Differences in student-AI interaction process on a drawing task: Focusing on students' attitude towards AI and the level of drawing skills

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Recent advances and applications of artificial intelligence (AI) have increased the opportunities for students to interact with AI in their learning tasks. Although various fields of scholarly research have investigated human-AI collaboration, the underlying processes of how students collaborate with AI in a student-AI teaming scenario have been scarcely investigated. To develop effective AI applications in education, it is necessary to understand differences in the student-AI interaction (SAI) process depending on students' characteristics. The present study attempts to fill this gap by exploring the differences in the SAI process amongst students with varying drawing proficiencies and attitudes towards AI in performing a public advertisement drawing task. Based on the empirical evidence obtained from the think-aloud protocols of 20 Korean undergraduate students, the study first conducted a lag sequential analysis to identify statistically significant linear patterns of each group and then chronologically incorporated them into the SAI duration via coded activity alignment series to distinguish the overall SAI process of each group. The study revealed the distinctive differences in SAI processes of students with different attitudes towards AI and drawing skills. To better facilitate student-AI teams for learning, a range of implications of educational AI development and instructional design is discussed.

Implications for practice or policy:

- Educational AI should not be limited to performing a specific task and solving well-defined problems. It should be designed with a holistic view of the end-to-end student-AI process, interconnected to different learning activities in the learning process.
- Educational AI should be capable of increasing students' metacognition and emotional engagement.
- An educational AI system architect team inclusive of diverse stakeholders should be formed to collaboratively design the AI system.

Keywords: student-AI interaction, student-AI collaboration, AI in education, educational AI development, human-computer interaction, sequential analysis

Introduction

Artificial intelligence (AI) has increasingly developed to collaborate with humans on diverse tasks extending from massive data processing to decision-making. In particular, advanced generative recurrent neural network-backed systems have possibly enabled AI to actively collaborate with humans in creative tasks and experiences, such as drawing tasks that bear intrinsic value for people. Such progress has brought growing attention to human-AI collaborative interactions, where the coordination of both human and intelligent agents occurs to carry on high-complexity tasks.

In line with this, there is a growing expectation that AI will serve in important educational roles, such as collaborative peer and personal tutor rather than a simple learning tool (Kim et al., 2022; Kim & Lee, 2023). As a result of these expectations, many researchers in the field of AI in education (AIED) have established a deeper understanding of AI uses for education and its advantages and limitations but with a focus on the technicalities of the technology. However, it would be naive to presume that simply optimising AI algorithms and providing new types and functionalities of AI would lead to the implementation of a successful student-AI interaction (SAI) for learning (Kim et al., 2022). Rather, the process of interacting with AI in learning task operation is a decidedly non-trivial one in which students need to make the most of AI characteristics as well as translate AI-provided information into meaningful knowledge and subsequently use them to guide their learning activity (N. Zhang et al., 2021). To enhance the design of AIED, it is crucial to study how students work with and act on AI during learning task operation and develop a robust understanding of these processes. This study, therefore, aims to explore and analyse the SAI processes on learning tasks, specifically on drawing tasks, making explicit the mechanisms through which the tasks are performed. In doing so, this study can provide insights into the process of teamwork by heterogeneous agents in learning scenarios to identify implications for educational AI design and instructional design to facilitate student-AI teams for students' learning.

Literature review

Student-AI collaborative interaction

Educational AI is now being developed to adapt to real-world educational environments. AI can augment students' abilities to detect learning situations and make sense of the information made available to them. When it comes to self-regulated learning with an AI tutor, the tutor assists students in both monitoring their own help-seeking behaviour and in recognising maladaptive utilisation of the system’s assistance features (Aleven et al., 2016). More recently, studies have explored how to design an AI-supported student-in-the-loop system to facilitate and empower both the student and AI-driven decision-making process and support mutual monitoring. For instance, Z. Zhang et al. (2023) developed the visual interactive system for argumentative writing with rapid draft prototyping to aid students in identifying and improving their ability to perceive the strengths, weaknesses, logical flaws and trade-offs of their argumentation structures and supporting evidence through synchronised text editing and visual programming during the writing process (e.g., ideation, drafting and revision).

AI systems enhance students’ sensing capacities and may also support students in reflecting on and interpreting the information they receive through the system so that they may effectively mediate and make sense of the AI’s interpretations (An et al., 2020). Emerging research efforts have initiated exploring the design of interfaces that can proactively steer students towards specific interpretations of learning data (e.g., Echeverria et al., 2018) or facilitate the scaffolding of more meaningful forms of reflection (e.g., Kim & Lee, 2023). Nevertheless, the optimal approach to effectively guiding students' interpretations while simultaneously leveraging and preserving their unique inferential capacities remains an open question that requires further investigation (An et al., 2020; Echeverria et al., 2018).

AI systems can also serve in the role of an improviser or ideation partner during SAI. Lin et al. (2020) illustrated how the AI-based drawing system called Cobbie provokes unforeseen ideas and engages design students in a collaborative ideation process (e.g., Cobbie captures a student’s sketch input and generates related ideas and sketches on paper for the students). It is interesting to note that Cobbie acts as a catalyst for a conceptual shift, stimulating human creativity and fostering new ideas as it aids the creative process of analogical reasoning. Specifically, Cobbie enables design students to map their input sketches to another sketch that shares visual and semantic similarities. By establishing connections between these sketches, students can uncover previously uncharted aspects that propel the creative process forward. The concept that interaction between students and AI aids the creative process exposes the possibility that collaborative SAI could also support creative learning tasks. However, limited research has been conducted concerning the sequential information during SAI (e.g., when and which type of learning activities individual learner performs; the reciprocal interaction between student and AI which may facilitate or frustrate the learning process).

Student characteristics that influence effective SAI

There is limited knowledge concerning how students come together with AI to produce creative outcomes such as drawings, but earlier literature on human-computer interaction suggests that interactions between humans and technology go beyond being strictly limited to engineers in scenarios like determining machine layout or developing mathematical simulation methodologies (Hoffman, 2019). Rather, it necessitates the effective coordination of complex activities which includes communication, joint action and the ability to adapt to human-aware execution to accomplish a task under a variety of environmental conditions (Lemaignan et al., 2017). Therefore, it is crucial to understand the user's individual factors as a key driving force for effective interaction between humans and technology. Similarly, much literature in education has found that although students utilise technology for learning, the way they use and interact with it often falls short of being sufficiently effective (Kim & Cho, 2023). In turn, a rich line of studies has investigated how students' characteristics affect the interaction between students and technology, including competency in technology use (Teo et al., 2015), perception of the utility of technological resources (Clark et al., 2009) and the availability of scaffolding to support the technology-enhanced learning experience (McLoughlin & Lee, 2010).

Among the many characteristics an individual may possess, studies have revealed that attitudes towards a particular technology are directly related to an individual's perceived usefulness and perceived ease of use of technology (Teo et al., 2015, Venkatesh et al., 2003). Positive attitudes towards using technology are closely linked to an individual's behavioural intention to use that technology; this, in turn, influences the users' actual adoption and utilisation of the technology. In short, the extended body of research underscores the significance of considering and comprehending the contribution of personal attitude towards the behavioural intention to use technology.

In addition, many studies have noted that an individual's level of domain-specific skills may lead to differences in their interactions and experiences with technology (e.g., Kaptelinin, 1996; Kim & Lee, 2023). As Kaptelinin discussed, the skillful use of technology itself is not the ultimate goal of utilising the technology; instead, people intend to address their unmet needs (problems) within a specific problem space (domains) to acquire quality outcomes and experiences. From this perspective, the problem-solving process between students and technology and the experience of that process cannot be separated from either the domain on which the content of the technology is based or the skills of the students.

Students' interaction with AI drawing system

Increasingly, research is being produced that examines and discusses the creative and explorative potentials of AI technologies in drawing practice. For instance, AI can improve students' ability to think from multiple angles, which impacts their artistic creation level (Kong, 2020; Lin et al., 2020). Additionally, the increasing online availability of digitised art collections gives new opportunities to analyse the history of art using AI technologies. In particular, the use of convolutional neural networks enables advanced levels of automation in classifying, categorising and visualising large collections of artwork image data (Cetinic & She, 2021). Furthermore, AI can expand students' imagination space. Partnership on AI (2019) presented an interesting example of how students and AI (the sketch recurrent neural network) can collaboratively draw pictures. Once the student starts drawing, the AI system attempts to advance or complete the student's drawing. An interesting feature of this co-creative drawing process between students and AI is that the AI draws unexpected strokes that take the sketch in an unplanned direction, which offers students new, serendipitous discoveries and directions in thinking.

When AI is applied to drawing activities, students can be engaged in creative activities without fear or burden. This allows students with a lower level of drawing skills to be empowered to create artwork regardless of their technical skills or expertise (Kim & Lee, 2023; Kong, 2020). Also, the immediate and vivid presentation of drawing results based on interaction with AI is effective in inducing students' interest in the drawing activity (U. G. Lee et al., 2020).

The review of literature opens the possibility of SAI to produce reasonable results in various learning tasks, including drawing tasks, yet the explicit SAI is underexplored. In addition, the SAI process on drawing tasks may have differences depending on students' attitudes towards AI and their level of drawing skills. Taken together, the present study aimed to investigate differences in the SAI process on drawing tasks amongst students with differing attitudes towards AI and drawing skills. To address the study's aim, the following research questions were framed:

(1) How are student attitude and drawing skill related to how they participate in the SAI process?
(2) What are the featured activity distributions that emerged during SAI amongst a group of students with different attitudes towards AI and levels of drawing skills?
(3) What are the group differences in the overall SAI process on a drawing task?

Methods

Participants

This study examined 20 Korean undergraduate students, ranging in age from 22 to 25 years old. To assess participants' drawing skills, participants submitted their drawings before the experiment to be evaluated by eight experts (four experts from art education and four from public advertisement) based on a total score of 5. As the average drawing score is 3.04 (*SD* = 1.45), students above the average were categorised in the high level of drawing skills (HD) and those less than average were in the low level of drawing skills (LD). In addition, each student's duration of art education experience was investigated. A pre-interview was conducted for each participant to examine their attitude towards AI by asking questions related to their perceived feelings regarding AI. After the pre-interview, students were divided into four groups: (a) five students with a positive attitude towards AI and a high level of drawing skill (PAHD); (b) five students with a positive attitude towards AI but a low level of drawing skill (PALD); (c) five students with a negative attitude towards AI but a high level of drawing skill (NAHD); (d) five students with a negative attitude towards AI and a low level of drawing skill (NALD) (see Appendix 1). This study received ethical approval from the university's Institutional Review Board as well as informed consent from all participants.

AI drawing system

Among numerous AI-based drawing systems, AutoDraw (https://www.autodraw.com), a free and easy-to-use tool provided by Google, was selected. Numerous researchers have highlighted the foundational nature of machine learning within core algorithms of AI applications like AutoDraw (Lujan-Moreno et al., 2018). AutoDraw utilises artificial neural network algorithms, which resemble the cognitive structure of the human brain with artificial neurons and neural layers. Also, AutoDraw has interactive features whereby it attempts to predict what is being depicted and drawn by users to suggest a series of alternative images and convert users' rough sketches into stylised drawings (see Figure 1).

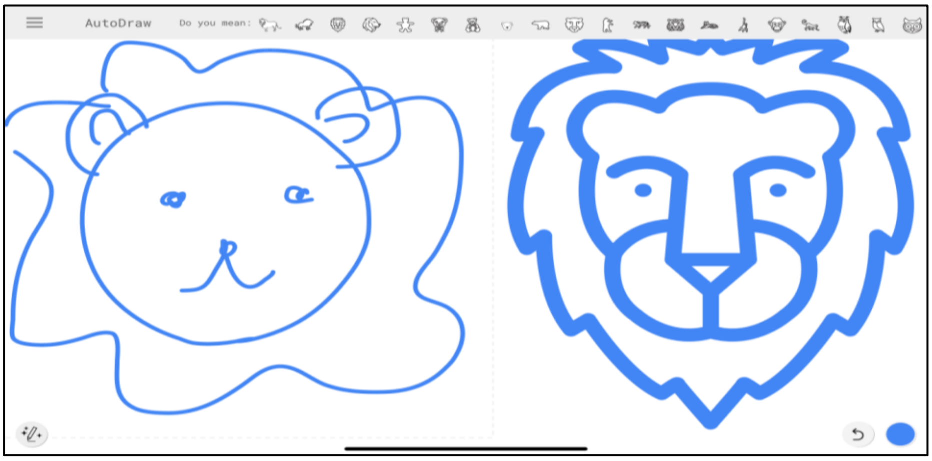

Figure 1. Example of AutoDraw operation

Drawing task

To address the research questions, the participants were assigned a drawing task to team with AutoDraw and create a public advertisement that communicated a clear call to action. During the collaborative drawing process, teammates shared their understanding through drawing, which could enable them and others to discover hidden relations and generate novel insights (Tversky et al., 2003). Hence, a vital objective of this study was to uncover the activity pattern underpinnings of collaborative drawing between students and AI. The themes were overcoming COVID-19 and coping with climate change. They were chosen for the drawing task to provide the task with a clear objective and offer students a research activity related to pressing contemporary issues during the time frame of the research to provide additional meaning to the drawing task. Each student was given the task instructions along with the theme and guidelines for drawing a public advertisement.

Research setting

To understand students' collaborative drawing activity patterns with AI, they were asked to perform a think-aloud – verbalise their actions and thoughts during the execution of the task (Kim & Lee, 2023). Before the experiment, each participant spent 1 hour learning and practising the think-aloud technique and another 20 minutes reading the task instructions. Then, the SAI on drawing activity was conducted on the AutoDraw website via a tablet Galaxy Tab 6 and its smartpen). Although the task completion time varied, most participants completed it within 2 hours. We made no intervention while participants performed the tasks, except when their think-aloud paused for more than 5 minutes. Each think-aloud was conducted in Korean, audio-recorded for later transcription and video-recorded the process of completing the drawing tasks.

Data collection and analysis

The transcribed think-aloud protocol was segmented into semantic units and analysed using the coding schemes (see Appendix 2) based on the literature review (Rourke & Anderson, 2004), which includes three dimensions: drawing activity including problem representation, solution generation, solution implementation and interaction with AI (Grigg & Benson, 2014; Pretz et al., 2003); meta-cognitive activity including planning, monitoring and regulations, and evaluation (Molenaar et al., 2011; Sonnenberg & Bannert, 2016); and socio-emotional activity including building relationship with AI, positive or negative emotional responses (Hoffman, 2019; S. S. Lee & Kim, 2020). Six specialists in AIED, collaborative learning and learning behaviour analysis were invited to corroborate the feasibility of the developed coding schemes and the corresponding definitions.

We independently coded the entire think-aloud protocols and their physical activities from the recorded video. These codes represent students' miscellaneous reactions or behaviours shown at least once for every activity to AI's drawing responses, some of which occurred within 1 second (e.g., browsing, clicking or selecting a suggested image) during the task. Inter-rater reliability of the protocols was tallied as Cohen's kappa (0.93), where all disagreements were fully resolved through discussion between us (see Appendix 3 for the participation frequencies).

To identify significant linear patterns in the SAI process of each group, we first conducted a lag sequential analysis (LSA). LSA requires the frequency data that sums all participants' activities according to the think-aloud protocols to find genuine transitions. Following the conventional practice, we arranged the preceding codes on the rows (lag 0) and the following codes (lag 1) on the columns. We tallied The contingency metrics of frequency according to the transition from one code (lag 0) to the subsequent code (lag 1) to calculate the transitional probabilities of two-code sets for identifying the frequencies of occurrences that were greater than chance. We, however, extended the Discussion Analysis Tool introduced by Jeong (2005) into 22 x 22 metrics using Pandas library in Python due to the constraints of the number of variables, a maximum of 12. Then, employing the adjusted residual equation (Bakerman & Gottman, 1997), we computed *z* scores to ascertain the significance of the transitional probabilities, the association strength of pre- and post-code-sets, not the degree to which the patterns take place. Although transitional probabilities and *z* scores can both be the main dependent variables, given the student-AI relationship has barely been studied, this exploratory study mainly considered transitional probabilities (Jeong, 2005). We employed Gephi version 0.9.2 to visualise the SAI process patterns from LSA of each group with weighted arrows connecting nodes, the significant activities in accordance with transitional probabilities.

The mere transitions found in LSA, nonetheless, do not adopt the sense of the chronology; the terminology process requires examining the pattern findings in tandem with the chronological order of the coded activities to discern distinctive features of each group. The student-AI think-aloud protocols, however, hardly gave pause since AI instantly responded to the students so that some activities (e.g., IA1, IA2) could only be counted in seconds, disallowing us to ascertain the distinctive patterns. To overcome such a limitation, we first listed the validated activity patterns from LSA on a spreadsheet and compared them with the written records of the think-aloud protocols. Next, we aligned each participant's activity list and scrutinised the common activity series within each group to visualise the chronological order named *activity series alignment* (Hoppe et al., 2020). The common activity series was found to be in two dimensions: the *prior activity* and *in times of drawing activity*. We then selected only the common activity series within the group that appeared in the same order in the same dimension. In doing so, we could corroborate the detected common activity series of each group within the confidence levels along with the task duration timeline. Then, we computed each common series in mean values of each group in terms of onset (the first code initiation in the path series) and offset (the path series termination). Only then the general SAI process could be expounded by each common activity series (in percentage) within each group during the drawing task. It should be noted that the coloured bars in the activity series alignments represent common pattern series, whereas the gaps between them show the randomly performed activities (Figure 3).

Results

To examine each group's statistically significant patterns in the SAI process, we tallied transitional probability and *z* scores. For a better understanding of groups, we excluded self-loop patterns (e.g., PR1→PR1) and selected transitional probability of more than .40 ($p \leq .01$) to find that PAHD demonstrated seven significant pattern sets (transitions) from 54 SAI process sequences; PALD presented 8 transitions out of 31; NAHD 9 transitions out of 35; NALD displayed 5 patterns out of 15. It should be noted that the SI1→IA1 path was found in every group, where students first sketched and then explored the AI figure suggestions; thus, it was excluded from the featured transitions of each group as it was considered the basic activity pattern of task coordination with AI.

As eliminating common patterns allowed us to discern the unique characteristics of each group, we identified four other common transitional activities corresponding to the attitude towards AI (PA and NA) and the levels of drawing skills (HD and LD). First, PAs performed the common path of (a) IA2→PE, in which students expressed positive emotion after adopting AI suggestions while NAs shared (b) IA4→NE path that illustrates the students expressed negative feelings upon reasoning and criticising AI-suggested figures. Another common path in NAs was (c) E→SI1 path, which explicates that the students moved on to drawing new figures upon evaluations. In addition, the mutual path found in HDs was (d) IA1→IA4, presenting students' exploration of AI suggestions followed by questioning and critiquing AI-suggested figures. Taken together, we deducted the common patterns among groups found above from the distinctive patterns of each group (see Table 1).

Table 1
Summary of the featured activity patterns

Types	PAHD	NAHD	PALD	NALD
Distinctive patterns	7	9	8	5
Common pattern details	2 (a) IA2→PE (d) IA1→IA4	3 (b) IA4→ NE (c) E→SI1 (d) IA1→IA4	1 (a) IA2→PE	2 (b) IA4→ NE (c) E→SI1
Featured pattern details (common patterns deducted)	5 (1) IA5→BR1 (2) IA4→IA3 (3) IA3→IA4 (4) SI2→E (5) MP2→PH4	6 (1) IA2→SI2 (2) SG1→SG2 (3) BR2→SI1 (4) IA3→NE (5) PH3→SI1 (6) SG2→SG1	7 (1) SG2→PH2 (2) IA4→PE (3) MP2→SI1 (4) BR1→SI1 (5) SG1→SG2 (6) PR2→SG1 (7) IA1→IA2	3 (1) PH4→E (2) BR2→PH4 (3) IA2→SI1

Note. IA: interaction with AI, PE: positive emotional response, NE: negative emotional response, E: evaluation, SI: solution implementation, BR: building relationship with AI, PR: problem representation, SG: solution generation, PH: planning, MP: monitoring & regulations during problem-solving process.

PAHD

Looking into the distinctive activity patterns of each group, PAHD demonstrated five strong transitions: (1) IA5→BR1 (*prob* = .77, *z* = 17.94), (2) IA4→IA3 (*prob* = .74, *z* = 34.55), (3) IA3→IA4 (*prob* = .54, *z* = 18.44), (4) SI2→E (*prob* = .40, *z* = 22.20), and (5) MP2→PH4 (*prob* = .40, *z* = 15.79). The strongest transition, (1) IA5→BR1, demonstrates PAHD forms a collegial relationship with AI upon generating alternative solutions in combination of students and AI figures. Their patterns were concentrated on IA-related activities. For example, what seemed like a linear relationship of (2) IA4→IA3 turned out to be a bilateral transition as (3) IA3→IA4 presented. When students witnessed the AI's misunderstanding of their intention, confirmed by reviewing the suggestions, they repetitively modified their figure drawings to enhance AI's understanding to suggest satisfactory figures. As to (4) SI2→E path, students evaluate their task outcomes after revising AI-suggested figures. In addition, (5) MP2→PH4 explains that the students changed the existing idea after adjusting the meaning of the composition arrangements in the conceptual structure. Given the activity patterns, in turn, PAHD students performed the act of coordination such as continuously refining the drawing for the AI to comprehend students' intention and adjustment in the conceptual structure on the drawing, the existing plan and the ideas on the task activity during SAI. With the most strengthened activity patterns delineated above, a total of 54 statistically distinctive activity transitions are arranged in Figure 2.

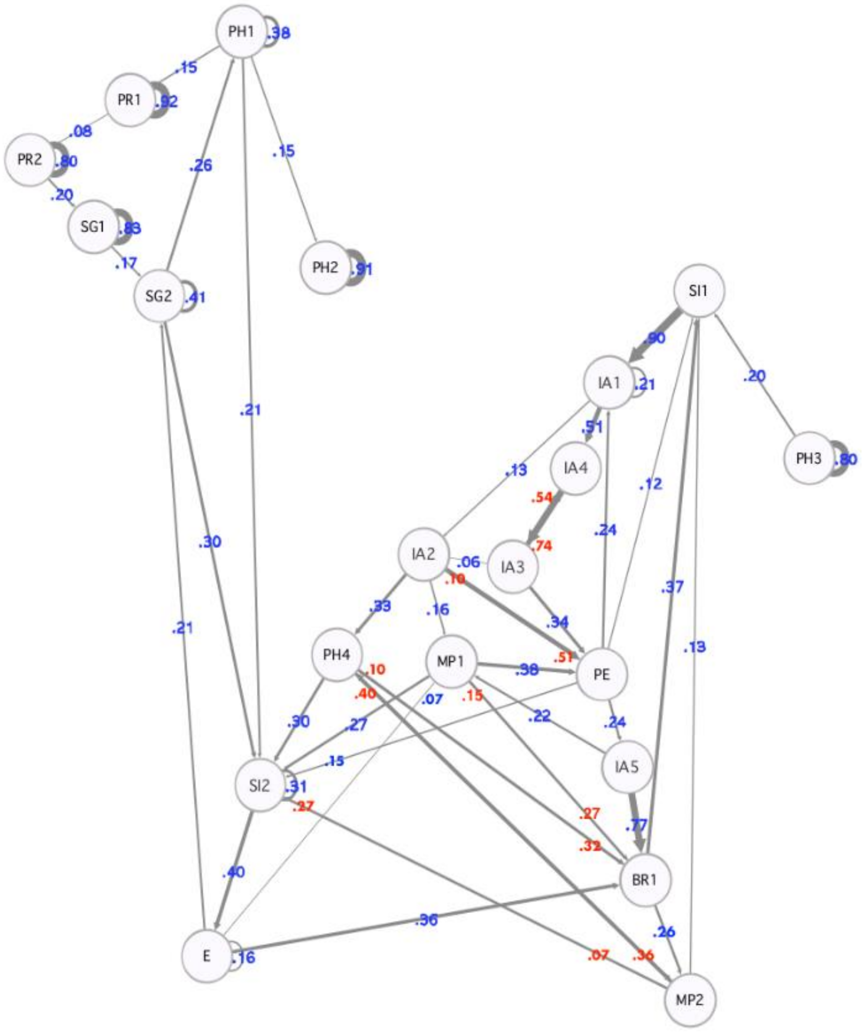

Figure 2. PAHD's SAI process patterns
Note. The thicker arrows indicate higher transitional probabilities, blue for linear relationships and red for bilateral relationships.

As the mere LSA transition findings cannot elucidate the complete SAI process, these subsequent activity patterns were conjugated in the chronological order of the SAI activities, including the self loops. PAHD's SAI process is characterised by (a) being goal-oriented, (b) performing interactive or joint coordination with AI and (c) continuous monitoring and regulation. PAHD initiated the SAI process by executing the longest time (14.21%, see Table 2) on activity series of (1) PH1→PR1→PR2→SG1→SG2→PH2 (see Figure 3), examining the task objective, identifying the problems, generating solutions and then exploring resources available between student and AI to fulfil the task.

What is intriguing about the activity series (2)–(3) is that activities, such as SI1, IA1 and 1A2 and PE, occurred between PH2 and PH3. PAHD were inclined to test AI's functionality and familiarise themselves with a pool of AI figures and its drawing style before the overall SAI plans on task performance process and role distribution between student and AI (PH3). In addition, it is noteworthy that PAHD manifested all IA-related activities (IA1–1A5) throughout the task. It was the only group that performed IA5, integrating alternative figures through evaluation of students drawing and AI's suggestion. PAHD expressed positive emotions towards AI and established a collegial relationship, as shown in activity series from (4) to (11). To be specific, students embraced AI's recommendations (IA2) to elaborate them for the task by either modestly modifying (SI2) or merging their ideas with AI suggestions to draw a new figure (IA5). Students put effort towards changing sketches repetitively to let AI grasp their intentions (IA3) when AI suggestions were dubious. Furthermore, PAHD demonstrated an act of coordination during a collaborative drawing with AI, for instance, by modifying the version of the existing plan under continuous monitoring (PH4) or reconceptualising the structure of the drawing task (MP2). Along with this, students accumulated positive emotions towards AI and built a partnership with it (BR1). Taken together, among all groups, PAHD most effectively coordinated collaboration with AI.

Table 2
PAHD's activity series number details with task duration

Dimension	No.	Activity series	Onset (sec.)	Offset (sec.)	%
Prior activity	1	PH1→PR1→PR2→SG1→SG2→PH2	0	766	14.21
	2	PE→IA1→IA2→PE→SI1→IA1	881	928	0.88
	3	PE→IA1→IA2→PE	993	1004	0.2
In times of drawing activity	4	PH3→SI1→IA1→IA2→PE→SI2	1040	1241	3.73
	5	PH4→SI2→MP2→PH4→MP2	1256	1365	2.03
	6	SI1→IA1→*IA4*↔*IA3*→PE→IA2→PH4→BR1	1655	1799	2.67
	7	SI1→IA1→*IA4*↔*IA3*→PE→IA5→BR1→MP2	1921	2033	2.08
	8	SI1→IA1→*IA4*↔*IA3*→PE→IA5→BR1→PH4→MP2→SI2→E→SG2 →SI2→E→BR1	2154	2424	5.01
	6	SI1→IA1→*IA4*↔*IA3*→PE→IA2→PH4→BR1	2909	3053	2.67
	8	SI1→IA1→*IA4*↔*IA3*→PE→IA5→BR1→PH4→MP2→SI2→E→SG2 →SI2→E→BR1	3416	3693	5.14
	8	SI1→IA1→*IA4*↔*IA3*→PE→IA5→BR1→PH4→MP2→SI2→E→SG2 →SI2→E→BR1	3960	4238	5.15
	6	SI1→IA1→*IA4*↔*IA3*→PE→IA2→PH4→BR1	4269	4425	2.89
	9	SI1→IA1→*IA4*↔*IA3*→PE→IA5→BR1→MP2→PH4→SI2→E→BR1	4566	4772	3.82
	10	SI1→IA1→*IA4*↔*IA3*→PE→IA5→BR1→PH4→MP2→SI2→E→SG2	4803	5023	4.08
	11	SI1→IA1→IA2→PE→SI2→MP2	5261	5389	2.38
Total					56.95

Note. Italic: bilateral interactions.

Figure 3. PAHD's activity series alignments along the task duration in percentage
Note. The colour presentations do not share any activity series in common among groups but distinguish the numbers of the activity series in each group.

NAHD

NAHD shows 6 distinctive patterns: (1) IA2→SI2 (*prob* = .84, *z* = 13.00), (2) SG1→SG2 (*prob* = .62, *z* = 17.18), (3) BR2→SI1 (*prob* = .54, *z* = 5.36), (4) IA3→NE (*prob* = .52, *z* = 8.54), (5) PH3→SI1 (*prob* = .45, *z* = 2.79), and (6) SG2→SG1(*prob* = .43, *z* = 10.07). Above all, (1) IA2→SI2 dedicates to the revision over the selected figure from AI suggestions. Moreover, (2) and (6) paths pertaining to SG1 and SG2 are bidirectional interactions; students generated alternative solutions and clarified the idea for solving problems through interpretation of the problem, and vice versa. (5) PH3→SI1 represents the overall task process planning followed by sketching figures. These transitions possibly suggest that NAHD tended to perform the task in accordance with their pre-established plans. Furthermore, activity transition (3) BR2 →SI1, for instance, indicates that before initiating drawings, students framed a hierarchical relationship with AI while sequence (4) IA3→NE represents that repeated sketch modifications for AI to comprehend students' intended figures led students to feel negative about AI. The overall NAHD's activity transitions are 35, including the distinctive patterns described above (see Figure 4).

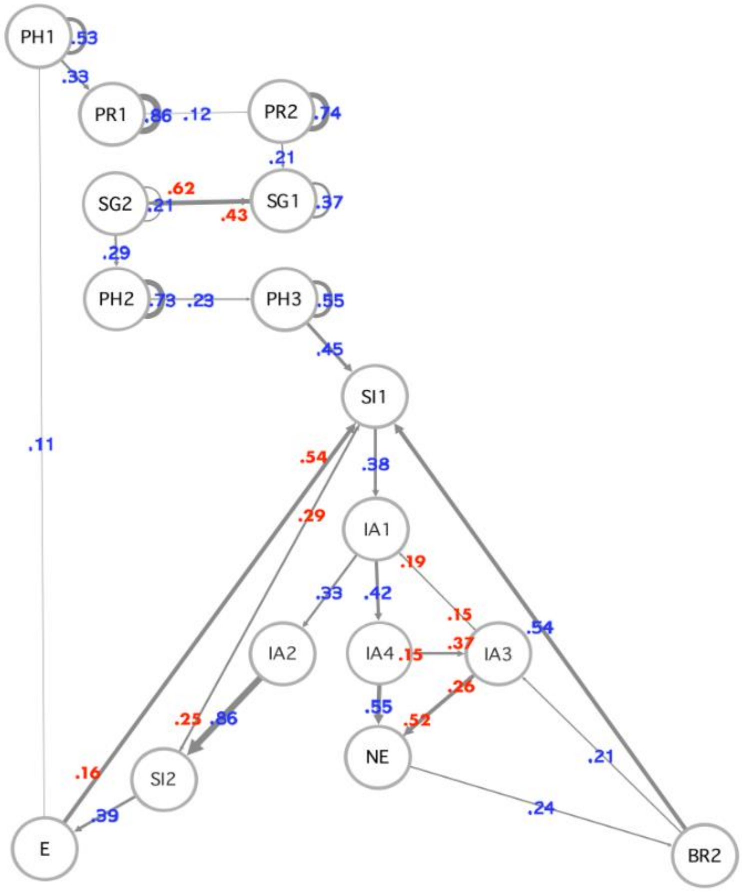

Figure 4. NAHD's SAI process patterns
Note. The thicker arrows indicate higher transitional probabilities, blue for linear relationships and red for bilateral relationships.

The SAI of NAHD is oriented towards being a student-driven drawing activity. NAHD typically spent most of their time on the (1) and (5) transitional activities, 25% and 25.60%, respectively (see Table 2 and Figure 5). This group demonstrated (1) activity series similar to PAHD during the prior activity. Nonetheless, NAHD tended to be neglectful of thorough examinations on AI's functionality and resource availability (PH2, 2.85%; see Appendix 3). This suggests that the students mostly devoted their time to PR and SG activities while giving scant consideration to the AI functionality before the overall plan of task performance (PH3, 1.61%; see Appendix 3). In times of drawing activity, what intrigues the most is that students demonstrated interaction with AI in two simple ways – see activity series (2) to (3). Either one is involved with their endeavour to work with AI by repetitively revising their figures for AI to understand their intended ideas (IA3) and their criticism made to AI suggestions (IA4). In addition, although students adopted AI-suggested figures (IA2), they revised them (SI2) to accomplish their intended concept of the drawing for the overall task evaluation (E) before resuming to sketch (SI1) as in activity series (4). This shows that NAHD tended to have a high level of agency and control in performing a task, expecting AI recommendations to be identically matched with their intended ideas and their unique drawing style. When AI failed to do so, they negatively assessed AI's performance and developed annoyed and hostile feelings and relationships. As a result, they completed the rest of the drawing unaccompanied by AI, as shown in the activity series (5). They drew figures (SI1) disregarding AI suggestions to improve their initial sketches (SI2) then conducted self-assessments (E).

Table 2
NAHD's activity series number details with task duration

Dimension	No.	Activity series	Onset (sec.)	Offset (sec.)	%
Prior activity	1	PH1→PR1→PR2→*SG1*↔*SG2*→PH2→PH3	0	616	25
In times of drawing activity	2	SI1→IA1→*IA3*↔*IA4*→NE	655	773	4.79
	3	SI1→IA1→*IA4*↔*IA3*→NE	893	990	3.95
	4	SI1→IA1→IA2→SI2→E→SI1	1015	1067	2.12
	4	SI1→IA1→IA2→SI2→E→SI1	1199	1252	2.16
	3	SI1→IA1→*IA4*↔*IA3*→NE	1417	1548	5.31
	4	SI1→IA1→IA2→SI2→E→SI1	1632	1709	3.12
	5	NE→BR2→SI1→E→SI1→SI2→SI1→E	1833	2464	25.6
Total					72.03

Note. Italic: bilateral interactions.

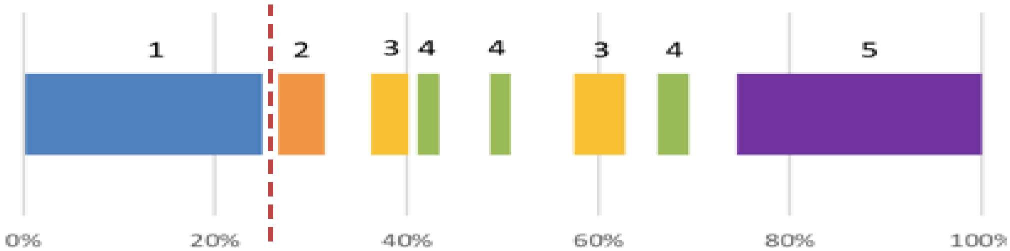

Figure 5. NAHD's activity series alignments along the task duration in percentage
Note. The colour presentations do not share any activity series in common among groups but distinguish the numbers of the activity series in each group.

PALD

PALD exhibited 7 featured patterns: (1) SG2→PH2 (*prob* = .71, *z* = 7.25), (2) IA4→PE (*prob* = .59, *z* = 9.16), (3) MP2→SI1 (*prob* = .43, *z* = 5.54), (4) BR1→SI1 (*prob* = .43, *z* = 5.54), (5) SG1→SG2 (*prob* = .42, *z* = 12.48), (6) PR2→SG1 (*prob* = .42, *z* = 9.36), (7) IA1→IA2 (*prob* = .41, *z* = 12.54). Compared to PAHD, PALD also demonstrated two IA-related activity patterns that were seemingly mundane. Although (7) IA1→IA2 depicts that this group simply adopted AI suggestion after browsing, when it came to (2) IA4→PE path, however, the students revealed positive emotional responses even after questioning the AI-suggested figures. Furthermore, (6) PR2→SG1 and (5) SG1→SG2 paths can linearly be an activity series. For instance, the students framed the focus of the task to generate ideas for solving problems. Such transitional activities carried on in (1) SG2→PH2, which ultimately links to checking resource availability, possibly rewritten in the PR2→SG1→SG2→PH2 path. Compared to two other sequences, (1) SG2→PH2 is the strongest activity path indicating the core aspect for this group, the resource availability inspection after clarifying the ideas for problem-solving. In addition, (3) MP2→SI1 and (4) BR1→SI1 paths delineate either (3) the students adjusted their conceptual structure of predetermined ideas or (4) built a collegial relationship with AI before they resumed their sketches. These 35 significant activity transitions are summarised in Figure 6.

PALD presented as an AI-reliant task performer with positive emotions. In terms of SAI activity participation, PALD revealed three activity series in the prior activity (see Table 3 and Figure 7). The series (1) is particularly similar to PAHD. Although they spent a total of 15.96% on this series, relatively higher than PAHD, the participation frequency of the PR and SG is relatively shallow (ranging from .76% to 2.38%) whereas they spent a longer time on PH2 (3.46%; see Appendix 3). As a part of series (1) to (3), PALD appeared to analyse AI's available resources and its limitations by performing as they attempted a drawing (PH2), explored AI-suggested figures (IA1) and adopted AI suggestions (IA2) and then established an overall plan for the task process (PH3). PALD then continued the actual drawing with AI by performing the sequential series from (4) to (6) and (2). In line with this, one striking feature captured within activity series from (2) to (6) was that students completed the drawing task mostly by adopting the AI-suggested figures (IA2) without any further modification upon their rough sketches (SI1). In addition, it is noteworthy that students presented PE while questioning AI's suggestions and reasoning. This may explain that AI's accuracy is not a direct factor inducing the students' PE towards AI. PALD would plainly enjoy the interactions with AI that later built a collegial relationship with AI (BR1) before they either adjusted conceptual structure (MP2) or evaluated the task completion process (E).

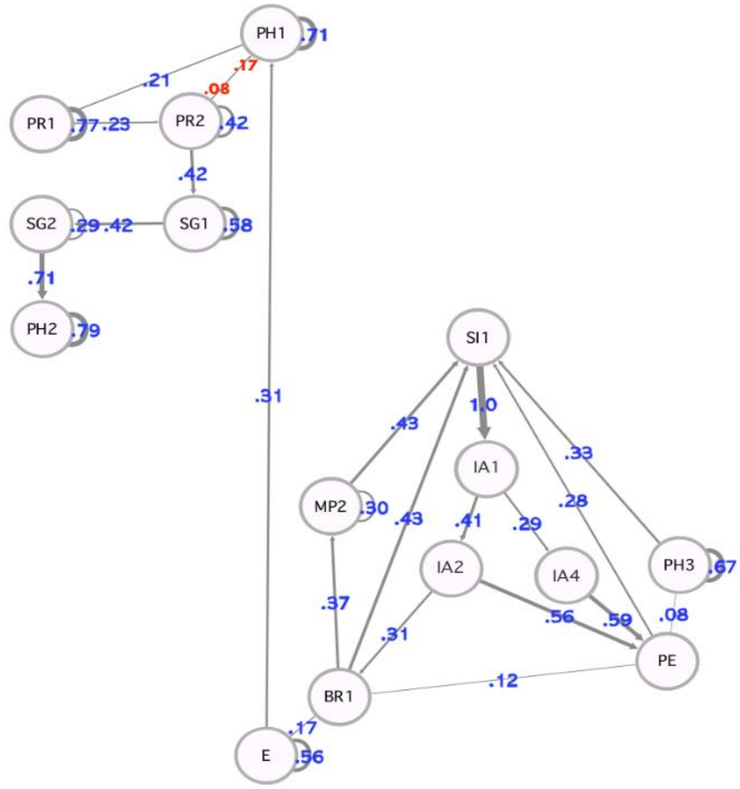

Figure 6. PALD’s SAI process patterns
Note. The thicker arrows indicate higher transitional probabilities, blue for linear relationships and red for bilateral relationships.

Table 3
PALD’s activity series number details with task duration

Dimension	No.	Activity series	Onset (sec.)	Offset (sec.)	%
Prior activity	1	PH1→PR1→*PR2↔PH1*→PR2→SG1→SG2→PH2	0	371	15.96
	2	SI1→IA1→IA2→PE	417	435	0.77
	3	SI1→IA1→IA2→PE →PH3	468	588	5.16
In times of drawing activity	4	SI1→IA1→IA4→PE	641	669	1.2
	2	SI1→IA1→IA2→PE	800	818	0.77
	4	SI1→IA1→IA4→PE	896	924	1.2
	4	SI1→IA1→IA4→PE	927	955	1.2
	5	SI1→IA1→IA4→PE →BR1→MP2	1114	1294	7.75
	5	SI1→IA1→IA4→PE →BR1→MP2	1906	2083	7.61
	6	SI1→IA1→IA2→PE →BR1 →E	2143	2325	7.82
Total					49.46

Note. Italic: bilateral interactions. PR: problem representation, SG: solution generation, SI: solution implementation, IA: interaction with AI, PH: planning, MP: monitoring & regulations during problem solving process, E: evaluation, BR: building relationship with AI, PE: positive emotional response, NE: negative emotional response.

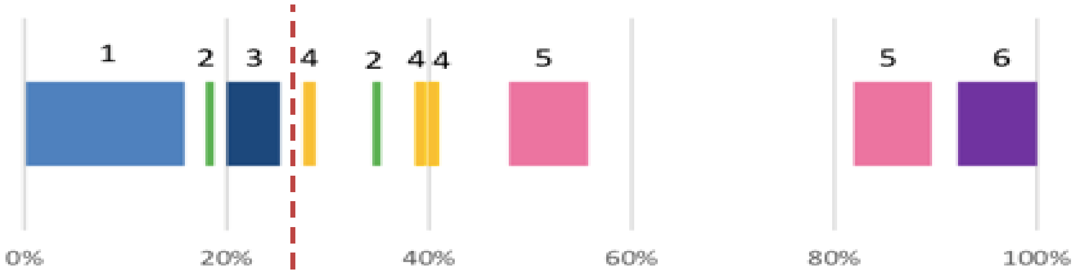

Figure 7. PALD’s activity series alignments along the task duration in percentage
Note. The colour presentations do not share any activity series in common among groups but distinguish the numbers of the activity series in each group.

NALD

Lastly, the overall activity patterns of NALD showed the three strongest transitions: (1) PH4→E (*prob* = .51, *z* = 10.61), (2) BR2→PH4 (*prob* = .38, *z* = 5.30), and (3) IA2→SI1 (*prob* = .37, *z* = 2.77). NALD did not demonstrate many SAI patterns. (1) PH4→E path elucidates the students' appraisal of task performance after modifying previously determined ideas; (3) IA2→SI1 explicates their mere adoption of what AI suggested before sketching another figure. In addition, (2) BR2→PH4 path was found; students built a hierarchical relationship with AI before they altered existing ideas. Along with the most probable transitional activities, NALD’s 15 SAI patterns are organised in Figure 8.

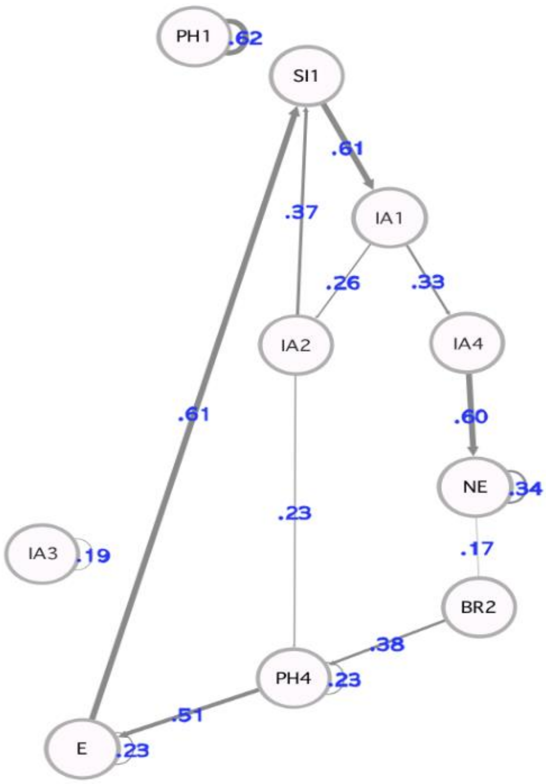

Figure 8. NALD’s SAI process patterns
Note. The thicker arrows indicate higher transitional probabilities, blue for linear relationships and red for bilateral relationships.

The SAI process of NALD (see Table 4 and Figure 9) was the simplest and AI-dependent performing group in negative emotion. The overall SAI duration was 32.8; however, it accounted for only 3.6% of goal establishments, the self-looped PH1 (the activity series (1)). This clearly shows that students repeatedly contemplated the task objective without performing any PR, SG, PH2–PH3 during the prior activity. The subsequent activity series from (2) to (4) in time of the drawing activity series revealed the group's reliance on AI's suggestions, yet with negative emotional experience, for the task completion. In the activity series (2), although students drew sketches (SI1) before browsing through the AI-recommended figures for task exploitation (IA1), they first criticised such suggestions (IA4) with NE arousal. And this activity series further developed into series (3). Here, students altered their pre-existing plans (PH4) upon mere adoption of the suggested figures (IA2) after the exploration (IA1). They then appraised drawing more sketches (SI1). In addition, activity series (4), the extended version of (2) series, indicates that students revised their pre-existing plan (PH4) and assessed their task outcomes (E) by criticising the figure suggestions (IA4) upon browsing figures (IA1) and having NE. Even though students treated AI with condescending attitudes, they kept on adjusting based on its recommendations.

Table 4
NALD's activity series number details with task duration

Dimension	No.	Activity series	Onset (sec.)	Offset (sec.)	%
Prior activity	1	PH1↔PH1 (self loop)	0	39	3.6
In times of	2	SI1→IA1→IA4→NE	88	118	2.7
drawing	2	SI1→IA1→IA4→NE	263	302	3.6
activity	3	SI1→IA1→IA2→PH4→E→SI1	464	541	7.1
	2	SI1→IA1→IA4→NE	832	906	6.8
	4	SI1→IA1→IA4→NE→BR2→PH4→E	990	1088	9
Total					32.8

Note. Italic: bilateral interactions.

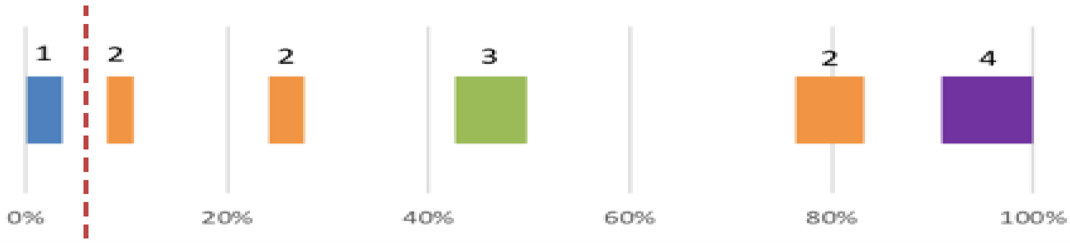

Figure 9. NALD's activity series alignments along the task duration in percent
Note. The colour presentations do not share any activity series in common among groups but distinguish the numbers of the activity series in each group.

Discussion

This study found different patterns among the four groups prior to beginning the drawing task with the AI tool. It is striking to see that the PAHD group spent the longest time in the overall PR and SG activities before executing the assigned drawing task compared to other groups. These findings echo the viewpoint of the theory of transactive memory system (TMS) arguing that individuals with meta-knowledge know (a) what needs to be accomplished, (b) what resource and expertise are needed to complete the task and (c) who has the given expertise can function most effectively during collaborative exercises such as the collaborative drawing task assigned for this research (Austin, 2003). In this regard, teachers may benefit from developing a better understanding of the dimensions of TMS (e.g., expertise, trust and coordination) and should consider structuring and promoting educational tasks and learning activities that stimulate SAI based on TMS. Furthermore, educational AI should better consider how to promote the components of TMS between a student and an AI to collaboratively perform the task, instead of simply accelerating the power of data processing and manipulation (Kim & Cho, 2023).

In parallel, students' engagement in problem representation and solution generation-related activities before beginning the actual act of drawing with AI reflects the creative problem-solving processes (CPS) model that includes problem findings or definition and solution findings as essential components in an early stage of CPS for further development of problem-solving (e.g., Treffinger et al., 2008). Reflecting on this, teachers implementing AI may consider allowing students to be actively engaged in the problem identification or definition to support alternative solution development and evaluation of these alternatives in a manner that is closely related to the actual stages of problem-solving (Klahr & Simon, 1999).

Along with this, the task process between students and AI should not be merely considered an activity limited to performing one single specific task and for solving well-defined problems only but as a series of learning task activities involved in the learning process that requires strong pedagogical support, as an earlier stage of CPS (e.g., problem definition and solution generation) is interconnected with the further development of problem-solving stages with AI. In this regard, the AI system architecture should be designed with a holistic view of the end-to-end learning process in which students and AI interact continuously, cross-linked on various learning activities in the learning process. This then requires a more detailed analysis of the roles of AI, the alignment of AI and learning goals, necessary instruction support strategy and evaluation alignment throughout the learning process.

Second, in line with the aforementioned differences before starting the task, each group also presented distinctive differences during active drawing. Both the PALD and NALD groups completed a task mostly by simply adopting the AI's suggestions (IA2) upon the exploration of figures suggested by AI (IA1). This illustrates that their interaction with AI is much more likely to be passive as well as the exploitation or usage of AI's suggestion. In contrast, PAHD and NAHD exhibited a higher frequency in IA3, drawing figures repetitively for AI's accurate suggestions in accordance with the students’ intention. One distinctive feature of IA3, however, was found between the PAHD and NAHD participants. Together with the IA3 activity, PAHD adopted AI's suggestion (IA2) with adequate modification (SI2), flexibly accommodated AI's suggestions and generated the alternative figures mingled with the students' original ideas (IA5). Concurrently, they adjusted the existing plan or idea (PH4) and conceptual structure of drawing (MP2) based on frequent monitoring of the task process with AI (MP1) and evaluation (E), which shows their SAI is interactive and jointly coordinated. On the other hand, NAHD gave up on their effort to make use of AI suggestions over the course of SAI, terminating interactions with AI only to end up relying solely on their own drawing skill to complete the task without the AI’s assistance. In part, these findings demonstrate that building multiple modes of regulation such as self-regulation, co-regulation and shared regulation, which are emphasised for interactive and dynamic learning situations in human-human collaborative learning context (Järvelä & Hadwin, 2013), is equally important for the SAI context. Teachers are in a position to guide students to (a) activate key regulation processes such as setting goals, making plans, adopting strategies and monitoring and evaluating (Järvelä et al., 2015) during SAI, (b) increase awareness of AI’s and the student's own and task performance processes and (c) externalise their own perception of the interaction between student and AI on the task operation processes. Along with this, educational AI should be developed to be more explainable to facilitate shared mental models between students and AI. AI should clearly present both the student and AI's understanding of task responsibilities and what the corresponding information needs are. In addition, educational AI should be developed with a mindset of augmenting students' meta-cognitive activity, and different modes of regulation for SAI by provoking questions, providing necessary scaffolding and allowing students to reflect on their learning process, rather than simply providing automated suggestions.

Third, this study found larger patterns in the socio-emotional relationship-related activities during SAI. Particularly, explicit differences in socio-emotional activity were found among students depending on their attitude towards AI. Both the PAHD and PALD groups exhibited PE towards AI and collegial relationship building with AI (BR1), while the NAHD and NALD groups presented solely NE towards AI and hierarchical relationship building with AI (BR2). These findings build on and extend research on affective AI that may better interact and create positive relationships with students (Kim & Lee, 2020). To account for socio-emotional interactions with students, AI should be capable of increasing students' emotional engagement by being empathic and personal. For example, AI may positively affect students' motivation levels by encouraging them to reflect on and acknowledge contributions (Kumar & Rosé, 2014). However, it should also be noted that simply having positive feelings towards AI may not always lead to interactive or constructive learning activities and interactions. Although both the PAHD and PALD groups demonstrated PE and BR1, PAHD performed various activities such as SI1, SI2, IA1 and IA5, whereas PALD participants mostly ended with PE itself that seldom performed in tandem with PH3. This finding is corroborated by research on student-student collaboration, highlighting that feelings of friendship in the group may inhibit students from working seriously, cause off-task behaviours and become less self-disciplined and critical (Le et al., 2018). Hence, this study calls for teachers to foster SAI quality by enhancing both students' cognitive (e.g., domain-specific skills) and collaborative competencies (e.g., defining learning goals, instructing beneficial students' behaviours during SAI, monitoring, supporting, consolidating and evaluating SAI) during the SAI process.

Conclusion

This study extends our understanding of differences in the SAI process when completing a learning task among students with varying attitudes towards AI and different levels of domain knowledge. It also offers a range of implications on the instructional and educational AI design to better structure SAI. Furthermore, this paper proposed a coding scheme for analysing SAI, which can serve as an alternative tool for focusing on the communication and interaction patterns of students with other AI systems. However, studies are necessary to address the following limitations of this study. One limitation of this study is that all the participants in the study were Korean undergraduate students and their interactions with AI were conducted in the specific context of a drawing task. Thus, the study findings may not fully reflect the total population of SAI on a learning task. Research is necessary to validate the findings in different educational levels of students along with various learning tasks. Additionally, research can further develop an understanding of the influence of divergent students' characteristics as well as AI characteristics on students-AI teaming in learning tasks. Furthermore, **we** encourage studies **to** undertake research in a real classroom setting to examine possible environmental factors that may influence the SAI process.

Author contributions

J. Kim: Conceptualisation, Investigation, Data curation, Formal analysis, Writing – original draft, review and editing; **S.-S. Lee**: Data curation, Formal analysis, Writing – original draft, review and editing; **Y. Ham**: Data curation.

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Appendix 1

Demographic characteristics of the participants

Groups	Age *M* (*SD*)	Level of domain-specific skills: Drawing score M (SD)	Level of domain-specific skills: Duration of art education *M* (*SD*)	Attitude towards AI	Perceived feelings regarding AI
PAHD	23.40 (0.89)	4.33 (0.66)	14.60 years (1.67)	Positive	Helpful and innovative; human-AI collaboration is important
PALD	23.20 (1.30)	1.88 (0.72)	0.45 year (0.33)		
NAHD	23.60 (1.14)	4.30 (0.69)	14.20 years (1.64)	Negative	Scary and concerned about the dystopian society caused by AI; not important to use and learn
NALD	22.80 (0.84)	1.68 (0.69)	0.47 year (0.49)		

Appendix 2

Coding scheme

Category	Subcategory	Code	Description
Drawing activity (DA)	Problem representation (PR)	PR1	Recalling information from previous experience or even other fields to address and define the current task problem (e.g., COVID-19 and climate change)
		PR2	Framing the focus of interest, setting the boundaries of the problem, selecting the focus of attention and imposing coherence in decision
	Solution generation (SG)	SG1	Generating alternative solution
		SG2	Clarifying an idea for solving problems through interpretation of the analysis and synthesis to the problem
	Solution implementation (SI)	SI1	Drawing a new figure
		SI2	Revising figure
	Interaction with AI (IA)	IA1	Exploring figures suggested by AI
		IA2	Simply adopting AI's suggestions without further elaboration or critique
		IA3	Repetitively modifying or refining the drawing for AI to understand student's intention
		IA4	Reasoning or critiquing AI's suggestions
		IA5	Integrating alternative figures through evaluation of student's drawing and AI's suggestion
Meta-cognitive activity (MC)	Planning how to solve a problem (PH)	PH1	Establishing the desired goals and objectives prioritised in which the task operates.
		PH2	Determining the planning premises by defining the resources available and limitations to complete the task
		PH3	Developing a strategic plan of how to proceed with the task performance, for instance, sequence of activities and role distribution
		PH4	Modifying the version of existing plan and strategies or sequences
	Monitoring & regulations during problem-solving process (MP)	MP1	Monitoring of the learning task process
		MP2	Adjustment in the conceptual structure by providing meaning to the arrangement of the composition
	Evaluation (E)	E	Evaluating the task outcomes and the task completion process

Socio-emotional activity (SE)	Building relationship with AI (BR)	BR1	(Collegiality relationship with AI) Building partnership bond and relationship united in a common purpose where student respects AI teammate's abilities to work towards the task objective given
		BR2	(Hierarchical relationship) Building the relationship between subordinate and superiors, where student represents a whole and a master and AI as their assistant
	Positive emotional response to AutoDraw (PE)	PE	Presenting or showing feelings of emotional closeness, personal association, and affective connection with AI teammate
	Negative emotional response to AutoDraw (NE)	NE	Presenting or showing negative emotions including anger, anxiety, fear, disgust, disappointment, shame and guilt, antipathy and hate

Appendix 3

Frequency of the SAI activity participation

Category	Code	PAHD		NAHD		PALD		NALD	
		M (*SD*)	%	*M* (*SD*)	%	*M* (*SD*)	%	*M* (*SD*)	%
Drawing activity (DA)	PR1	13.2 (1.79)	4.44	12.8 (1.79)	7.94	4.4 (1.52)	2.38	0 (0)	0
	PR2	4.2 (0.84)	1.41	4.4 (0.55)	2.73	2.4 (0.55)	1.3	0 (0)	0
	SG1	4.8 (0.84)	1.62	5 (0.71)	3.	2.4 (0.55)	1.3	0 (0)	0
	SG2	12.2 (0.84)	4.11	2.8 (1.30)	1.74	1.4 (0.55)	0.76	0 (0)	0
	SI1	14.4 (5.37)	4.85	44.2 (6.61)	27.4	17 (6.16)	9.2	17.4 (6.88)	11.8
	SI2	27.4 (10.31)	9.23	13.2 (4.49)	8.19	0 (0)	0	0 (0)	0
	IA1	38.6 (1.52)	13.00	12 (2.92)	7.44	75.8 (7.69)	41	44.8 (6.76)	30.3
	IA2	8.8 (4.82)	2.96	5 (3.16)	3.1	9.4 (4.39)	5.09	12.6 (6.43)	8.53
	IA3	29.6 (3.29)	9.97	10.4 (3.58)	6.45	0 (0)	0	10.8 (2.59)	7.31
	IA4	16.2 (2.77)	5.45	10 (3.67)	6.2	31.6 (7.30)	17.1	31.4 (8.44)	21.2
	IA5	4.6 (1.34)	1.55	0 (0)	0	0 (0)	0	0 (0)	0
Meta-cognitive activity (MC)	PH1	6.8 (1.30)	2.29	3.4 (0.89)	2.11	2.8 (1.10)	1.52	2.8 (0.84)	1.89
	PH2	11 (0)	3.7	4.6 (1.34)	2.85	6.4 (0.55)	3.46	0 (0)	0
	PH3	2.4 (0.55)	0.81	2.6 (0.55)	1.61	2.4 (0.55)	1.3	0 (0)	0
	PH4	14.2 (1.30)	4.78	0 (0)	0	0 (0)	0	5.4 (2.07)	3.65
	MP1	14.6 (4.28)	4.92	0 (0)	0	0 (0)	0	0 (0)	0
	MP2	13.2 (1.79)	4.44	0 (0)	0	9 (1.58)	4.87	0 (0)	0
	E	18.4 (1.14)	6.2	11.2 (4.32)	6.95	2.4 (0.55)	1.3	5.2 (1.30)	3.52
Socio-emotional activity (SE)	BR1	11.8 (2.39)	3.97	0 (0)	0	4.8 (1.10)	2.6	0 (0)	0
	BR2	0 (0)	0	5.2 (1.30)	3.23	0 (0)	0	3 (0.71)	2.03
	PE	30.6 (3.65)	10.3	0 (0)	0	12.6 (2.97)	6.82	0 (0)	0
	NE	0 (0)	0	14.4 (2.61)	8.93	0 (0)	0	14.4 (2.79)	9.74
Total		297 (10.27)	100	161.2 (9.61)	100	184.8 (16.80)	100	147.8 (11.67)	100