



The effects of generative AI agents and scaffolding on enhancing students' comprehension of visual learning analytics



Lixiang Yan ^a , Roberto Martinez-Maldonado ^a, Yueqiao Jin ^a,
Vanessa Echeverria ^{a,b} , Mikaela Milesi ^a , Jie Fan ^a , Linxuan Zhao ^a,
Riordan Alfredo ^a , Xinyu Li ^a, Dragan Gašević ^a

^a Centre for Learning Analytics at Monash, Faculty of Information Technology, Monash University, Clayton, Victoria, 3168, Australia

^b Escuela Superior Politécnica del Litoral, Guayaquil, Ecuador

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ABSTRACT

Visual learning analytics (VLA) is becoming increasingly adopted in educational technologies and learning analytics dashboards to convey critical insights to students and educators. Yet many students experienced difficulties in comprehending complex VLA due to their limited data visualisation literacy. While conventional scaffolding approaches like data storytelling have shown effectiveness in enhancing students' comprehension of VLA, these approaches remain difficult to scale and adapt to individual learning needs. Generative AI (GenAI) technologies, especially conversational agents, offer potential solutions by providing personalised and dynamic support to enhance students' comprehension of VLA. This controlled lab study investigates the effectiveness of GenAI agents, particularly when integrated with scaffolding techniques, in improving students' comprehension of VLA. A randomised controlled trial was conducted with 117 higher education students to compare the effects of two types of GenAI agents: *passive agents*, which respond to student queries, and *proactive agents*, which utilise scaffolding questions, against standalone scaffolding in a VLA comprehension task. The results show that passive agents yield comparable improvements to standalone scaffolding both during and after the intervention. Notably, proactive GenAI agents significantly enhance students' VLA comprehension compared to both passive agents and standalone scaffolding, with these benefits persisting beyond the intervention. These findings suggest that integrating GenAI agents with scaffolding can have lasting positive effects on students' comprehension skills and support genuine learning.

1. Introduction

Technological advancements have enabled the capture and analysis of vast amounts of data, making visual analytics increasingly essential in education (Noroozi et al., 2019). Visual learning analytics (VLA) are becoming more prevalent in learning analytics dashboards (LADs), classroom settings, and massive open online courses (MOOCs), serving as crucial tools for communicating insights to educators and students (Vieira, Parsons, & Byrd, 2018). For example, VLA is frequently used in learning analytics dashboards to display student collaboration metrics, heat maps of engagement levels, or progress tracking charts, which aim to provide students and educators with insights into learning behaviours and outcomes (Sahin & Ifenthaler, 2021). Although LADs

* Correspondence to: 25 Exhibition Walk, Clayton, Victoria, 3168, Australia.

E-mail addresses: Lixiang.Yan@monash.edu (L. Yan), Roberto.MartinezMaldonado@monash.edu (R. Martinez-Maldonado), Ariel.Jin@monash.edu (Y. Jin), Vanessa.Echeverria@monash.edu (V. Echeverria), Mikaela.Milesi@monash.edu (M. Milesi), Jie.Fan@monash.edu (J. Fan), Linxuan.Zhao@monash.edu (L. Zhao), Riordan.Alfredo@monash.edu (R. Alfredo), Xinyu.Li1@monash.edu (X. Li), Dragan.Gasevic@monash.edu (D. Gašević).

may also include non-visual elements such as predictive analytics or descriptive textual summaries, VLA specifically focuses on the visual representation of data to effectively close the learning analytics loop by transforming raw data into actionable insights, thus guiding instructional strategies and enhancing educational experiences (Verbert, Ochoa, De Croon, Dourado, & De Laet, 2020).

Despite the potential of VLA, many students and educators struggle to interpret these complex visualisations due to a lack of data visualisation literacy (Donohoe & Costello, 2020; Pozdniakov et al., 2023). This issue arises because interpreting VLA often requires not only familiarity with the visualisation format but also the ability to discern critical patterns, trends, and relationships embedded within the data (Sahin & Ifenthaler, 2021). For instance, students and educators may misinterpret axes, fail to identify significant outliers, or overlook key correlations when engaging with highly detailed or multimodal visualisations (Donohoe & Costello, 2020). Moreover, the cognitive load associated with processing dense visual analytics can overwhelm students and educators, making it difficult to extract meaningful insights (Pozdniakov et al., 2023). These challenges may intensify as VLA becomes more intricate with advancements in artificial intelligence (AI) and the integration of multimodal sensory data (Ochoa, 2022). These developments not only increase the volume of educational data but also expand its dimensions and modalities, potentially resulting in more complex VLA that are even harder to comprehend (Corrin, 2018; Echeverria, Martinez-Maldonado, Granda et al., 2018). Consequently, there is a growing need to support educational stakeholders' comprehension of VLA and ensure these analytics do not lead to cognitive overload, especially for students without much prior knowledge or exposure to complex VLA (Donohoe & Costello, 2020; Ramaswami, Susnjak, Mathrani, & Umer, 2022).

Supporting students' understanding of complex VLA could be achieved through the integration of explanatory and interactive features that scaffold their interaction with VLA (Echeverria, Martinez-Maldonado, Granda et al., 2018; Yan, Martinez-Maldonado, & Gasevic, 2024). While conventional scaffolding approaches like data storytelling are effective in enhancing comprehension of VLA (Shao, Martinez-Maldonado, Echeverria, Yan, & Gasevic, 2024), these methods face significant limitations in scalability and adaptability. For instance, manual scaffolding often depends on direct, time-intensive intervention by educators, who may not always be available to provide ongoing guidance to every student (Echeverria, Martinez-Maldonado, Granda et al., 2018). Personalising these approaches to cater to individual learning needs further compounds these challenges, as it requires extensive knowledge of each learner's abilities, learning strategies, and gaps in understanding (Fernandez-Nieto, Martinez-Maldonado, Echeverria, Kitto, Gašević, & Buckingham Shum, 2024). Additionally, real-time support, which is crucial for promoting deeper engagement with VLA, is difficult to achieve using conventional methods (Li, Wang, & Qu, 2024). These constraints highlight the need for innovative, scalable solutions that can offer adaptive and personalised support to students at scale (Fernandez-Nieto et al., 2024; Li et al., 2024).

The advancement of generative artificial intelligence (GenAI), particularly with its multimodal capabilities, paves the way for GenAI-powered conversational agents. These agents can infuse interactivity into VLAs, transitioning from exploratory pattern identification to providing deeper, explanatory insights (Echeverria, Martinez-Maldonado, Shum et al., 2018; Ooi et al., 2023). Evidence suggests that such GenAI agents offer real-time, personalised explanations, significantly easing the cognitive burden on students (Kuhail, Alturki, Alramlawi, & Alhejori, 2022; Okonkwo & Ade-Ibijola, 2021). Additionally, the implementation of retrieval-augmented generation (RAG) techniques can elevate VLA from static information displays to dynamic, conversational systems. This transformation fosters a supportive learning environment where students can seek clarifications and obtain immediate, relevant responses (Verbert et al., 2020; Yan, Martinez-Maldonado et al., 2024). Moreover, adopting an agentic system design can further evolve traditional AI systems (passive responsive) to proactive GenAI agents that actively navigate students through crucial components of VLA, thereby enhancing comprehension and facilitating improved learning outcomes (Gibbons, 2002; Kim, Belland, & Walker, 2018).

While GenAI agents offer promising opportunities to enhance students' comprehension of VLA (Ma, Ding, Wang, Han, & Zhang, 2023; Yan, Zhao et al., 2024), the empirical evidence supporting their effectiveness is still limited. To understand the impact of GenAI on students' comprehension of VLA, more rigorous studies are needed to distinguish between genuine learning gains and temporary performance boosts (Khosravi, Viberg, Kovanovic, & Ferguson, 2023; Soderstrom & Bjork, 2015). It is crucial to assess the tangible impact of GenAI agents on fostering a deep, lasting understanding of VLA, rather than merely facilitating a temporary grasp (Cukurova, 2024; Giannakos et al., 2024). Although students might show improved comprehension due to the explanations and guidance provided by GenAI, these improvements may not persist without continued support and do not necessarily reflect an increase in actual competency and learning (Soderstrom & Bjork, 2015; Zimmerman & Schunk, 2011). There is a risk that students could develop an "illusion of competence", where they believe they comprehend complex VLA through GenAI assistance without genuinely internalising the knowledge (Koriat & Bjork, 2005). To address this issue, there is an urgent need for rigorous empirical research to evaluate the effects of GenAI agents on students' ability to comprehend complex VLA, particularly focusing on whether any improvements are sustained after the withdrawal of GenAI support.

This controlled lab study aims to fill the gaps in the literature identified above by empirically evaluating the impact of *three intervention conditions*: data storytelling, passive GenAI agents (those that can reactively respond to questions), and proactive GenAI agents (those that can proactively guide students to make sense of visual data by asking questions or providing suggestions) on students' effectiveness and efficiency in extracting insights from VLA. Specifically, we sought to quantitatively assess how each condition enhances accuracy and reduces the time required for insights extraction from visual data across *three intervention phases*: pre-intervention, during the intervention, and post-intervention (after the intervention is removed). Including a post-intervention phase is crucial for understanding whether these supports function merely as temporary tools or also facilitate the learning of key comprehension skills of VLA during the process (Asamoah, 2022; Bahtaji, 2020). This motivates the first research question:

- **RQ1:** To what extent do students' *effectiveness* and *efficiency* in comprehending visual data **change** from pre- to post-intervention phases across the three intervention conditions?

We also aimed to compare the effectiveness and efficiency of the three interventions to identify the most effective method for sustaining comprehension improvements. This between-subject comparison is critical for understanding the relative efficacy of novel methods, such as GenAI agents, compared to state-of-the-art scaffolding approaches like data storytelling for enhancing VLA comprehension (Li et al., 2024). This leads to the second research question:

- **RQ2:** To what extent do students' *effectiveness* and *efficiency* in comprehending visual data differ between the three intervention conditions in pre-intervention, the intervention, and post-intervention phases?

Finally, considering the important role that visualisation literacy plays in VLA comprehension (Pozdniakov et al., 2023; Shao et al., 2024), we aimed to examine the effects of visualisation literacy on the three intervention conditions through the third research question:

- **RQ3:** To what extent do *visualisation literacy* impact students' effectiveness and efficiency in comprehending visual data in each of the three intervention conditions?

The findings of this study contribute valuable insights into how GenAI agents, particularly proactive ones, can enhance students' comprehension of VLA by incorporating structured guidance, highlighting their potential to genuinely improve student competency beyond mere temporary performance enhancements.

2. Background and related work

2.1. Visual learning analytics

VLA is an evolving domain that intersects learning analytics and visualisation techniques to enhance the interpretation of complex educational data by stakeholders, including students, educators, and administrators (Vieira et al., 2018). The primary aim of VLA is to decode vast amounts of educational data into intuitive visual forms that facilitate understanding and decision-making, thereby improving teaching practices and learning outcomes (Noroozi et al., 2019; Vieira et al., 2018). The significance of VLA lies in its ability to uncover insights from data that might be overlooked in traditional tabular or textual representations (Noroozi et al., 2019; Sahin & Ifenthaler, 2021). By transforming data into visual forms such as graphs and heat maps, visualisations uncover hidden patterns and trends in students' actions (Noroozi et al., 2019). For example, heat maps of engagement data can pinpoint specific times or activities where students are most or least active, providing actionable insights into their learning behaviours (Sahin & Ifenthaler, 2021). Visualisations also enable comparative analyses, such as identifying performance gaps between students or examining the effectiveness of different teaching strategies on learning outcomes (Vieira et al., 2018). These insights are valuable not only for educators and administrators to refine pedagogical practices but also for students to self-assess and shape their own learning trajectories. Therefore, fostering the skills needed to interpret these visualisations is crucial to ensure stakeholders can extract meaningful insights and fully leverage the benefits of VLA (Noroozi et al., 2019; Sahin & Ifenthaler, 2021; Vieira et al., 2018). However, many students and educators lack sufficient data visualisation literacy, which poses a significant barrier to effectively utilising the insights VLA provides (Donohoe & Costello, 2020).

2.2. Scaffolding with data stories

Scaffolding, a well-established educational approach, could play a crucial role in facilitating students' comprehension of VLA by breaking down complex information into manageable components. This method involves posing guiding questions and providing targeted feedback to aid students in grasping specific concepts (Gibbons, 2002). By promoting self-regulated learning, scaffolding encourages metacognitive processes and monitoring behaviours (Lim et al., 2023; Wen et al., 2024), which could potentially lead to improved comprehension when interpreting VLA. Empirical evidence supports its effectiveness in facilitating a deeper understanding and mastery of subject matter, offering contextual guidance throughout the learning process (Gibbons, 2002; Kim et al., 2018).

Data storytelling has emerged as an effective scaffolding technique to enhance individuals' comprehension of complex VLA (Echeverria, Martinez-Maldonado, Shum et al., 2018; Pozdniakov et al., 2023). Rather than leaving students and educators to interpret raw visualisations independently (e.g., bar charts showing performance metrics or heatmaps depicting engagement levels), data stories integrate these visuals into narratives that contextualise the information (Segel & Heer, 2010). For example, education dashboards could pair collaboration metrics with narratives revealing how communication among team members evolved and impacted performance (Echeverria, Martinez-Maldonado, Shum et al., 2018). By providing structured annotations and cues, data stories bridge the gap between data and insights, making findings meaningful and actionable.

Research indicates that this approach can efficiently direct attention to key pedagogical insights (Echeverria, Martinez-Maldonado, Granda et al., 2018; Martinez-Maldonado, Echeverria, Fernandez Nieto, & Buckingham Shum, 2020), foster deep reflections, and help teachers and students understand their learning processes (Echeverria, Martinez-Maldonado, Granda et al., 2018; Fernandez Nieto, Kitto, Buckingham Shum, & Martínez-Maldonado, 2022). It is particularly beneficial for individuals with low data visualisation literacy, aiding them in efficiently interpreting information (Pozdniakov et al., 2023). The advantages of data storytelling are further supported by research showing its effectiveness in improving the efficiency of insight comprehension. Shao et al. (2024) found that data stories enhance information retrieval and the understanding of visual data, regardless of an individual's prior data visualisation literacy. However, it remains uncertain whether these improvements persist after the removal of storytelling

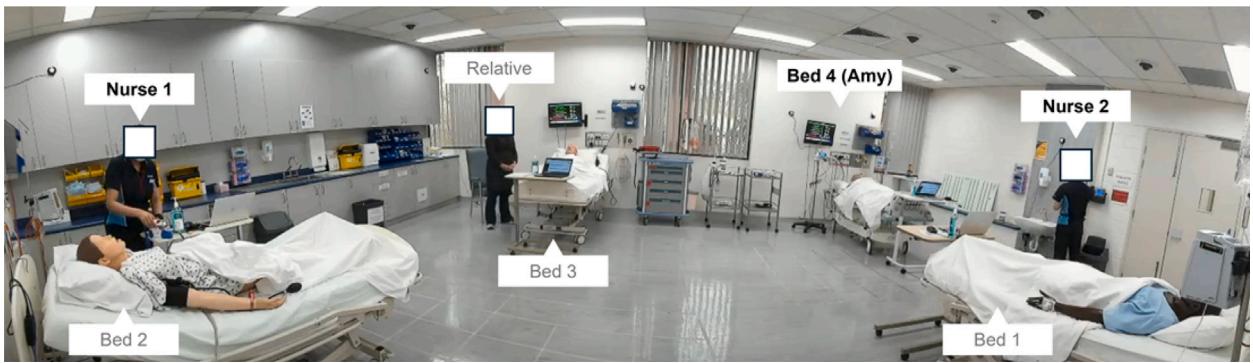


Fig. 1. Picture of the healthcare simulation activity with key components labelled and identities masked.

elements, or if they lead to lasting comprehension of key concepts. Challenges continue in adapting and scaling data storytelling in educational settings (Fernandez-Nieto et al., 2024; Li et al., 2024). Notably, research by Li et al. (2024) highlights potential integrations of data storytelling and scaffolding with emerging AI technologies, such as GenAI agents, to provide personalised support for students.

2.3. Generative AI agents

The latest developments in GenAI have opened new avenues for facilitating students' comprehension of VLA (Chen, Shuai, Zhang, Sun, & Cao, 2024; Li et al., 2024). Large language models (LLMs) such as GPT and Llama are adept at generating text-based content from prompts, which is invaluable for summarising complex datasets and visualisations, providing explanatory narratives, and crafting data stories with minimal human oversight (Chung et al., 2022; Yan, Zhao et al., 2024). The emergence of multimodal models like GPT-4o further enhances GenAI's capability to interpret and synthesise both textual and visual data, promising more comprehensive explanations (Chen et al., 2024; Ye et al., 2024). This advancement points towards potential methods that render VLA comprehension more interactive, where students can communicate with VLA for future information (e.g., through clicking on an information button or interacting with a chatbot) (Li et al., 2024; Ye et al., 2024). However, simply generating descriptions of visual data might not facilitate understanding and learning (Zdanovic, Lembcke, & Bogers, 2022), necessitating contextually grounded explanations for effective comprehension and deeper learning insights (Borges, Correa, & Silveira, 2022; Milesi & Martinez-Maldonado, 2024). A significant barrier has been the tendency of GenAI to produce well-articulated but inaccurate content, known as hallucination (Ji et al., 2023; Leiser et al., 2024). This can be mitigated by retrieval-augmented generation (RAG), which confines content generation to relevant material (Shuster, Poff, Chen, Kiela, & Weston, 2021). By converting relevant information into vector embeddings that capture semantic meanings and retrieving this information through semantic search (Li, Jin et al., 2024), this approach reduces hallucinations and increases domain-specific accuracy (Siriwardhana et al., 2023). Therefore, integrating RAG with GenAI could offer real-time, contextually relevant explanations to help students understand VLA and address potential confusion (Yan, Zhao et al., 2024).

The development of GenAI agents, which are autonomous, adaptive entities that operate independently to achieve predefined goals without constant user input (Wu et al., 2023), can also contribute to enhancing students' comprehension of VLA by proactively guiding them with scaffolding questions (Oertel et al., 2020; Park et al., 2023). Unlike passive agents that merely respond to queries, proactive GenAI agents can prompt students to focus on specific parts of visualisations with step-by-step guidance, similar to how an educator might ask, "What trends do you notice in this graph?" or "Why do you think this data point is an outlier?" (Gibbons, 2002). This structured approach could potentially support deeper understanding by breaking down complex information and offering guidance as students build their knowledge and skills (Kim et al., 2018). The educational potential of these agents aligns closely with Vygotsky's Zone of Proximal Development (ZPD), suggesting learning is most effective when students receive guidance for tasks beyond their current independent capabilities (Vygotsky & Cole, 1978). As a 'more knowledgeable other,' these agents could encourage exploration and problem-solving with VLA, offering hints and scaffolded questions that help students progressively build their understanding (Wen et al., 2024; Yan, Greiff, Teuber, & Gašević, 2024). Although this method seems promising and innovative system frameworks are being developed (Ma et al., 2023; Yan, Zhao et al., 2024), empirical evidence remains limited on whether such agents improve the effectiveness and efficiency of students' comprehension of VLA compared to conventional scaffolding approaches like data storytelling. It also remains unclear whether genuine learning occurs rather than just temporary performance improvements.

2.4. Data visualisation literacy

Effectively communicating data visualisations can be challenging, even with well-designed tools that are based on data stories and GenAI agents (Donohoe & Costello, 2020). *Data visualisation literacy*, the ability to interpret visualisations, extract insights,

and draw informed conclusions, is crucial for navigating complex visual representations, particularly in educational contexts where insights from visual learning analytics influence decision-making and outcomes (Boy, Rensink, Bertini, & Fekete, 2014; Firat, Joshi, & Laramee, 2022). Differences in visualisation literacy significantly affect how students and educators interpret and benefit from visualisations. Low literacy often leads to difficulties recognising patterns, interpreting axes, and connecting data points, resulting in confusion or misinterpretation (Donohoe & Costello, 2020; Firat et al., 2022). For instance, Pozdniakov et al. (2023) found that individuals with lower visualisation literacy benefit most from data storytelling, as it reduces cognitive load and helps bridge interpretation gaps. Conversely, Shao et al. (2024) showed that data stories enhance insight extraction for participants across all literacy levels, including those with higher proficiency. Despite these insights, research on the interaction between visualisation literacy and scaffolding strategies, such as storytelling or GenAI tools, remains limited and produces mixed results. Further research is needed to clarify how visualisation literacy influences the effectiveness of these interventions, helping to design personalised, adaptive tools that support diverse students and educators while ensuring equitable access to meaningful data interpretation.

3. Method

3.1. Study contexts and visual learning analytics

The current study leverages a multimodal dataset to investigate the comprehension of VLA in a healthcare simulation learning setting. The simulated learning environment (see Fig. 1), featuring four patient beds equipped with medical devices like oxygen masks and vital signs monitors, used advanced patient manikins that could simulate different heart rates and pulses, controlled by teaching staff via a tablet. The main goal of the VLA was to provide insights into students' teamwork, communication, and prioritisation skills in handling clinical emergencies during the simulation. More details about the learning objectives of this simulation activity are available in Appendix A. This setting is highly dynamic, with multimodal behaviours such as communication, teamwork, and clinical actions occurring simultaneously. The resulting VLA spans a range of complexity, making it an ideal context to address the research questions by examining how different scaffolding approaches enhance comprehension and efficiency in interpreting diverse and challenging visual data.

The study was conducted in a controlled lab environment, with participants recruited via Prolific (further elaborated in Section 3.5). Importantly, the study participants were not the individuals whose actions were recorded in the healthcare simulation; instead, they interacted with pre-existing visualisation data from those simulations to assess their comprehension of VLA. This study aimed to assess how scaffolding methods, such as storytelling and GenAI agents, support understanding of VLA after the simulation events, rather than adapting actions within the simulation itself. Unlike scaffolding applied in real-time scenarios, this approach focuses solely on enhancing post-simulation data comprehension rather than influencing live decisions.

The dataset used to generate the VLA (further elaborated below) included three primary types of physical and physiological data: positioning, audio, and heart rate. Students' x-y positioning data were collected using the Pozyx creator toolkit,¹ audio data were captured using wireless headsets with unidirectional microphones for multi-channel audio recording, and heart rate data were recorded using Empatica E4 wristbands.

This dataset was selected because the VLA have already been validated and utilised by healthcare educators and students for reflective purposes (Yan et al., 2024). As depicted in Fig. 2, three different visualisations with increasing complexity were used. The first visualisation is a bar chart illustrating four prioritisation strategies demonstrated by students during the simulation. This type of visualisation is typically effective for comparing different categories (Saket, Endert, & Demiralp, 2018). For instance, the bar chart allows for a clear interpretation of the proportion of time each team spent on various prioritisation behaviours. However, the ease of interpretation can depend on the user's level of visualisation literacy. While individuals with sufficient data visualisation skills can readily identify patterns, those with low visualisation literacy may still struggle to extract meaningful insights (e.g., making comparisons), even from simple visuals (Donohoe & Costello, 2020).

The second visualisation is a social network, or sociogram, mapping the communication behaviours among students and other actors in the simulation. Social network analysis is commonly used in collaborative learning and computer-supported cooperative work studies (Dado & Bodemer, 2017; De Laat, Lally, Lippinen, & Simons, 2007). This visualisation can help students to understand interaction dynamics within the team, identifying who communicated most frequently and the direction of these communications. It can also highlight interactions with the patient, the doctor, and the relative, providing insights into the roles and engagement levels of each participant.

The third visualisation is a ward map that displays students' physical positions, verbal communication duration, and peak heart rate locations. Inspired by advanced techniques in sports analytics (Goldsberry, 2012), this visualisation combines heatmaps (Gu, 2022) with specific healthcare-relevant information. The heatmap component illustrates the frequency and distribution of verbal communications, with saturated colours indicating areas of high verbal activity. Additionally, the map shows the spatial distribution of students around the simulation space (e.g., a greater number of hexagons in an area indicates a longer time spent in that position), providing a comprehensive view of their physical and behavioural engagement. Furthermore, the map includes the location and value of each student's peak heart rate, indicating areas of highest physiological arousal. This information provides insights into how students respond to high-pressure situations during the simulation, which is critical in understanding students' stress levels and engagement, particularly in dynamic and high-stakes clinical settings. These visualisations collectively offer insights

¹ <https://www.pozyx.io/creator>

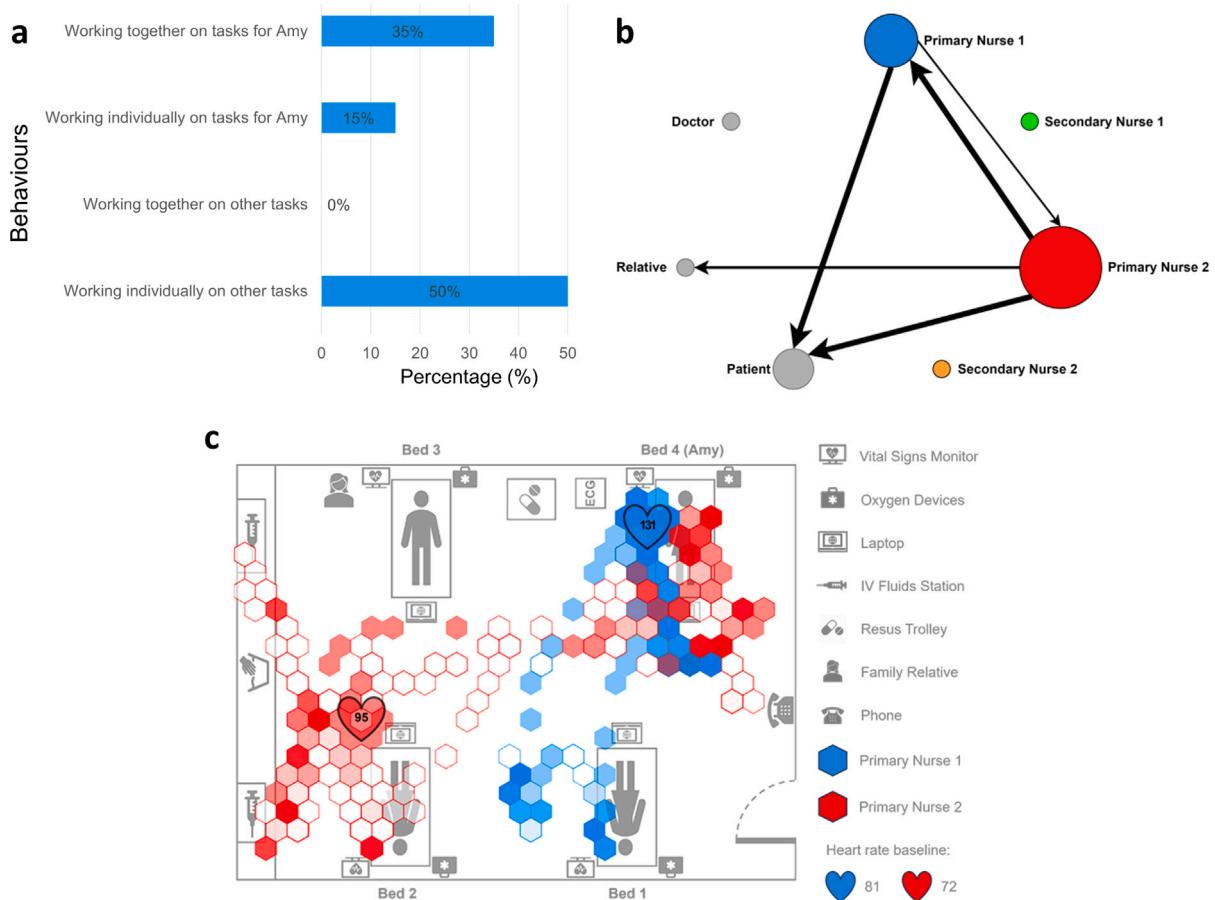


Fig. 2. Visual learning analytics of teamwork in healthcare simulations: (a) a bar chart showing students' four prioritisation strategies, (b) a social network illustrating communication behaviours among students and other actors, and (c) a ward map displaying students' physical positions (hexagon position), verbal communication durations (colour saturation), and peak heart rate locations.

into prioritisation, teamwork, and communication strategies, which are challenging to comprehend without advanced visualisation literacy (Yan et al., 2024).

To align with the study's objectives, we deliberately selected specific scenarios for the visualisations. For instance, in the visualisation depicted in Fig. 2b, the two nurses (e.g., Secondary Nurses 1 and 2) and the doctor were not interacting with others during the selected period, as they were located outside the room at that time. This inclusion was intentional to assess whether students could accurately identify and interpret moments of non-interaction in the visual learning analytics, a critical skill for understanding complex multimodal scenarios.

3.2. Intervention design: Generative AI agents

To investigate the impact of passive and proactive GenAI agents on students' ability to comprehend the VLA, we utilised an open-sourced prototype of [Anonymised].² This prototype integrates multimodal GenAI (e.g., OpenAI GPT-4o³), RAG frameworks (e.g., LangChain), and agentic system designs (e.g., Autogen Wu et al., 2023) to ensure the accuracy and contextual relevance of information provided by the GenAI agents. Multimodal GenAI processes both graphical and textual data, tailoring AI-generated responses specifically to the visualisations participants inquire about. RAG incorporation ensures GenAI agents access relevant and accurate knowledge for context-specific prompts (Gao et al., 2023; Lewis et al., 2020). Agentic systems (Park et al., 2023) enable GenAI agents to address irrelevant responses generated by incomplete user prompts (White et al., 2023). As shown in Fig. 3, the design of the passive and proactive GenAI agents includes five main components: (i) agent characteristics, (ii) prompt integration, (iii) knowledge database, (iv) response generation, and (v) exemplar behaviours.

² Hidden for double-blinded review.

³ <https://openai.com/index/hello-gpt-4/>

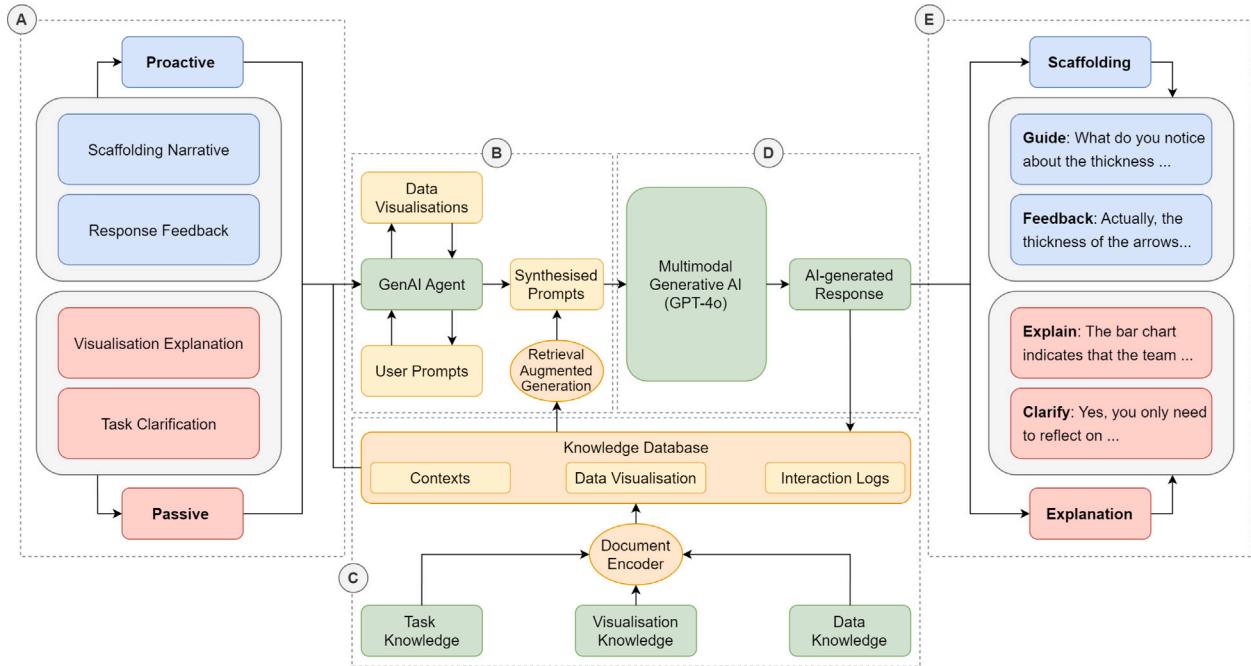


Fig. 3. System design of the passive and proactive generative AI (GenAI) agents, illustrating five main components: (A) unique characteristics that differentiate the passive agent from the proactive agent, (B) interaction among user prompts, data visualisation, and the GenAI agent for prompt synthesis using retrieval-augmented generation, (C) a knowledge database containing essential contextual information for the current task, (D) generation of contextually relevant responses using multimodal GenAI, and (E) examples of the resulting behaviours of the passive GenAI agent, which focuses on explanation and clarity, and the proactive GenAI agent, which provides scaffolding with guided questions and feedback.

3.2.1. Agent characteristics

The core interaction styles distinguish the passive and proactive GenAI agents. Passive GenAI agents are reactive, waiting for student-initiated queries before responding (Ma et al., 2023; Yan, Zhao et al., 2024). They are characterised by their ability to deliver precise and contextually relevant information without initiating unsolicited interactions. In contrast, proactive GenAI agents are more engaging and interactive (Oertel et al., 2020; Park et al., 2023). They not only respond to student queries but also guide students through the visualisations with structured narratives and scaffolding questions (crafted by educators and researchers based on Hattie and Timperley (2007)'s feedback model; Appendix B). This dual approach allows for a comparative analysis of how different interaction styles impact user understanding and insight extraction from VLA.

3.2.2. Prompt integration

Prompt integration is critical for both passive and proactive GenAI agents. For passive agents, the process starts with student-initiated queries, which are processed to generate contextually relevant responses. This involves interpreting the natural language input and matching it with the visualisation and the knowledge database using RAG. Proactive agents, however, go a step further by synthesising prompts based on user interactions and a pre-defined scaffolding narrative consisting of guiding questions that facilitate the exploration of the visualisations. They generate prompts to guide students through the visualisations, helping them understand the data more structurally and providing feedback based on students' responses. This is achieved through a combination of pre-stored knowledge and real-time data interpretation, ensuring accurate and tailored responses.

3.2.3. Knowledge database

The knowledge database is the backbone of the GenAI agents, providing the necessary contextual information for accurate and relevant responses. Built using LangChain⁴ and Chroma,⁵ the database is populated with task-specific materials, descriptions, and detailed explanations of visualisation components. These materials are directly drawn from the learning design documents of the healthcare simulation unit and peer-reviewed publications describing each visualisation [Anonymised]. Textual materials are converted into vector embeddings using OpenAI's embedding model (text-embedding-ada-002), allowing for efficient semantic searches. This enables the agents to retrieve pertinent information based on the cosine similarity of the embeddings (Gao et al., 2023). The knowledge database is dynamic, evolving with each user interaction. New information from student-agent conversations is continuously ingested, enhancing the personalisation and relevance of subsequent interactions.

⁴ <https://www.langchain.com/>

⁵ <https://www.trychroma.com/>

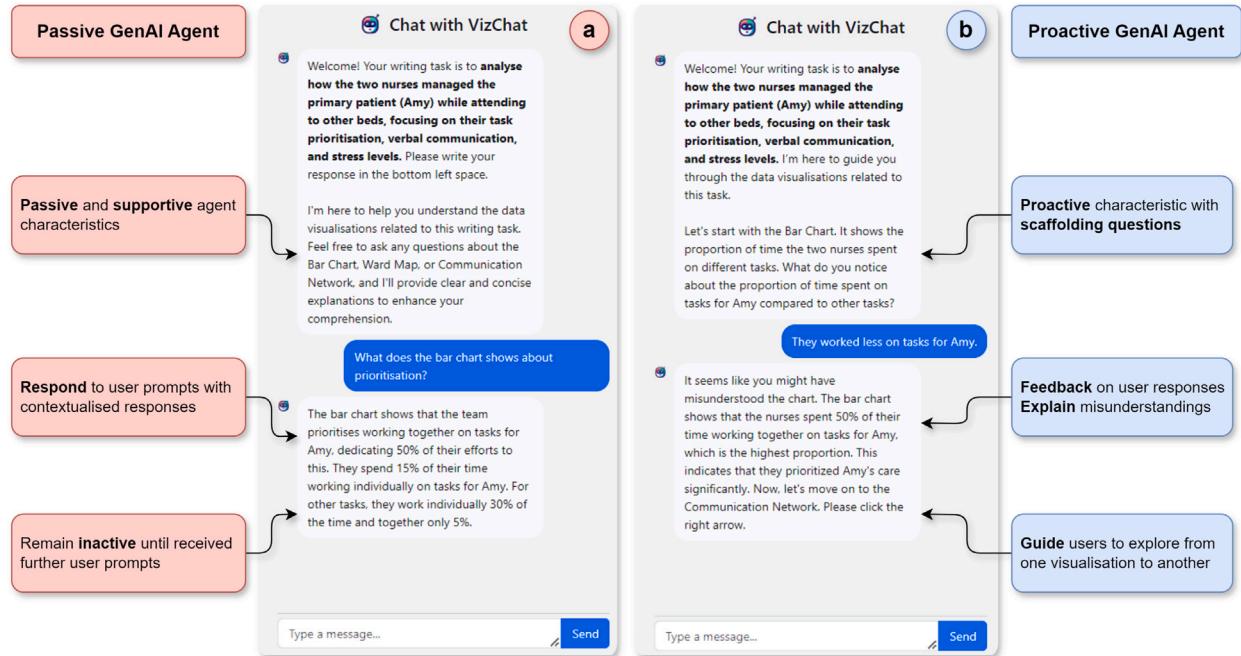


Fig. 4. Example interactions with the two generative AI (GenAI) agents, illustrating the key characteristics of (a) the passive GenAI agent and (b) the proactive GenAI agent.

3.2.4. Response generation

Response generation in both passive and proactive GenAI agents leverages the multimodal capabilities of GPT-4o, ensuring responses are accurate and contextually relevant. When a user submits a natural language query, the GenAI agent interprets it and links it to the appropriate context from the visualisations. Using the RAG framework, the system performs a semantic search over the knowledge database by converting the query into a vector format, matching it with pre-stored context embeddings of the visualisations. Retrieved information enriches the prompt, enabling the GenAI model (e.g., GPT-4o) to produce responses that align with user intent and the visual data. For passive agents, responses are directly generated from user queries by retrieving relevant information via RAG. Proactive agents, in contrast, use pre-defined scaffolding narratives with guiding questions. Their responses provide feedback on students' inputs, prompting elaboration, reflection, or progression to subsequent questions. Proactive agents also evaluate the correctness of students' answers and generate tailored feedback to encourage deeper understanding.

3.2.5. Exemplar behaviours

The behaviours of the passive and proactive GenAI agents are exemplified by their interaction styles (Fig. 4). Passive agents focus on explanation and clarity, providing students with straightforward answers to their queries. For example, when asked about the representation of a bar chart, a passive agent retrieves and presents the relevant information from the knowledge database. Proactive agents, however, offer scaffolding with guided questions and feedback. They actively engage students by asking clarifying questions, offering step-by-step explanations, and facilitating the exploration of the visualisations within a scaffolding framework (e.g., a set of guiding questions targeting each element of the visualisations) (Xun & Land, 2004). For example, to facilitate students' understanding of a social network, a proactive agent might start by asking questions about the thickness of the edges connecting two nodes. After confirming students have a clear understanding through their responses, it will then move on to questions about the direction of the edges. This scaffolding approach aims to structurally enhance comprehension and cultivate the ability to comprehend data visualisations.

3.3. Intervention design: Data stories

To reliably create data visualisations enhanced with storytelling elements, we identified key techniques based on the framework by Zdanovic et al. (2022) and followed a structured three-phase process: exploring the data, creating the visualisation, and telling the story. Key elements included choosing the right visualisation technique to match storytelling goals (Knafllic, 2015), simplifying visuals by eliminating clutter to enhance readability (Heer & Shneiderman, 2012; Tufte, 2001), directing attention using bold lines or contrasting colours for key insights (Knafllic, 2015; Ware, 2019), adding annotations for context (Hullman, Drucker, Riche, Lee, Fisher, & Adar, 2013), and crafting explanatory titles that guide viewers (Kong, Liu, & Karahalios, 2018; Pozdniakov et al., 2023). As shown in Fig. 5, our process did not involve changing chart types, maintaining complexity progression from bar charts to social

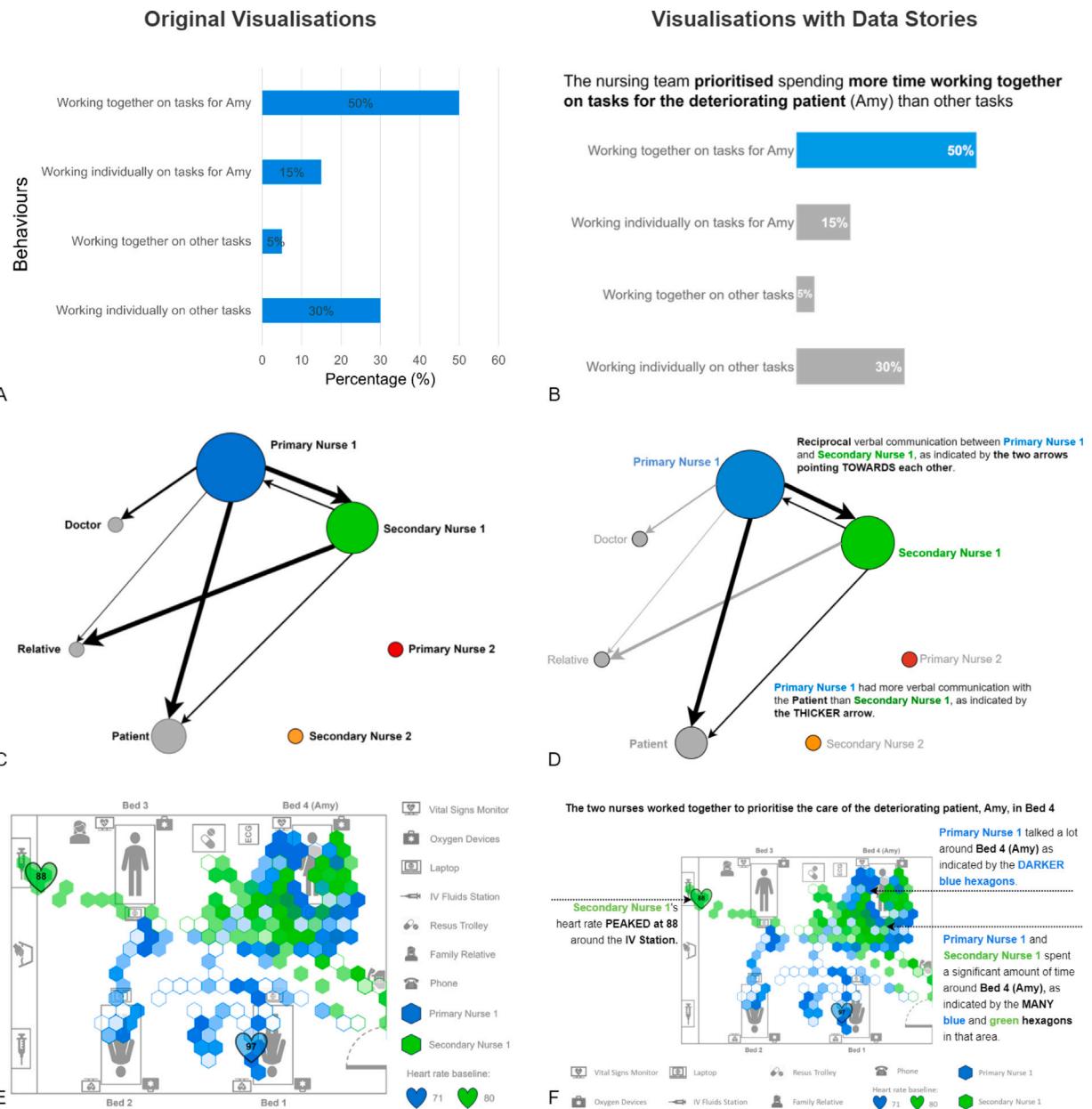


Fig. 5. Visual learning analytics infused with data storytelling elements.

network visualisations, and custom-made ward maps. Initially, one researcher drafted the data stories, which were then reviewed and refined collaboratively by researchers with expertise in data storytelling, ensuring alignment with research objectives. This iterative approach ensured thoughtfully developed visual elements, adhering to Zdanovic's framework for effective storytelling.

While data storytelling and proactive GenAI agents share similarities in their use of scaffolding techniques to guide participants through the interpretation of complex visualisations, key differences exist in their interactivity and adaptability. Data storytelling operates as a static support mechanism, providing pre-defined narratives, annotations, and visual cues that cannot adapt to individual user queries or challenges in real time. In contrast, proactive GenAI agents dynamically interact with participants, adjusting their guidance and feedback based on the participants' specific inputs or progress. This distinction makes data storytelling particularly effective for situations where generalised guidance suffices, such as introducing overarching insights or themes in the data. However, the static nature of data stories may limit their ability to address unique interpretations or misconceptions as they arise. Passive GenAI agents, on the other hand, focus on delivering precise answers to user queries without offering scaffolding elements, making them less aligned with the pedagogical principles implicit in data storytelling. These distinctions highlight the varying degrees of adaptability and guidance offered by each intervention method.

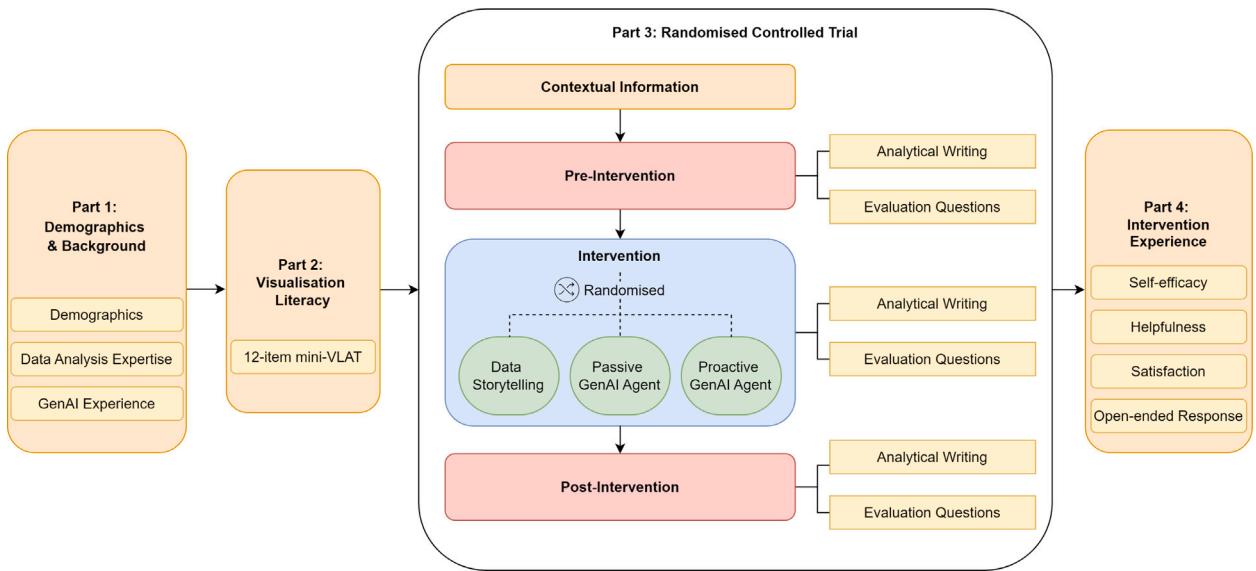


Fig. 6. Experiment design and procedure: Detailed breakdown of participant flow through demographics and background questionnaires, visualisation literacy assessment, the randomised controlled trial, and intervention experience questionnaire.

3.4. Experiment design and procedure

This randomised controlled study was designed following gold standards for effectiveness research (Hariton & Locascio, 2018). We conducted a mixed-design (3x3) experiment, using both within-subject and between-subject comparisons to evaluate the effectiveness of data storytelling, passive GenAI agents, and proactive GenAI agents in enhancing insight extraction from VLA. The study was conducted using Qualtrics,⁶ an online platform for designing and conducting experiments, integrated with a custom-developed website. Participants were recruited from Prolific,⁷ compensated £8, and the study was structured to be completed within one hour. Ethics approval was obtained from [Anonymised] University (Project Number: Anonymised). Informed consent was secured from each participant.

Participants were randomly assigned to one of three intervention conditions: passive GenAI agents, proactive GenAI agents, or data storytelling. Passive GenAI agents responded to user queries without initiating further dialogue or guidance, while proactive GenAI agents guided participants with scaffolding questions. The data storytelling condition presented visualisations within a narrative format, highlighting key insights and trends. Each participant interacted with their assigned condition during the intervention phase to support insight extraction from visualisations. The effectiveness of each method was evaluated through pre-, during, and post-intervention assessments.

The study followed a structured procedure to ensure consistency across conditions, comprising five main parts: (i) the participants received an introduction to the study and completed demographic and background questions on Qualtrics; (ii) they answered 12 items from the mini-Visualisation Literacy Assessment Test (mini-VLAT) (Pandey & Ottley, 2023) to measure their visualisation literacy; (iii) the participants were directed to our custom platform to complete three analytical writing tasks, each followed by six evaluation questions (in Qualtrics) to assess their understanding of the VLA; and (iv) finally, the participants completed a questionnaire to provide feedback on their experience with the assigned intervention method. Fig. 6 illustrates the experiment design and procedure. Details are elaborated below.

3.4.1. Part 1: Demographics and background questions

Participants were initially queried on demographic information, including self-reported gender and region. Subsequently, we assessed participants' self-reported experience in data analysis and GenAI tools. For data analysis, participants rated their experience on a 5-point scale, ranging from 1 ("None - I have little to no experience with data analysis") to 5 ("Expert - I have extensive experience and can perform data analysis tasks confidently"). Similarly, for GenAI tools, participants rated their experience on a 5-point scale, from 1 ("None - I have no prior experience with generative AI tools") to 5 ("Expert - I have deep expertise and often develop or customise generative AI tools for specialised purposes").

⁶ <https://www.qualtrics.com/>

⁷ <https://www.prolific.co/>

3.4.2. Part 2: Visualisation literacy

The 12-item mini-VLAT was used to assess participants' visualisation literacy (Pandey & Ottley, 2023). This instrument was selected due to its demonstrated reliability and validity, comparable to the full 53-item VLAT (Lee, Kim, & Kwon, 2016) while offering a more concise measure of visualisation literacy. These features made it particularly suitable for our extended study, as it minimised cognitive load on participants. The scores were corrected for guessing using the correction-for-guessing formula (Thorndike, Cunningham, Thorndike, & Hagen, 1991):

$$CS = R - W / (C - 1) \quad (1)$$

In this formula, CS represents the final score corrected for guessing behaviours, R represents the number of correctly answered items of a given participant, W represents the number of wrongly answered items, and C represents the number of choices per item, which is four for the mini-VLAT.

3.4.3. Part 3: Randomised controlled trial

The randomised controlled trial consisted of four main activities: (i) reading contextual information about the visualisations, (ii) all participants completing the same baseline analytical writing activity (*Pre-intervention*) where no intervention was provided, followed by six evaluation questions, (iii) each participant being randomly assigned to one of the three intervention conditions (*Intervention*), having access to either data storytelling, passive GenAI agents, or proactive GenAI agents, followed by six evaluation questions, and (iv) all participants completing another, yet different, baseline activity (*Post-intervention*) with the intervention removed, followed by six evaluation questions.

The visualisation format remained consistent across the pre-intervention phase, the intervention phase, and the post-intervention phase (e.g., bar chart, social network, and ward map), although the data and insights contained within these visualisations varied across these different phases. Likewise, the six evaluation questions maintained the same format, with the questions and answers tailored to the insights for each activity. Details of the contextual information, analytical writing tasks, and evaluation questions are elaborated below:

Contextual information. Participants were provided with a picture (Fig. 1) and a description of a healthcare simulation where two nursing students took over care of four manikin patients (Beds 1–4) during their shift. Each patient required at least two tasks, with the primary focus on the deteriorating patient in Bed 4 (Amy), while the needs of other patients (Beds 1–3) also required attention. An actor played a relative of the patient in Bed 3, frequently distracting the nurses. The simulation aimed to practice teamwork, communication, and prioritisation skills. By the end, students were expected to (i) demonstrate a structured approach to patient assessment and management, (ii) recognise and respond to early signs of deterioration, and (iii) contribute to effective teamwork. This background was essential for participants to engage in the subsequent writing tasks effectively.

Analytical writing tasks. Participants were directed to a custom-developed website (Fig. 7) to complete an analytical writing task. They were asked to analyse three visualisations (bar chart, social network, and ward map) and write a 100–150 word response on *how the two nurses managed the primary patient (Amy) while attending to other beds, focusing on their task prioritisation, verbal communication, and stress levels*. The website was designed with simplicity in mind (Stone, Jarrett, Woodroffe, & Minocha, 2005), ensuring easy navigation and task completion.

The website had three key components. First, the display component (Fig. 7a) presented the visualisations one at a time to avoid information overload and visual clutter (Ellis & Dix, 2007). Second, the writing space (Fig. 7b) allowed participants to articulate their analysis, synthesising information from the visualisations. Lastly, the instructions component (Fig. 7c) provided standard task instructions for the pre-intervention and post-intervention baselines and the data storytelling condition. In the passive and proactive GenAI conditions, participants interacted with GenAI agents via a chat function for additional support and guidance (Fig. 7d).

This design helped participants focus on the analytical writing task without distractions, facilitating clear and effective exposure to each intervention condition and providing opportunities to develop their ability to comprehend data visualisations.

Evaluation questions. After each analytical writing task, participants were asked to complete six multiple-choice questions (four choices per question; two for each visualisation; Appendix C). They complete these questions without any form of support in Qualtric instead of on the custom-built website. These questions were designed to evaluate their ability to comprehend data visualisations. Structured based on the first two levels of Bloom's taxonomy, knowledge (Level 1) and comprehension (Level 2) (Bloom, Krathwohl, Masia, et al., 1984), these questions directly align with common practices in visualisation research (Arneson & Offerdahl, 2018; Mnguni, Schönborn, & Anderson, 2016). For the knowledge questions, participants were required to identify specific data points or patterns in the visualisations, such as pinpointing the prioritisation behaviour that two nurses spent the most time on from a bar chart. These questions assessed their ability to retrieve pertinent information. For the comprehension questions, participants had to interpret and derive meaningful insights, such as comparing the spatial and verbal activities between two nurses through the ward map. These questions evaluated their ability to interpret multiple insights and identify inconsistencies or misleading information. Higher levels of Bloom's taxonomy, such as application (Level 3), were not addressed, as the study involved online participants with limited contextual knowledge.

Two researchers familiar with the learning contexts and visualisations designed the six evaluation questions. A third researcher validated this design to ensure its applicability across all three sets of visualisations: pre-intervention, intervention, and post-intervention. Any discrepancies were resolved through discussion, leading to a consensus on the final evaluation questions. These questions ensured alignment with the data insights in the visualisations and the appropriate Bloom's taxonomy levels. While the order of the questions remained consistent across all phases, the order of the answer choices was randomised to minimise bias and improve reliability and validity (Association, Association, & on Measurement in Education, 2014). A fifth option, 'I am not sure,' was

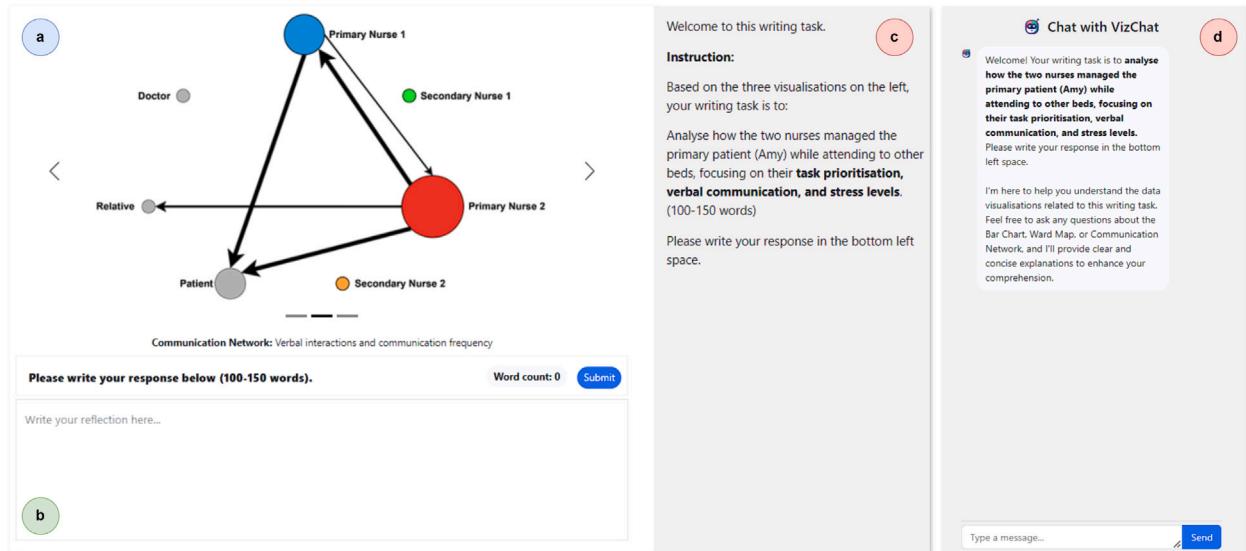


Fig. 7. Custom-developed website for the analytical writing task. (a) a display component for the visualisations, (b) a writing space, (c) task instructions used in the pre-intervention, post-intervention baselines, and data storytelling condition, and (d) a chat function with GenAI agents for the passive or proactive conditions.

Table 1
Intervention experience items.

Dimension	Item
Self-efficacy	I feel more confident in my ability to interpret data visualisations after participating in the intervention.
Helpfulness	The intervention helped me better understand the data visualisations.
Satisfaction	I am satisfied with my overall experience during the intervention.

added to each question to reduce guessing, following recommendations in mini-VLAT and VLAT (Lee et al., 2016; Pandey & Ottley, 2023). The time taken to answer each question correctly was measured to evaluate the efficiency of insights extraction, while the accuracy rate was recorded to provide insights into the effectiveness of comprehension (further elaborated in Section 3.6).

3.4.4. Part 4: Intervention experience

For the last part of the study, participants were asked to evaluate their experiences with the intervention (e.g., data storytelling, passive GenAI agents, or proactive GenAI agents) through three single-choice items and one open-ended question. Each item was rated on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Table 1 shows the items. Although the internal reliability of these single-item items cannot be estimated, they have shown evident reliability in capturing individuals' attitudes and beliefs (Wanous & Reichers, 1996). The open-ended question targeted further qualitative elaborations – “Please describe your experience with the intervention. To what extent did it enhance or diminish your ability to interpret the data visualisations?”

3.5. Participants

We conducted a priori power analysis for a mixed-design study with three between-subject conditions and three within-subject repeated measures using G*Power (Faul, Erdfelder, Buchner, & Lang, 2009). The analysis indicated that a minimum sample size of 108 participants (36 per condition) was needed to detect a medium effect size (0.25) with 80% power at a 0.05 significance level. To account for an anticipated attrition rate of 15% to 20% due to potential data issues, particularly given the one-hour duration of the online study, we aimed to recruit 150 participants. Participants were required to be fluent in English and use a laptop or desktop to ensure consistent visualisation displays. We specifically recruited higher education students with healthcare, medical, or nursing backgrounds to control for familiarity with the healthcare simulation context of the VLA.

Before the main study, a pilot study with 27 participants (9 per condition) was conducted to refine the Qualtrics survey for clarity and ease of use. We also tested the custom-developed website to ensure timely responses from both passive and proactive GenAI agents. Data from the pilot study were excluded from the final analysis due to subsequent improvements in the study flow, such as mandatory reading time for each task instruction and improved clarity of several context description sentences.

For the main study, participants had to complete all three writing tasks, essential for internalising their understanding of data visualisations. Incomplete responses, including failure to complete any writing task or the entire survey, were deemed invalid. Out of the 141 responses received, 24 were invalid due to incomplete writing tasks, resulting in a final sample of 117 valid responses.

Specifically, 36 participants completed the data storytelling condition, 41 completed the passive GenAI agents condition, and 40 completed the proactive GenAI agents condition.

The participants came from six different regions, with the majority coming from North America/Central America (51), Europe (28), and Africa (25). The remainder were from Australia (5), South America (4), and other regions (4). They identified as female (68), male (48), and non-binary (1). Regarding experience with data analysis, most participants were at an intermediate level (50), with a moderate level of experience. Others were beginners (36), advanced users (17), had no experience (12), or were experts (2). In terms of familiarity with GenAI tools, most participants were at an intermediate level (63), having used the tools on several occasions. Others were beginners (34), advanced users (15), experts (4), or had no prior experience (1). The participants primarily consisted of undergraduate (77) and graduate students (21), with a smaller number of vocational (13) and doctoral (6) students. All participants were health and medical students (95) or nursing students (22).

3.6. Analysis

The analysis aimed to address three research questions (RQs) regarding the impacts of different interventions on enhancing participants' effectiveness and efficiency in extracting insights from VLA. We first calculated a set of metrics related to the RQs using the responses and times for six evaluation questions for each task ([Appendix C](#)). These metrics were calculated for both within- and between-subject analyses, including the three intervention phases, specifically, the pre-intervention baseline (Pre), the intervention phase, and the post-intervention phase (Post), as well as for the three intervention conditions, namely data storytelling (DS), passive GenAI agents (GAI), or proactive GenAI agents (DSAI). In particular, the following metrics were calculated:

- **Correct Score:** To investigate the effectiveness of insights extraction from data visualisations (RQ1-2), we computed the correct score for the six evaluation questions for each condition by summing the total number of questions that participants answered correctly (each score ranges from 0 to 6), resulting in three correct scores for each participant (Pre_score, Intervention_score, and Post_score). The correction-for-guessing formula ([Thorndike et al., 1991](#)) was applied to account for guessing in these multiple-choice questions (with four options).
- **Success Time:** To investigate participants' efficiency in data insights extraction (RQ1-2), we summed the total time they spent on answering the six evaluation questions for each condition in seconds and then divided by the corresponding correct score for that given condition ([Shao et al., 2024](#)), resulting in three success time metrics for each participant (Pre_time, Intervention_time, and Post_time).

In addition to the above two metrics, visualisation literacy (mini-VLAT) was calculated separately for each participant to address RQ3. This calculation was done by summing the number of correct responses. Specifically, visualisation literacy ranges from 0 to 12. For both literacy scores, the correction-for-guessing formula ([Thorndike et al., 1991](#)) was applied to account for guessing behaviours. All calculations and analyses were conducted in Python using packages including NumPy, SciPy, and Statsmodels. The following sections elaborate on the analysis for each RQ.

3.6.1. Preliminary analysis: Learning effects and comparability

Before addressing each research question, we first assessed whether learning effects exist due to the repeated design, which is critical for attributing any observed improvements to the interventions instead of repeated exposure ([Charness, Gneezy, & Kuhn, 2012](#)). We conducted a mixed linear model analysis with correct scores (Pre_score, Intervention_score, and Post_score) as the dependent variable. We included phase (pre-intervention, intervention, post-intervention) as the fixed effect and incorporated each participant as a random effect to account for variability within subjects. We analysed score changes from pre-intervention to post-intervention phases across all conditions to identify any improvements that could be attributed to repeated task exposure rather than intervention effects.

We also conducted a preliminary analysis to ensure that the three intervention conditions were comparable in terms of participants' visualisation literacy (mini-VLAT), data analysis, and GenAI expertise (demographics ranging from 1–None to 5–Expert). This preliminary analysis is essential to ensure the findings for the subsequent analyses are robust and reliable ([Charness et al., 2012](#)). We used the Kruskal–Wallis test, a non-parametric test that compares the medians of more than two independent groups, to assess whether there were statistically significant differences in participants' visualisation literacy, data analysis, and GenAI expertise ([McKight & Najab, 2010](#)). A non-significant finding for each of these metrics is critical to confirm the comparability of the three intervention conditions. Additionally, boxplots were drawn to visualise the sample distribution for each condition.

3.6.2. RQ1: Within-subject analysis

To address RQ1, we performed within-subject analyses to examine changes in participants' effectiveness and efficiency in extracting insights from data visualisations across three repeated measures for different intervention conditions. First, we utilised the Friedman test ([Sheldon, Fillyaw, & Thompson, 1996](#)), a non-parametric test suitable for detecting differences in scores across multiple conditions. This test was chosen because of the repeated measures design and the ordinal nature of the data, as well as violations of normality in data distribution identified using the Shapiro–Wilk W-test. The Friedman test compared median correct scores (Pre_score, Intervention_score, and Post_score) and median success times (Pre_time, Intervention_time, and Post_time) within participants across the three study phases. The effect size was calculated using Kendall's W ([Pereira, Afonso, & Medeiros, 2015](#)). Following significant results from the Friedman test, we conducted pairwise comparisons using Wilcoxon signed-rank

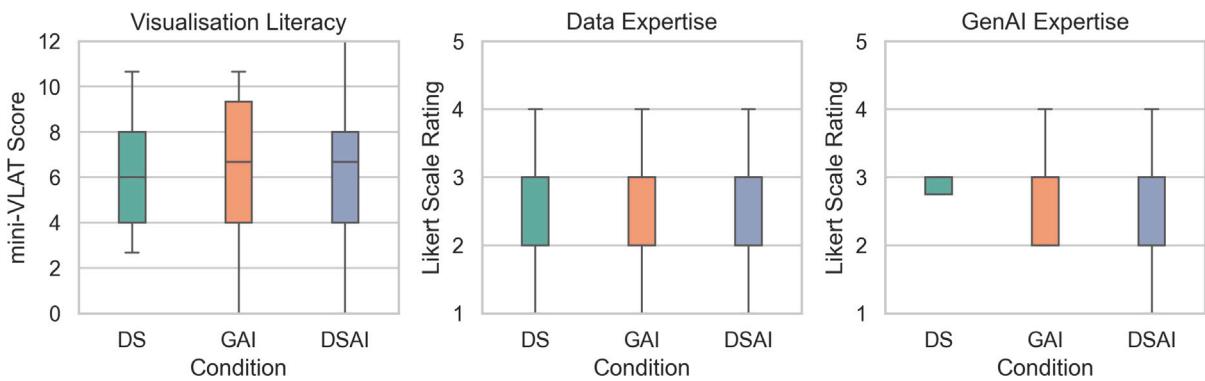


Fig. 8. Comparison of visualisation literacy, data analysis, and generative AI expertise across intervention conditions.

tests (Wilcoxon, Katti, Wilcox, et al., 1970). This non-parametric test compared two related samples to determine whether their population mean ranks differ, making it robust for handling non-normally distributed data. This allowed us to identify which specific conditions differed significantly. The Holm-Bonferroni method was used to adjust for multiple comparisons, with an initial alpha of 0.05. Effect sizes for these tests were calculated using Rank-Biserial correlation to assess the magnitude of observed differences (Kerby, 2014).

3.6.3. RQ2: Between-subject analysis

To address RQ2, we conducted between-subject analyses to compare the effectiveness and efficiency of different intervention conditions across participants. We began with the Kruskal-Wallis test, a non-parametric method suitable for this analysis due to observed violations of normality, especially for Post_score. This test compared the correct scores (Pre_score, Intervention_score, and Post_score) and success times (Pre_time, Intervention_time, and Post_time) across different intervention conditions to assess statistically significant differences between the conditions. The effect size was calculated using eta-squared. When the Kruskal-Wallis test indicated significant differences, we used the Mann-Whitney U test to explore differences between pairs of independent groups further. This non-parametric test is appropriate for non-normally distributed data and assesses whether two independent samples come from the same distribution. The Holm-Bonferroni method was applied to adjust for multiple comparisons with an initial alpha of 0.05. We also calculated effect sizes for these tests to quantify the strength of observed differences using the Rank-Biserial correlation (Kerby, 2014).

3.6.4. RQ3: Regression analysis

For RQ3, we used ordinary least squares (OLS) regression to examine the relationship between intervention conditions and visualisation literacy on participants' effectiveness and efficiency in extracting insights from data visualisations. This analysis considered both main effects (e.g., intervention conditions) and interaction effects (e.g., intervention conditions and visualisation literacy), holding other variables constant. The pre-intervention baseline (Pre) was excluded to focus on the effects during and after the intervention. First, we standardised the mini-VLAT scores by subtracting the mean and dividing by the standard deviation, ensuring normal distribution. Outliers for scores (Intervention_score and Post_score) and time-related metrics (Intervention_time and Post_time) were removed using the interquartile range (IQR) method, and data were transformed using the Box-Cox transformation to stabilise variance and normalise data distribution. For each metric (Intervention_score, Intervention_time, Post_score, Post_time), we constructed a formula to investigate the effects of visualisation literacy (mini-VLAT) across all three intervention conditions. The formula included an intercept (β_0), main effects for the GAI condition (β_1) and the DSAI condition (β_2), visualisation literacy (β_3), and interaction terms between intervention conditions and visualisation literacy (β_4 and β_5), with the DS condition as the reference. We fitted the models using the OLS function from the Statsmodels library. The assumptions were validated through several methods. Linearity was assessed by plotting predicted versus observed values. The normality of residuals was checked using the Shapiro-Wilk test and QQ plots. Homoscedasticity was evaluated using the Breusch-Pagan test, and the independence of residuals was assessed using the Durbin-Watson test. All assumptions were met.

$$\begin{aligned} \text{Score or Time} = & \beta_0 + \beta_1 \times \text{condition [GAI]} + \beta_2 \times \text{condition [DSAI]} + \beta_3 \times \text{mini-VLAT} \\ & + \beta_4(\text{condition [GAI]} \times \text{mini-VLAT}) + \beta_5(\text{condition [DSAI]} \times \text{mini-VLAT}) \end{aligned} \quad (2)$$

4. Results

4.1. Preliminary analysis – Learning effects and intervention comparability

The preliminary analysis of the phase effects demonstrated no significant change in scores from the intervention to the post-intervention phase ($\beta = 0.120, z = 0.948, p = 0.343$), indicating minimal learning effects due to repeated exposure. However, a significant decrease was observed from pre-intervention to the intervention phase ($\beta = -1.359, z = -10.769, p < 0.001$), which aligns

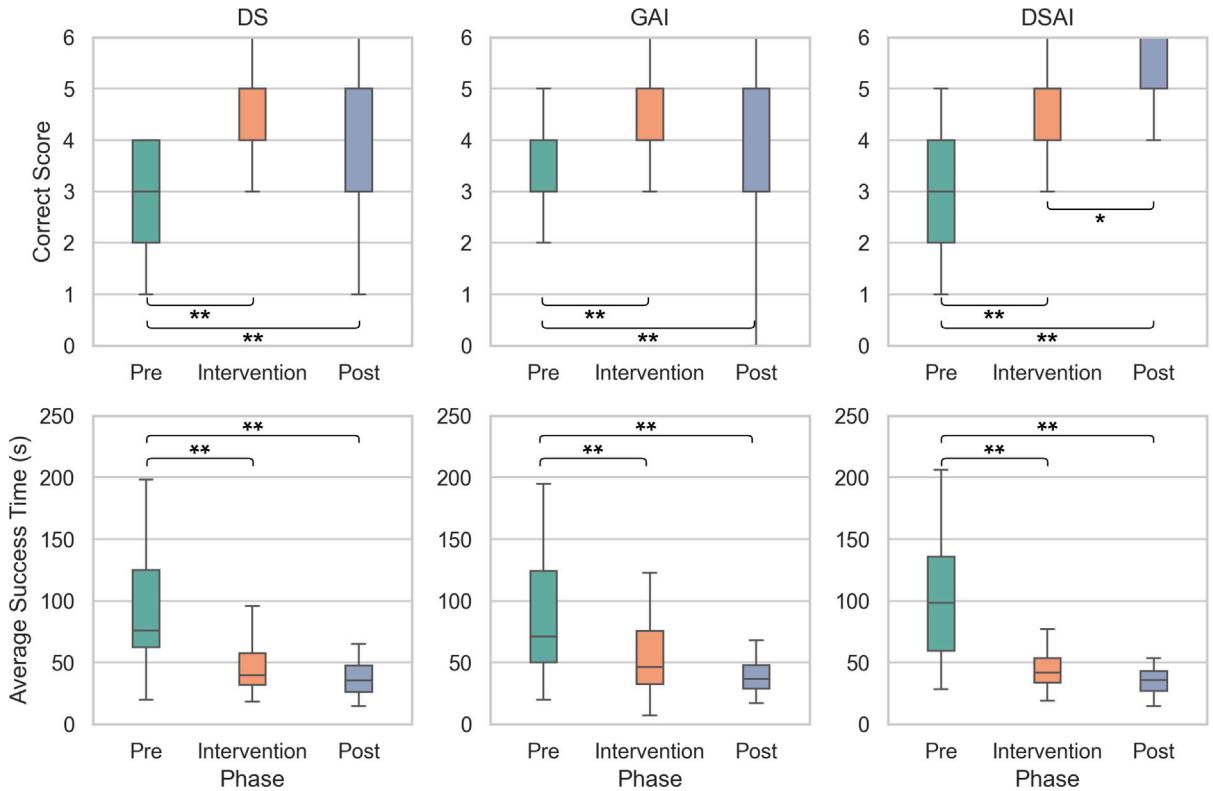


Fig. 9. Changes in correct scores and success time across phases for different intervention conditions. * $p < 0.05$ ** $p < 0.001$.

with expected baseline shifts as participants engage with interventions. The group variance (Group Var = 0.441) captured variance across individual differences not attributable to fixed effects. These findings suggest that any observed improvements in subsequent analyses can be attributed to specific intervention effects rather than learning effects and familiarisation with the task.

To ensure the comparability of the three intervention conditions, we conducted a preliminary analysis evaluating participants' visualisation literacy (measured by mini-VLAT), data analysis expertise, and GenAI expertise. The Kruskal-Wallis test results indicated no significant differences in visualisation literacy between the three conditions: DS (Median = 6.0, IQR = 4.0), GAI (Median = 6.67, IQR = 5.33), and DSAI (Median = 6.67, IQR = 4.0), $H(2) = 0.49, n = 117, p = .784$. Similarly, data expertise scores did not significantly differ between the conditions: DS (Median = 3.0, IQR = 1.0), GAI (Median = 3.0, IQR = 1.0), and DSAI (Median = 3.0, IQR = 1.0), $H(2) = 1.02, n = 117, p = .601$. For GenAI expertise, no significant differences were found across the conditions: DS (Median = 3.0, IQR = 0.25), GAI (Median = 3.0, IQR = 1.0), and DSAI (Median = 3.0, IQR = 1.0), $H(2) = 1.42, n = 117, p = .491$. These non-significant findings in visualisation literacy, data expertise, and GenAI expertise indicate that the groups were comparable. Boxplots were created to visualise the distribution of scores within each condition, further confirming the similarity across groups (see Fig. 8). Thus, any differences observed in subsequent analyses can be attributed to the interventions rather than pre-existing disparities among participants.

4.2. RQ1 – Changes in effectiveness and efficiency between phases

Fig. 9 illustrates the within-subject changes across the three phases for each intervention condition. For the DS condition ($N=36$), the Friedman test revealed a significant difference in correct scores across the three phases, $\chi^2(2) = 30.05, p < .001, W = 0.35$ (medium effect Pereira et al., 2015). Post-hoc Wilcoxon signed-rank tests indicated that the correct scores significantly improved from the pre-intervention (Median = 3.0, IQR = 2.0) to the intervention phase (Median = 5.0, IQR = 1.0), $W = 46, p < .001, r = 0.91$ (large effect Kerby, 2014), and from the pre-intervention to the post-intervention phase (Median = 5.0, IQR = 2.0), $W = 52, p < .001, r = 0.88$ (large effect). However, the change from the intervention phase to the post-intervention phase was not significant. In terms of success time for the DS condition, the Friedman test also showed significant differences, $\chi^2(2) = 33.17, p < .001, W = 0.46$ (medium effect). Wilcoxon signed-rank tests revealed that the success time significantly decreased from the pre-intervention (Median = 75.72 s, IQR = 62.53 s) to the intervention phase (Median = 39.61 s, IQR = 25.96 s), $W = 76, p < .001, r = 0.89$ (large effect), and from the pre-intervention to the post-intervention phase (Median = 35.58 s, IQR = 21.27 s), $W = 22, p < .001, r = 0.97$ (large effect). The change from the intervention to the post-intervention phase was not significant. These results suggest that the DS intervention significantly improved the participants' ability to extract correct insights from data visualisations and reduced the time taken to do

so. The improvements from the pre-intervention to the intervention phase and from the pre-intervention to the post-intervention phase were significant, indicating the effectiveness of the DS condition. However, there was no significant difference between the intervention and the post-intervention phase, suggesting that the gains in performance were maintained post-intervention.

For the GAI condition (N=41), the Friedman test indicated significant differences in correct scores, $\chi^2(2) = 29.56, p < .001, W = 0.29$ (small effect). Post-hoc tests showed significant improvements from the pre-intervention (Median = 3.0, IQR = 1.0) to the intervention phase (Median = 4.0, IQR = 1.0), $W = 71, p < .001, r = 0.87$ (large effect), and from the pre-intervention to the post-intervention phase (Median = 5.0, IQR = 2.0), $W = 104, p < .001, r = 0.81$ (large effect). The change from the intervention to the post-intervention phase was not significant. The success time for the GAI condition also showed significant differences, $\chi^2(2) = 40.59, p < .001, W = 0.49$ (medium effect). Wilcoxon signed-rank tests indicated significant reductions from the pre-intervention (Median = 72.12 s, IQR = 77.27 s) to the intervention phase (Median = 46.34 s, IQR = 42.88 s), $W = 57, p < .001, r = 0.93$ (large effect), and from the pre-intervention to the post-intervention phase (Median = 36.8 s, IQR = 19.74 s), $W = 86, p < .001, r = 0.90$ (large effect). The change from the intervention to the post-intervention phase was not significant. These findings indicate that the GAI intervention was effective in enhancing participants' correct scores and reducing their success times from the baseline to both the intervention and the post-intervention phase. However, the lack of significant differences between the intervention and the post-intervention phase suggests that the improvements were sustained post-intervention, similar to the DS condition.

For the DSAI condition (N=40), the Friedman test revealed significant differences in correct scores, $\chi^2(2) = 46.48, p < .001, W = 0.50$ (large effect). Post-hoc Wilcoxon signed-rank tests indicated significant improvements from the pre-intervention (Median = 3.0, IQR = 2.0) to the intervention phase (Median = 5.0, IQR = 1.0), $W = 32, p < .001, r = 0.94$ (large effect), and from the pre-intervention to the post-intervention phase (Median = 6.0, IQR = 1.0), $W = 19, p < .001, r = 0.97$ (large effect). Additionally, there was a significant improvement from the intervention to the post-intervention phase, $W = 209, p = .019, r = 0.52$ (large effect). Significant differences were also found in the success time for the DSAI condition, $\chi^2(2) = 43.65, p < .001, W = 0.55$ (large effect). Wilcoxon signed-rank tests indicated significant reductions from the pre-intervention (Median = 98.28 s, IQR = 76.31 s) to the intervention phase (Median = 41.94 s, IQR = 19.77 s), $W = 20, p < .001, r = 0.98$ (large effect), and from the pre-intervention to the post-intervention phase (Median = 35.75 s, IQR = 16.06 s), $W = 42, p < .001, r = 0.95$ (large effect). The change from the intervention to the post-intervention phase was not significant. These results demonstrate significant improvements in both correct scores and success times from the baseline to the intervention and the post-intervention phase. Unlike the other conditions, the DSAI intervention also showed significant improvement from the intervention to the post-intervention phase, indicating a continued positive improvement post-intervention.

4.3. RQ2 – Changes in effectiveness and efficiency between interventions

Fig. 10 illustrates the between-subject changes across the three conditions for each intervention phase. The Kruskal–Wallis test did not reveal significant differences between the three conditions for the correct scores in both the pre-intervention and the intervention phase. However, for the post-intervention correct scores, the Kruskal–Wallis test revealed significant differences, $H(2) = 10.62, n = 117, p = .005, \eta^2 = 0.08$ (medium effect). Pairwise comparisons using the Mann–Whitney U test indicated significant differences between the DSAI and DS conditions ($U = 967.5, p = .007, r = 0.30$; medium effect), and between the DSAI and GAI conditions ($U = 1119.0, p = .003, r = 0.31$; medium effect). Specifically, the median correct score for DSAI was 6.0 (IQR = 1.0), which was significantly higher than the median scores for DS (Median = 5.0, IQR = 2.0) and GAI (Median = 5.0, IQR = 2.0). For the success times, the Kruskal–Wallis tests revealed no significant differences between the intervention conditions across all three phases. These between-subject results suggest that while all three interventions (DS, GAI, and DSAI) were effective in improving correct scores and reducing success times within subjects (from RQ1 findings), the DSAI condition was particularly effective in achieving higher correct scores in the post-intervention phase compared to the DS and GAI conditions. This indicates that the DSAI intervention may be more effective in sustaining performance improvements post-intervention. There were no significant differences in success times between the conditions, suggesting that all interventions were similarly effective in reducing the time taken to extract insights from the visualisations.

4.4. RQ3 – Visualisation literacy

4.4.1. Intervention score and time

The OLS regression revealed no significant main effects or interaction effects for visualisation literacy on the intervention score for all three conditions. Regarding the success time, the OLS regression also did not reveal any significant main or interaction effects for visualisation literacy across the DS, GAI, or DSAI conditions.

4.4.2. Post-intervention score and time

The regression revealed a significant main effect for visualisation literacy ($\beta = 0.41, SE = 0.17, t = 2.33, p = 0.022$) and the DSAI condition ($\beta = 0.55, SE = 0.25, t = 2.52, p = 0.013$) on the post-intervention score. This indicates that an increase of one standard deviation in visualisation literacy results in a 0.405 standard deviation increase in the post-intervention score across all three conditions. Additionally, being in the DSAI condition results in a 0.546 standard deviation increase in the post-intervention score compared to the DS and GAI conditions while holding visualisation literacy constant. The model explained 27.7% of the variance in post-intervention scores ($F(5, 93) = 7.11, p < 0.001$). Whereas, the OLS regression for post-intervention time revealed no significant main or interaction effects for visualisation literacy on the post-intervention time for the DS, GAI, or DSAI conditions. However, the model is significant but merely explained 11.8% of the variance in post-intervention scores ($(F(5, 93) = 2.35, p = 0.047)$).

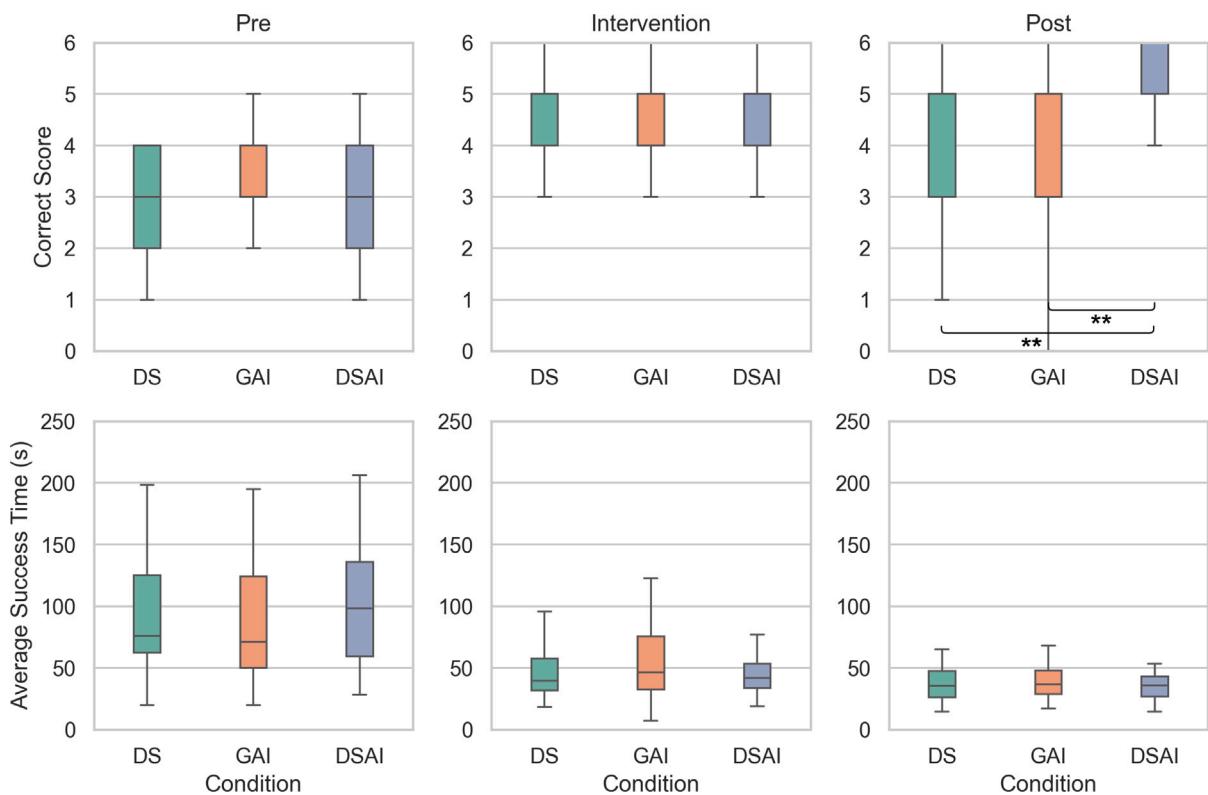


Fig. 10. Comparison of correct scores and success times across intervention conditions for each phase. * $p < 0.05$ ** $p < 0.01$.

5. Discussion

5.1. Summary of findings and research questions

As VLA become more integrated into educational settings, the ability to interpret complex visualisations is increasingly essential for making informed decisions and fostering effective learning experiences (Vieira et al., 2018). Complex visualisations often reveal hidden patterns and trends that are critical for understanding student behaviours, identifying learning challenges, and improving teaching strategies. However, many students and educators encounter significant barriers in interpreting these visualisations due to low levels of data visualisation literacy (Donohoe & Costello, 2020; Noroozi et al., 2019). Developing scalable strategies to support students and educators in navigating these intricate visual tools is therefore vital for ensuring equitable access to actionable insights and improving educational outcomes. Our study specifically addresses this need by evaluating the impact of three different intervention approaches, data storytelling, passive GenAI agents, and proactive GenAI agents, on enhancing the comprehension of VLA.

Regarding the first research question, our findings show that all three interventions significantly improved both the effectiveness (measured by correct scores) and efficiency (measured by average success time) of extracting insights from VLA. These improvements persisted post-intervention for data storytelling and passive GenAI agents, while proactive GenAI agents showed continued enhancement even after their removal. This provides empirical evidence to support the use of GenAI agents as viable alternatives to data storytelling for facilitating accurate and efficient comprehension, echoing recent recommendations to harness advanced AI systems for understanding data visualisations (Fernandez-Nieto et al., 2024; Li et al., 2024). Furthermore, the ongoing improvements after intervention removal suggest these methods not only provide temporary assistance but also contribute to the learning of vital visualisation comprehension skills, extending their educational benefits (Asamoah, 2022; Bahtaji, 2020).

In terms of the second research question, we found that the proactive GenAI agent infused with scaffolding techniques significantly outperformed both data stories and the passive GenAI agent in the effectiveness of extracting insights from data visualisations after the intervention was removed. This finding supports the effectiveness of scaffolding techniques for mastering a subject (Kim et al., 2018; Van de Pol, Volman, & Beishuizen, 2010), which in this study pertains to students' ability to comprehend VLA. As these techniques are also frequently used in the creation of data stories (Fernandez-Nieto et al., 2024; Shao et al., 2024), the proactive agent can be viewed as a combination of scaffolding (e.g., data storytelling) and the passive GenAI agent. It actively conveys data narratives by prompting students with targeted questions instead of passively responding to students' prompts. In this

sense, the current finding also provides empirical evidence to support the combined effects of integrating scaffolding with GenAI technologies to achieve better comprehension and learning skills in the interpretation of VLA.

For the third research question, the absence of interactional effects between intervention conditions and visualisation literacy on participants' effectiveness in understanding VLA is consistent with Shao et al. (2024)'s findings. This indicates that all three interventions are equally beneficial for students, regardless of their level of visualisation literacy. Contrary to the common belief supported by previous studies (Pozdniakov et al., 2023; Zhang, Reynolds, Lugmayr, Damjanov, & Hassan, 2022), our results did not statistically confirm that any supportive methods, including data storytelling, are more advantageous for individuals with lower visualisation literacy. Furthermore, the significant results demonstrating the proactive GenAI agent's ability to enhance participants' effectiveness in comprehending VLA after the intervention was removed, while accounting for visualisation literacy, further validate its benefits for students across all levels of visualisation literacy.

5.2. Implications for educational research

This study has significant implications for the fields of education and learning analytics. Our findings suggest that leveraging advanced GenAI technologies can provide effective alternatives or complements to conventional scaffolding methods like data storytelling, thereby enhancing students' understanding of complex visual analytics in educational settings (Li et al., 2024; Yan, Zhao et al., 2024). Specifically, the proactive GenAI agent's superior post-intervention performance highlights the potential of scaffolding techniques for cultivating essential comprehension skills in VLA (Gibbons, 2002; Kim et al., 2018). The scaffolding methods provided by proactive GenAI agents directly address gaps in visualisation comprehension by dynamically responding to students and educators' specific challenges. By offering real-time guidance, prompting reflection, and breaking down complex visual elements into manageable parts, these agents effectively reduce cognitive load and empower students and educators to extract actionable insights from VLA. Researchers are encouraged to explore the development of these GenAI agents further to offer adaptive, context-aware support that evolves alongside students' growing analytical skills (Asamoah, 2022; Bahtaji, 2020).

The positive effects observed with GenAI agents do not diminish the value of conventional scaffolding methods like data storytelling. Instead, they reinforce the effectiveness of the principal design elements of data stories (Segel & Heer, 2010; Zdanovic et al., 2022), which align with established educational scaffolding techniques (Kim et al., 2018; Van de Pol et al., 2010). However, the current study focuses on improved effectiveness and efficiency in comprehending insights from visual analytics and does not necessarily equate to enhanced memory retention, learner engagement, or emotional reaction to VLA (Noroozi et al., 2019; Vieira et al., 2018). Thus, our study advocates for a broader research initiative into human–AI collaboration in designing educational tools that both support students and educators in interpreting VLA and foster the development of comprehension skills. This has become increasingly important across various educational contexts (Verbert et al., 2020; Vieira et al., 2018).

The lack of significant interactional effects between visualisation literacy and intervention conditions aligns with Shao et al. (2024)'s findings, suggesting that visualisation literacy may not be as pivotal as previously thought in determining the effectiveness of supportive interventions (Pozdniakov et al., 2023). Nevertheless, it remains a crucial factor once external support is removed, paving the way for more nuanced investigations into how visualisation literacy interacts with supportive tools to aid comprehension. Further research should also consider other individual differences, like cognitive load or domain-specific expertise, that might impact the effectiveness of these educational interventions.

5.3. Implications for educational practice

This study offers actionable insights for improving data visualisation comprehension in educational environments. Integrating GenAI agents and data storytelling into educational tools can significantly aid students and educators in extracting and understanding insights from complex visual analytics (Ma et al., 2023; Yan, Zhao et al., 2024). The improvements in effectiveness and efficiency of these methods can facilitate more informed decision-making and understanding in educational contexts, ensuring timely and accurate comprehension of insights communicated via VLA (Vieira et al., 2018). The sustained post-intervention improvements highlight their role in educational settings, particularly for students, who often struggle with low visualisation literacy (Donohoe & Costello, 2020).

As these methods are effective regardless of visualisation literacy levels, educators should consider them as educational tools that go beyond temporary aids. Training programs and workshops could incorporate these technologies to deepen students' understanding of visualisation principles. Notably, the proactive GenAI agent's ability to sustain improvements post-intervention suggests it offers unique advantages for enhancing both learning and performance (Soderstrom & Bjork, 2015). It is particularly useful for guiding students through complex VLA, especially when integrating insights from multiple sources is required (Martinez-Maldonado et al., 2020; Noroozi et al., 2019). Such learning processes are valuable for educational programmes across various domains, such as science, business, and social studies, where interpreting visual data is critical for learning and knowledge development (Sahin & Ifenthaler, 2021; Vieira et al., 2018).

However, integrating GenAI technologies into educational settings must be approached with caution, particularly concerning data privacy and security (Yan, Sha et al., 2024; Zohny, McMillan, & King, 2023). Establishing knowledge databases to store contextual information for GenAI systems may raise privacy concerns, necessitating compliance with regulatory standards to ensure ethical application.

5.4. Limitations and future directions

While this study provides valuable insights, certain limitations should be addressed in future research. Firstly, the controlled experimental environment may not fully mirror the complexities encountered in real-world educational settings involving VLA. In this study, participants viewed the visualisations one by one to minimise distractions, whereas in authentic settings, students and educators typically engage with comprehensive dashboards containing multiple visualisations simultaneously. This difference may impact the interpretation of results, as learners in the real-world might face distractions and increased cognitive load that could influence the effectiveness of the scaffolding techniques. Future research should examine the performance of these methods in more authentic dashboard interactions. Also, the study's one-hour intervention period limits the ability to assess genuine, long-term learning gains. While the immediate post-intervention measures showed improvement, future studies should implement extended interventions, such as multi-session studies spread over several weeks, to assess the permanence of learning outcomes. A longitudinal design would provide more reliable insights into visualisation literacy development and the retention of skills learned through scaffolding interventions. Secondly, the participant pool was predominantly from North America and Europe due to recruitment limitations. For future studies, incorporating a more diverse participant group is essential to ensure broader applicability of the findings. Thirdly, although the study demonstrated the promise of proactive GenAI agents, it did not thoroughly investigate the specific design features and interaction mechanisms contributing to their effectiveness. Future research should delve into the design and implementation of these agents, focusing on enhancing scaffolding techniques and feedback mechanisms to optimise students' comprehension of VLA. Moreover, although the findings should be generalisable to other VLA applications in different educational contexts, given the involvement of participants with limited contextual knowledge in this study, future research should evaluate the interventions' effectiveness in promoting higher levels of Bloom's Taxonomy beyond knowledge (Level 1) and comprehension (Level 2). Additionally, we did not analyse students' analytical writing content due to potential subjectivity and its limited relevance to the study's primary focus. Future work will utilise automated essay grading and learning analytics to gain deeper insights into students' interactions with supportive methods and their impacts on the writing process (Kovanovic, Joksimovic, Gašević, Hatala, & Siemens, 2017; Ramesh & Sanampudi, 2022). Finally, incorporating Objective Structured Clinical Examination (OSCE)-like evaluations in future research could provide comprehensive insights into the relationship between clinical competency and VLA outcomes, particularly in dynamic and professionally relevant simulation contexts.

6. Conclusion

This study advances our understanding of how data storytelling, passive GenAI agents, and proactive GenAI agents enhance students' comprehension of VLA. Addressing our research questions, we found that all three methods significantly improved both the effectiveness and efficiency of extracting insights from VLA, with proactive GenAI agents demonstrating unique advantages. Unlike previous methods, proactive agents not only maintained comprehension improvement but also continued to support comprehension in the post-intervention phase, showcasing their potential to reinforce learning outcomes. These findings contribute to existing pedagogical theories by confirming that the integration of advanced GenAI technologies with traditional scaffolding techniques, such as data storytelling, can substantially benefit educational stakeholders. Our results offer empirical evidence that advances theories concerning the pedagogical use of GenAI agents, illustrating that proactive GenAI agents can be designed to respond dynamically to and guide students throughout their learning process, thus facilitating deeper understanding and genuine learning.

CRediT authorship contribution statement

Lixiang Yan: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Roberto Martinez-Maldonado:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Yueqiao Jin:** Writing – review & editing, Visualization, Methodology, Data curation, Conceptualization. **Vanessa Echeverria:** Writing – review & editing, Methodology, Conceptualization. **Mikaela Milesi:** Writing – review & editing, Methodology, Conceptualization. **Jie Fan:** Software, Data curation, Conceptualization. **Linxuan Zhao:** Writing – review & editing, Software, Methodology, Conceptualization. **Riordan Alfredo:** Writing – review & editing, Software, Methodology, Conceptualization. **Xinyu Li:** Writing – review & editing, Software, Conceptualization. **Dragan Gašević:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

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Appendix A. Learning objectives of the healthcare simulation

At the end of this simulation scenario, learners should be able to:

- Demonstrate a structured approach to patient assessment and management.
- Recognise and respond to early signs of patient deterioration.
- Appropriately activate MET calls.
- Contribute to effective teamwork.
- Communicate information effectively to the health care team.
- Demonstrate an understanding of the roles of the multidisciplinary team.

Appendix B. Scaffolding design

B.1. Hattie and Timperley's feedback model

Task-Level Feedback: providing corrective or confirmatory feedback on the specific task (e.g., interpreting prioritisation strategies from a bar chart).

Example. “Your analysis correctly identifies that Nurse 1 spent the majority of their time near Bed 4. However, you should also consider how the other nurses distributed their tasks”.

Process-Level Feedback: explaining strategies to improve learning processes and interpretation, promoting a deeper understanding.

Example. “To fully interpret this social network, consider both the direction and thickness of the edges to identify who initiated communication and how frequently”.

B.2. Scaffolding prompts

Scaffolding Approach. Guide participants through understanding each visualisation step-by-step. For each visualisation, start by providing a one-sentence description and ask only one question at a time. Avoid asking repeated questions. Give feedback on participants' responses. Once all questions for one visualisation are covered, direct participants to the next visualisation by asking them to click the right arrow. Only ask questions related to the visualisation that was sent to you. Ensure you cover all the **Scaffolding Questions** for each visualisation, including 1 for the Bar Chart, 2 for the Communication Network, and 3 for the Ward Map. Use a friendly and conversational tone. If participants get something wrong, provide a hint and ask them to rethink and re-answer.

B.3. Visualisation descriptions and scaffolding questions

Bar Chart

- **Description:** It shows the proportion of time the two nurses spent on different tasks.
- **Scaffolding Question:**

1. What do you notice about Amy's proportion of time spent on tasks, and what does this indicate about her prioritisation?

Communication Network

- **Description:** It shows verbal communication interactions among each student and their communication with the doctor, relative, and patient manikins. Arrows indicate the direction of communication, and edge thickness indicates the duration of communication.

- **Scaffolding Questions:**

1. Who are the main communicators in the network, and what does the thickness of the arrows tell us?
2. How often did the nurses communicate with each other compared to the doctor, patient, and relative?

Ward Map

- **Description:** It shows the verbal and spatial distribution of each student during a simulation session. Saturated colours indicate frequent verbal communication, while the hexagons' locations show spatial distributions. The peak heart rate of each student is also displayed on the Ward Map, represented by a heart shape.

Table 2
Evaluation questions.

Visualisation	Bloom's level	Evaluation question
Bar Chart	Knowledge	<p>Q: Which behaviour did the two nurses spend the <i>least</i> time on?</p> <ul style="list-style-type: none"> - Working together on other tasks - Working individually on other tasks - Working together on tasks for Amy - Working individually on tasks for Amy
Bar Chart	Comprehension	<p>Q: How did the nurses spend their time working on tasks for Amy compared to other tasks?</p> <ul style="list-style-type: none"> - Two nurses spent more time working individually on tasks for Amy than on other tasks. - Two nurses spent more time working together on other tasks than on tasks for Amy. - Two nurses spent the same amount of time working individually on other tasks and on tasks for Amy. - Two nurses spent the same amount of time working on other tasks and on tasks for Amy.
Social Network	Knowledge	<p>Q: Who did the Primary Nurse 2 communicate with?</p> <ul style="list-style-type: none"> - Secondary Nurse 1, Patient, and Doctor - Secondary Nurse 1, Patient, and Relative - Primary Nurse 1, Doctor, and Relative - Primary Nurse 1, Patient, and Relative
Social Network	Comprehension	<p>Q: Which of the following statements is correct?</p> <ul style="list-style-type: none"> - Primary Nurse 2 communicated more with the Relative than Primary Nurse 1 - Primary Nurse 2 communicated more with the Patient than Primary Nurse 1 - Primary Nurse 1 communicated more with the Relative than Primary Nurse 2 - Primary Nurse 1 communicated more with the Patient than Primary Nurse 2
Ward Map	Knowledge	<p>Q: Which of the following statements best describes the behaviours of the two nurses?</p> <ul style="list-style-type: none"> - The two nurses spent a significant amount of time but did not talk much around Bed 4. Primary Nurse 1's heart rate peaked at 131 around Bed 4. - The two nurses spent a significant amount of time but did not talk much around Bed 3. Primary Nurse 2's heart rate peaked at 95 around Bed 4. - The two nurses spent a significant amount of time and talked a lot around Bed 4. Primary Nurse 1's heart rate peaked at 131 around Bed 4. - The two nurses spent a significant amount of time and talked a lot around Bed 3. Primary Nurse 2's heart rate peaked at 95 around Bed 4.
Ward Map	Comprehension	<p>Q: Which of the following statements is correct?</p> <ul style="list-style-type: none"> - Primary Nurse 1's spatial and verbal activities were more around Bed 1 than Primary Nurse 2's. Primary Nurse 1 had a higher increase in heart rate than Primary Nurse 2. - Primary Nurse 1's spatial and verbal activities were more around Bed 2 than Primary Nurse 2's. Primary Nurse 1 had a higher increase in heart rate than Primary Nurse 2. - Primary Nurse 2's spatial and verbal activities were more around Bed 1 than Primary Nurse 1's. Primary Nurse 2 had a higher increase in heart rate than Primary Nurse 1. - Primary Nurse 2's spatial and verbal activities were more around Bed 2 than Primary Nurse 1's. Primary Nurse 2 had a higher increase in heart rate than Primary Nurse 1.

• **Scaffolding Questions:**

1. Which areas of the ward did the nurses spend the most time in, and how does that relate to their task prioritisation?
2. How can the colour intensity give us insights into verbal communication patterns?
3. What does the peak heart rate tell us about the stress levels of the nurses in different areas of the ward?

Appendix C. Evaluation questions

See Table 2.

Data availability

Data will be made available on request.

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