis, C. M., West, M., & Zilles, C. (2024, July 18–20). Plagiarism in the age of generative AI: Cheating method change and learning loss in an intro to CS course. *Proceedings of the Eleventh*

ACM Conference on Learning @ Scale (pp. 75–85). Atlanta, GA, USA. https://doi.org/10.1145/3657604.3662046

Chheang, V., Sharmin, S., Márquez-Hernández, R., Patel, M., Rajasekaran, D., Caulfield, G., Kiafar, B., Li, J., Kullu, P., & Barmaki, R. L. (2024, January 17–19). Towards anatomy education with generative AI-based virtual assistants in immersive virtual reality environments. *2024 IEEE International Conference on Artificial Intelligence and eXtended and Virtual Reality (AIxVR)* (pp. 21–30). Los Angeles, CA, USA. https://doi.org/10.1109/AIxVR59861.2024.00011

Chi, M. T. H., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist*, *49*(4), 219–243. https://doi.org/10.1080/00461520.2014.965823

Cukurova, M. (2024). The interplay of learning, analytics and artificial intelligence in education: A vision for hybrid intelligence. *British Journal of Educational Technology*, *56*(2), 469–488. https://doi.org/10.1111/bjet.13514

Dalalah, D., & Dalalah, O. M. A. (2023). The false positives and false negatives of generative AI detection tools in education and academic research: The case of ChatGPT. *International Journal of Management Education*, *21*(2), 100822. https://doi.org/10.1016/j.ijme.2023.100822

Dang, B., Vitiello, R., Nguyen, A., Rose, C., & Järvelä, S. (2023, June 10–15). How do students deliberate for socially shared regulation in collaborative learning? A process-oriented approach. *Proceedings of International Conference on Computer Supported Collaborative Learning (CSCL)*, Montréal, QC, Canda Slotta, J. D. & Charles, E. S. (The International Society of Learning Sciences). https://doi.org/10.22318/cscl2023.280974

Doyle, P. R., Gessinger, I., Edwards, J., Clark, L., Dumbleton, O., Garaialde, D., Rough, D., Bleakley, A., Branigan, H. P., & Cowan, B. R. (2025). The partner modelling questionnaire: A validated self-report measure of perceptions toward machines as dialogue partners. *ACM Transactions on Computer-Human Interaction*. https://doi.org/10.1145/3729170

Edwards, J., Nguyen, A., Lämsä, J., Sobocinski, M., Whitehead, R., Dang, B., Roberts, A.-S., & Järvelä, S. (2024). Human-AI collaboration: Designing artificial agents to facilitate socially shared regulation among learners. *British Journal of Educational Technology*, *56*(2), 712–733. https://doi.org/10.1111/bjet.13534

Farrokhnia, M., Banihashem, S. K., Noroozi, O., & Wals, A. (2024). A SWOT analysis of ChatGPT: Implications for educational practice and research. *Innovations in Education and Teaching International*, *61*(3), 460–474. https://doi.org/10.1080/14703297.2023.2195846

Fleischmann, K. (2024). The commodification of creativity: Integrating generative artificial intelligence in higher education design curriculum. *Innovations in Education and Teaching International*, 1–15. https://doi.org/10.1080/14703297.2024.2427039

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences*, *111*(23), 8410–8415. https://doi.org/10.1073/pnas.1319030111

Giannakos, M., Azevedo, R., Brusilovsky, P., Cukurova, M., Dimitriadis, Y., Hernandez-Leo, D., Järvelä, S., Mavrikis, M., & Rienties, B. (2024). The promise and challenges of generative AI in education. *Behaviour & Information Technology*, 1–27. https://doi.org/10.1080/0144929X.2024.2394886

Hadwin, A. F., & Winne, P. H. (2012). Promoting Learning Skills in Undergraduate Students Kirby, J. R. & Lawson, M. J.*Enhancing the Quality of Learning: Dispositions, Instruction, and Mental Structures* (Cambridge University Press), 201–227.

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, *28*(1), 75–105. https://doi.org/10.2307/25148625

Järvelä, S., Nguyen, A., & Hadwin, A. (2023). Human and artificial intelligence collaboration for socially shared regulation in learning. *British Journal of Educational Technology*, *54*(5), 1057–1076. https://doi.org/10.1111/bjet.13325

Jauhiainen, J. S., & Guerra, A. G. (2024). Generative AI in education: ChatGPT-4 in evaluating students' written responses. *Innovations in Education and Teaching International*, 1–18. https://doi.org/10.1080/14703297.2024.2422337

Jennett, C., Cox, A. L., Cairns, P., Dhoparee, S., Epps, A., Tijs, T., & Walton, A. (2008). Measuring and defining the experience of immersion in games. *International Journal of Human-Computer Studies*, *66*(9), 641–661. https://doi.org/10.1016/j.ijhcs.2008.04.004

Kishore, S., Hong, Y., Nguyen, A., & Qutab, S. (2023, December 11). Should ChatGPT be banned at schools? Organizing visions for generative artificial intelligence (AI) in education. *International Conference on Information Systems (ICIS)*, Hyderabad, India. https://aisel.aisnet.org/icis2023/learnandiscurricula/learnandiscurricula/5/

Kong, S.-C., & Yang, Y. (2024). A human-centered learning and teaching framework using generative artificial intelligence for self-regulated learning development through domain knowledge learning in K-12 settings. *IEEE Transactions on Learning Technologies*, *17*, 1588–1599. https://doi.org/10.1109/TLT.2024.3392830

Lee, V. R., Pope, D., Miles, S., & Zárate, R. C. (2024). Cheating in the age of generative AI: A high school survey study of cheating behaviors before and after the release of ChatGPT. *Computers and Education: Artificial Intelligence*, *7*, 100253. https://doi.org/10.1016/j.caeai.2024.100253

Lynn, S. K., Loyall, B., & Niehaus, J. (2023). Growing an embodied generative cognitive agent. *Proceedings of the AAAI Symposium Series*, *2*(1), 315–319. https://doi.org/10.1609/aaaiss.v2i1.27694

Lyu, C., & Deng, S. (2024). Effectiveness of embodied learning on learning performance: A meta-analysis based on the cognitive load theory perspective. *Learning and Individual Differences*, *116*, 102564. https://doi.org/10.1016/j.lindif.2024.102564

Mayer, R. E., & Fiorella, L. (2021). Principles for managing essential processing in multimedia learning: Segmenting, pre-training, and modality principles. In L. Fiorella & R. E. Mayer (Eds.), *The Cambridge handbook of multimedia learning* (3rd ed, pp. 243–260). Cambridge University Press.

Michael, J. (2006). Where's the evidence that active learning works? *Advances in Physiology Education*, *30*(4), 159–167. https://doi.org/10.1152/advan.00053.2006

Molenaar, I. (2022). The concept of hybrid human-AI regulation: Exemplifying how to support young learners' self-regulated learning. *Computers and Education: Artificial Intelligence*, *3*, 100070. https://doi.org/10.1016/j.caeai.2022.100070

Ng, D. T. K., Tan, C. W., & Leung, J. K. L. (2024). Empowering student self-regulated learning and science education through ChatGPT: A pioneering pilot study. *British Journal of Educational Technology*, *55*(4), 1328–1353. https://doi.org/10.1111/bjet.13454

Nguyen, A., Hong, Y., Dang, B., & Huang, X. (2024). Human-AI collaboration patterns in AI-assisted academic writing. *Studies in Higher Education* 49 5 , 847–864. https://doi.org/10.1080/03075079.2024.2416492

Nguyen, A., Kremantzis, M., Essien, A., Petrounias, I., & Hosseini, S. (2024). Editorial: Enhancing student engagement through artificial intelligence (AI): Understanding the basics, opportunities, and challenges. *Journal of University Teaching and Learning Practice*, *21*(6), Article 06. https://doi.org/10.53761/caraaq92

Obrenovic, B., Gu, X., Wang, G., Godinic, D., & Jakhongirov, I. (2024). Generative AI and human–robot interaction: Implications and future agenda for business, society and ethics. *AI & SOCIETY*, *40*(2), 677–690. https://doi.org/10.1007/s00146-024-01889-0

OECD. (2023). *OECD future of education and skills 2030-organisation for economic Co-operation and development*. https://www.oecd.org/education/2030-project/

OpenAI. (2024). *Creating next-gen characters*. https://openai.com/index/inworld-ai/

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, *24*(3), 45–77. https://doi.org/10.2753/MIS0742-1222240302

Perkins, M., Roe, J., Postma, D., McGaughran, J., & Hickerson, D. (2024). Detection of GPT-4 generated text in higher education: Combining academic judgement and software to identify generative AI tool misuse. *Journal of Academic Ethics*, *22*(1), 89–113. https://doi.org/10.1007/s10805-023-09492-6

Pintrich, P. R. (2000). Chapter 14-the role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451–502). Academic Press. https://doi.org/10.1016/B978-012109890-2/50043-3

Purwati, P., Rahmiati, R., Asra, S., & Fadlia, F. (2019). The impact non-verbal communication the learning process. *Journal of Education, Linguistics, Literature and Language Teaching*, *2*(2), 1–12.

Tuunanen, T., Winter, R., & Brocke, J. V. (2024). Dealing with complexity in design science research: A methodology using design echelons. *MIS Quarterly*, *48*(2), 427–458. https://doi.org/10.25300/MISQ/2023/16700

Whitehead, R., Nguyen, A., & Järvelä, S. (2024). Exploring the role of gaze behaviour in socially shared regulation of collaborative learning in a group task. *Journal of Computer Assisted Learning*, *40*(5), 2226–2247. https://doi.org/10.1111/jcal.13022

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. Hacker, J. Dunlosky, & A. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Lawrence Erlbaum Associates Publishers.

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal*, *45*(1), 166–183. https://doi.org/10.3102/0002831207312909