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Designing AI for team ideation: How content strategy and participation style affect creative performance through team emergent states

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ABSTRACT

Generative AI is increasingly used in team ideation, but how its design features affect creative performance is unclear. Research on human teams suggests that such effects are mediated by team emergent states (TESs, the team's cognitive and emotional dynamics and feelings). Yet, whether TESs play a similar role in team-AI co-ideation remains unknown. This study explored the effects of AI content strategies (breadth-first vs. depth-first) and participation styles (active vs. passive) on TESs and performance during team-AI collaborative ideation by a mixed-design experiment with 52 students and in-depth interviews with seven professionals from industry. In the experiment, two participants and AI as a team brainstormed and developed design solutions. We found depth-first strategies fostered stronger convergence among ideas and members and further enhanced solution completeness, whereas breadth-first AI increased divergent performance and solution practicability. AI design influenced both cognitive and affective TESs, which predicted objective and subjective performance differentially. This study reveals how the design of generative AI affects human-AI collaborative ideation through the perspective of TES and suggests designing generative AI to adjust to TESs and the creative process.

1. Introduction

Generative Artificial Intelligence (AI) tools such as ChatGPT and Midjourney are increasingly integrated into team-based ideation processes, supporting tasks such as brainstorming and concept development (Ding et al., 2023; Schmutz et al., 2024; Yu-Han and Chun-Ching, 2023). As these systems take on more active roles, a critical challenge lies in designing AI to effectively support both team dynamics and creative outcomes (Diederich et al., 2022; Flathmann et al., 2023). Two key design dimensions are particularly salient: what content AI provides (i.e., content strategy), and how it delivers that content (i.e., participation style).

Regarding **content strategies**, AI can follow either a **breadth-first approach,** exploring and introducing novel topics, or a **depth-first approach,** elaborating on existing ideas to deepen discussion (Y. Liu et al., 2024; Rayan et al., 2024). These strategies may differentially influence cognitive processes such as divergence (exploring diverse ideas) and convergence (refining ideas) during ideation (Cropley, 2006; Goldschmidt, 2016), potentially shaping both the scope and quality of generated ideas. Meanwhile, a **participation style** refers to whether AI acts proactively (**active**) or responds only to human input (**passive**). Active AI is supposed to enhance engagement and stimulate creativity (Davis et al., 2015), yet empirical evidence remains limited.

While designers increasingly use AI for individual ideation, the creative process remains deeply social, heavily relying on team discussions to develop ideas (Kavadias and Sommer, 2009; P. Paulus, 2000). Emerging multi-user AI platforms (e.g., Microsoft Copilot Agents in Teams, Slack AI) now enable teams to interact with AI collectively; however, research remains largely focused on individual human-AI interaction, leaving team-AI co-creation underexplored. Previous studies about human teams emphasize that team performance can be strongly affected by team emergent states (TESs) (Mathieu et al., 2006, 2019; Rapp et al., 2021), which means the transient cognitive and affective conditions such as shared understanding, psychological safety, and emotional climate (Coultas et al., 2014; Marks et al., 2001). Therefore, in team-AI collaborative ideation, AI's design features (content strategies and participation styles) could affect creative performance not only directly but also through TESs. While previous research has linked certain TESs to performance, it remains unclear which states are most influential in AI-supported ideation, and how they are shaped

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by specific AI's design features.

Therefore, this study aims to answer the research question: how do AI design features (i.e., content strategies and participation styles) affect creative performance in team-AI ideation, and how are these effects associated with team emergent states? This question unfolds into three interrelated inquiries:

RQ1: How do AI's content strategies (breadth-first or depth-first) and participation styles (active or passive) influence team emergent states?
RQ2: How do these design features affect the creative performance of ideation?
RQ3: Which team emergent states contribute most to the creative performance of ideation?

2. Literature review

2.1. The concepts of AI content strategies and participation styles

Studies have investigated AI content strategies such as the role of linguistic style (Mallick et al., 2024), human-like communication behaviors (Van et al., 2020), and response strategies (Chattaraman et al., 2019; Gyory et al., 2022), whereas research on ideation predominantly focuses on stimulus selection and inspirational triggers (Acar and Runco, 2014; Gomes et al., 2022; Sozo and Ogliari, 2019). A widely used theoretical foundation for ideation is associative theories of creativity (Mednick, 1962; Malaga, 2000; Beaty and Kenett, 2023), which suggest that creativity arises from novel connections between disparate, often unrelated, ideas or concepts. Therefore, ideation is strongly affected by the semantic distance between existing knowledge activated in the brain and the external stimuli (Acar and Runco, 2014; Beaty et al., 2014; Malaga, 2000).

In the context of human-AI collaborative ideation, AI-generated content serves as such an external stimulus, and its semantic distance from designers' ideas can affect creative outcomes (Chan et al., 2017). To manipulate this semantic distance, previous studies proposed two AI content strategies: breadth-first and depth-first strategies (Y. Liu et al., 2024; Rayan et al., 2024). The breadth-first strategy means that AI introduces a wide variety of new ideas with longer semantic distances, and the depth-first strategy means that AI expands existing ideas or provides details with closer semantic distances to designers' ideas.

Besides content strategies, creative outcomes can also be affected by how AI participates in the collaboration. Numerous studies recommend adaptive and responsive AI for collaboration (Xia and Chen, 2024; J.-S. Chen et al., 2021; Dignum, 2021; Rzepka and Berger, 2018; Van et al., 2020), and designers expect AI to actively adapt to environmental changes (Gmeiner et al., 2023). Some studies on team-AI collaboration also suggest that highly automatic AI is often perceived as an intelligent, helpful, and trustworthy team player (McNeese et al., 2018; Pan et al., 2024; Salikutluk et al., 2024). However, little empirical research has explicitly examined how creative performance could be affected by the way AI participates in ideation. This study investigates this effect by comparing two opposing types of AI participation styles: active and passive. Active AI engages in conversation actively without specific instructions, and passive AI only responds to human commands.

2.2. TESs and their effects on creative performance in human teams

As team-AI co-creation remains underexplored, research on team emergent states (TESs) has largely focused on human-only teams. TESs are "properties of the team that are typically dynamic in nature and vary as a function of team context, inputs, processes, and outcomes"(Marks et al., 2001). Rapp et al. (2021) summarized over fifty TESs, and some of them were more related to creative tasks. The present research primarily addresses the following cognitive and affective TESs.

2.2.1. Cognitive TESs

In team creativity research, a commonly studied cognitive TES is knowledge sharing. **Knowledge sharing** denotes the perceived exchange and discourse of knowledge among team members through various modalities. Many studies involving employees demonstrated that knowledge sharing increased creativity and team performance (N. Li et al., 2022; C.-C. Huang, 2009; Choi et al., 2010; M.-L. Liu et al., 2020). These studies explained that knowledge sharing enables teams to collect, process, integrate, and communicate information, facilitates knowledge application, and ultimately enhances performance.

Another frequently studied TES is the **shared mental model** (SMM), which means knowledge or structures that are shared by team members aiming to form accurate explanations and expectations about the task (Klimoski and Mohammed, 1994; Mathieu et al., 2000; Stout et al., 1999). SMM is critical for complex collaborative problem-solving tasks (Stout et al., 1999) and develops and changes over a long time period (Andrews et al., 2023). However, ideation or brainstorming processes are usually short, open-ended, and require less shared previous expertise (Rossiter and Lilien, 1994), which means SMM may be less applicable to team ideation research. Effective short-term ideation also involves a gradual convergence of ideas through interactions, which shares functional similarities with SMM but operates on a more transient and semantic level. Therefore, we refer to this phenomenon as **cognitive convergence**: the dynamic and thematic alignment of team members' thinking during ideation.

Although not explicitly labeled, cognitive convergence has been implicitly conceptualized or measured in previous studies, such as knowledge convergence (Jeong and Chi, 2007; Kodama and Kimura, 2020), semantic coherence (Dong et al., 2004), and design convergence (Tiwana, 2012). These studies often used student samples and behavioral measures to capture convergence. For example, Jeong and Chi (2007) measured knowledge convergence through template scoring based on knowledge pieces, Lu et al. (2020) used the index of convergence (IOC) to measure the extent to which group members combine their ideas with others, and Hatcher et al. (2018) employed linkography to compute network metrics (e.g., link ratio, entropy) reflecting idea integration. They found higher convergence correlated with more member interaction (Jeong and Chi, 2007) and better idea quality (Dong et al., 2004), while linkography-based studies suggest moderate or balanced convergence leads to the best creative performance. Together, these findings highlight cognitive convergence as a key TES in team ideation. In this study, we use IOC and linkography indices to measure convergence among members and among ideas, respectively.

2.2.2. Affective TESs

This study examined the effects of three potentially critical affective TESs: team emotion, team cohesion, and team climate. **Emotion** has three dimensions, including valence, denoting positive or negative; arousal, indicating intensity; and dominance, reflecting the perception of control, according to Russell's (1980) classification. As the creative process requires enthusiasm, studies on both students and employees supported that activating moods or high-arousal emotions could boost creative fluency and flexibility (Agnoli et al., 2019; Martindale and Greenough, 1973) and facilitate creativity (De Dreu et al., 2008; St-Louis and Vallerand, 2015).

Team cohesion has been described as the extent to which a group of individuals is drawn together as a team for extended periods (Bonny, 2018), essentially representing an emotional attraction to a particular team and a "bond" among team members (Coultas et al., 2014). Team cohesion was composed of multiple components: interpersonal attraction, task commitment, and group pride (Mullen and Copper, 1994). Both student and employee studies showed that team cohesion promoted information sharing among team members and thus increased performance and creativity (Craig and Kelly, 1999; Joo et al., 2012; Reiter-Palmon et al., 2021). However, team cohesion could also hinder creativity by reinforcing group norms, interaction patterns, social influence, and hierarchy (Staw, 2009).

Team climate encompasses the collective perceptions (Anderson and West, 1998) of the set of norms, attitudes, and expectations operating within the team (Fyhn et al., 2023; Schneider, 1990). Both student and employee studies suggested that a positive team climate fosters creativity by activating cognitive processes (Gaggioli et al., 2015; Zhu et al., 2018). In addition, some team climate components, such as support for innovation, task orientation, and vision, strongly support innovative work in corporate teams (G. Chen et al., 2013; Hülsheger et al., 2009).

2.3. Potential effects of AI content strategies and participation styles on TESs and creative performance

2.3.1. Effects of AI content strategies

Few studies explored the impacts of AI content strategies on knowledge sharing or cognitive convergence. Some human team studies have focused on knowledge diversity, which can be increased by the breadth-first content from AI. Diverse knowledge across disciplinary boundaries was often regarded as a positive factor enhancing team cognitive processes such as shared mental models, as suggested by a review study (Mohammed and Dumville, 2001). Yet, diverse knowledge or information can trigger team conflicts arising from differences in focus, knowledge background, or representational gaps (Cronin and Weingart, 2007; Mello and Delise, 2015), and thus may hinder cognitive convergence in fast-paced creative tasks. A social-cognitive framework (Paletz and Schunn, 2010) further explains the mechanisms of how knowledge diversity affects different stages of the creative process through the cognitive processes: diverse knowledge could, on the one hand, promote information sharing and further increase divergent performance, on the other hand, hinder the development of shared mental models and further reduce convergent performance. Therefore, AI's breadth-first strategies may promote knowledge sharing, and depth-first strategies may foster cognitive convergence.

Many studies involving student participants suggest that the breadth-first AI may foster positive team emotion and team climate. Specifically, breadth-first AI has been evaluated as trustworthy and creative, and these favorable features enhance positive emotion (Y. Liu et al., 2024). In addition, the diverse content generated by breadth-first AI could establish a highly creative environment that sustains a positive team climate throughout the team lifecycle (Primus and Jiang, 2019). Nevertheless, researchers have also cautioned against AI's limitations in emotional states and the lack of emotional care and human touch (Amankwah-Amoah et al., 2024).

Both student and employee studies suggested that breadth-first and depth-first AI may enhance team performance differently. Some empirical research where individual designers used generative AI in creative tasks suggested that breadth-first AI could enhance human creativity (Jin et al., 2024; Borgianni et al., 2017; Zhang et al., 2022). Similarly, knowledge diversity has been supported to enhance divergent performance by many empirical studies with employees (Oldham and Da Silva, 2015; Mathuki and Zhang, 2022; X. Huang et al., 2014; Hou et al., 2021; Sung and Choi, 2019). The social-cognitive framework (Paletz and Schunn, 2010) also supported that knowledge diversity could increase knowledge sharing and divergent creativity by exposing teams to diverse ideas. In addition, this framework suggests that breadth-first content may be preferred in early stages, while depth-first content becomes more valuable later, which is also indicated by empirical evidence (Y. Liu et al., 2024; Zhang et al., 2022). In contrast, depth-first strategies remain understudied in empirical creativity research.

2.3.2. Effects of participation styles

Although AI systems are supposed to proactively collaborate with humans (Davis et al., 2015), few studies have investigated the impact of active AI on TESs or performance. On the one hand, active AI may enhance satisfaction and creativity. Evidence suggests that both student and professional designers prefer more conversational and affable AI interactions (Gmeiner et al., 2023). Moreover, some student studies indicated that active participation of human members could promote emotional contagion (Linnenbrink-Garcia et al., 2011; Rhee et al., 2020) and further enhance team cohesion (P. B. Paulus and Brown, 2007; P. B. Paulus and Dzindolet, 1993; Gu et al., 2011). Furthermore, active AI increases the opportunities to be inspired by AI and thus can stimulate creativity (Oldham and Da Silva, 2015; B. Wang et al., 2024).

On the other hand, passive AI offers distinct advantages. A study involving both students and employees suggested that passive AI could increase human control (Hauptman et al., 2024), which could increase satisfaction suggested by a student study (Turner et al., 2020). In addition, with the help of passive AI, human members may relieve task-related tension and gain mental support, thereby fostering positive team emotional states. Therefore, which participation style is likely to positive effect on TES or performance remains uncertain.

In addition, AI content strategies and participation styles may have an interaction effect on creative performance. Chan et al. (2017) conducted an online experiment to explore how inspirations' novelty and stimulus timing affected human ideation. They found that AI-generated inspiration could decrease creativity when AI actively provides novel inspirations (semantically far from the human's ideas), especially when the human was in a productive and fluent mental state. This finding indicates that AI content strategies' impact on TESs or performance could be influenced by active or passive participation styles.

2.4. From individuals to teams: expanding the scope of AI in creative collaboration

To summarize, much of the existing research on AI-assisted creativity has focused on individual designers, examining how AI tools support personal ideation, iteration, and decision-making. While these studies provide valuable insights for designing AI for ideation, they offer a limited understanding of how AI influences collaborative creativity in team settings, where cognitive and emotional dynamics are inherently interactive and emergent.

A few theoretical perspectives addressed this mechanism in team settings. For example, Seeber et al. (2020) proposed that integrating AI into human teams will produce both positive and negative effects on cognitive and emotional states. However, little empirical research has examined the AI's role in team ideation. Based on research in human teams, where team emergent states (TESs) have been established as a key set of mediators between team features and team performance (Ilgen et al., 2005; Mathieu et al., 2019), this study investigates the unknown mechanisms between AI features and team creativity from the perspective of TESs.

Methodologically, most empirical studies involving professionals relied on cross-sectional surveys or interviews, whereas controlled and in-person comparative experiments usually enrolled student participants. It limited causal inference and ecological validity in workplace contexts. Therefore, this study combines controlled experiments with student design teams and in-depth interviews with industry professionals. This mixed approach enables both the direct examination of AI's effects in TESs and team creativity and the validation of the findings in the workplace, bridging the experimental rigor with practical relevance. To summarize, Fig. 1 presents the concepts and their potential relationships examined in this study.

3. Method

To investigate how the content strategy and participation style of AI affect the team emergent states and creative performance, we conducted a controlled experiment with students and validation interviews with professionals. The experiment used a 2*2 factorial mixed design, involving four conditions: active breadth-first AI, active depth-first AI,

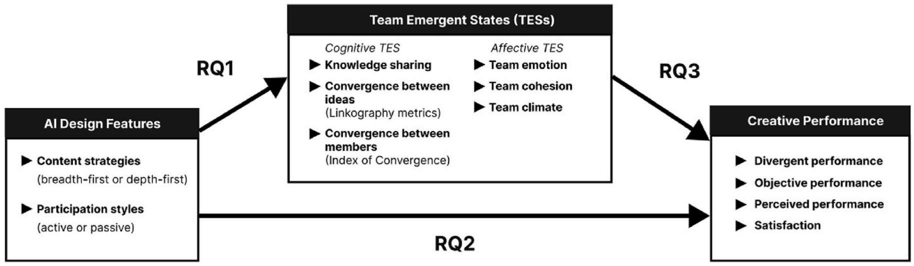

Fig. 1. Conceptual framework of this study. This study aims to explore how AI design features affect creative performance from the perspective of TESs.

passive breadth-first AI, and passive depth-first AI. The content strategy of AI was a within-subject variable, while the participation style of AI was a between-subjects variable. The experiments were conducted after obtaining approval from the ethics committee of the university. After the student experiment, we interviewed seven industry professionals to validate the generalizability of the findings.

3.1. Participants in the student experiment

We recruited 52 student participants (33 females, mean age = 22.67, range from 19 to 26). Participants were randomly assigned to 26 dyadic teams. Forty-two participants were graduate students, and the remaining ten were undergraduates. Most participants had internship experience in design-related positions. Forty-nine participants majored in design-related fields (e.g., industrial and environmental design), and three majored in mechanical or electronic engineering. All participants had prior experience in design projects and were familiar with AI tools. Participants who finalize the experiment will be awarded around 80 yuan.

3.2. Experimental tasks

Since the content strategy was a two-level within-group variable, all teams were asked to complete two separate design tasks on improving campus life. One focused on shared spaces for roommates with conflicting lifestyles or sleeping habits, and the other on redesigning the campus cafeteria to attract students. Each task included a brainstorming (divergent) phase for generating many ideas and a solution development (convergent) phase where teams selected and developed one idea into a design with sketches.

3.3. Laboratory setting and platform

The experiments were conducted face-to-face in a quiet room, as shown in Fig. 2. When performing the tasks, each participant in a team used an iPad with a stylus and a keyboard to edit and share an online document on the Boardmix (an online whiteboard platform). The interface comprised three panels: the idea record panel, the solution demonstration panel, and the AI inspiration panel (as shown in Fig. 3). During the brainstorming phase, two participants discussed orally and typed their alternative ideas instantly in the idea record panel. AI generated task-related ideas actively or passively in the AI inspiration panel. To control the experiment, we restricted the interactive functions of the AI inspiration panel. Participants could only request or receive inspiration but were restricted from accessing other information (e.g., external knowledge). During the solution development phase, participants chose and developed an idea by sketching it on the solution demonstration panel. In addition, participants' interactions and behaviors were recorded by two cameras in the room.

3.4. Manipulation of AI design features

We manipulated the AI's content strategies and participation styles

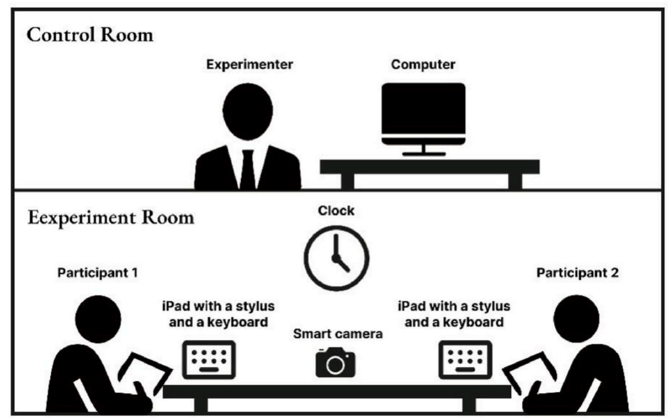

Fig. 2. Laboratory setting of the experiment. The experiment was conducted using the Wizard of Oz method. Two participants utilized iPads, styluses, and keyboards to complete the experimental tasks, and the experimenter worked behind the scenes to manipulate the shared documents to play the role of the AI.

using the Wizard of Oz method. Participants were told that they were interacting with an autonomous AI agent, but a researcher controlled the AI's responses from a separate room (see Appendix A for detailed procedures). The content strategy was determined by the semantic similarity between AI-generated ideas and the team's prior discussion, following the paradigms of previous studies (Chan et al., 2017; Green, 2016; Y. Liu et al., 2024; Wise and Kenett, 2024). AI's responses were generated by ChatGPT and filtered by a sentence transformer model to control the similarity levels. In the passive condition, the AI responded only to the participants' requests, whereas in the active condition, the AI autonomously contributed ideas under predefined timing rules. This approach ensured error-free and consistent AI behaviors and prevented the confounding effects from AI's algorithmic performance.

3.5. Measurements in the student experiment

TESs and perceived performance were measured by questionnaires or behavioral coding of the records. All scales in the questionnaires were translated from English to Chinese, back-translated, and proofread by two researchers to ensure accuracy. All the TESs that were measured by questionnaires were aggregated by averaging team members' ratings following Ou et al.'s study (2023).

3.5.1. Cognitive TESs

Knowledge sharing was measured using a nine-item five-point Likert scale adopted from the "general task and team knowledge" dimension in Johnson et al. (2007)'s instrument. Other dimensions of the original instrument were excluded due to irrelevance (e.g., working environment) or overlap with other variables in this study. The scale in this study showed strong internal reliability (Cronbach's alpha = 0.877).

Convergence between ideas was measured with a Linkography metric, namely **link ratio.** Linkography was frequently used in

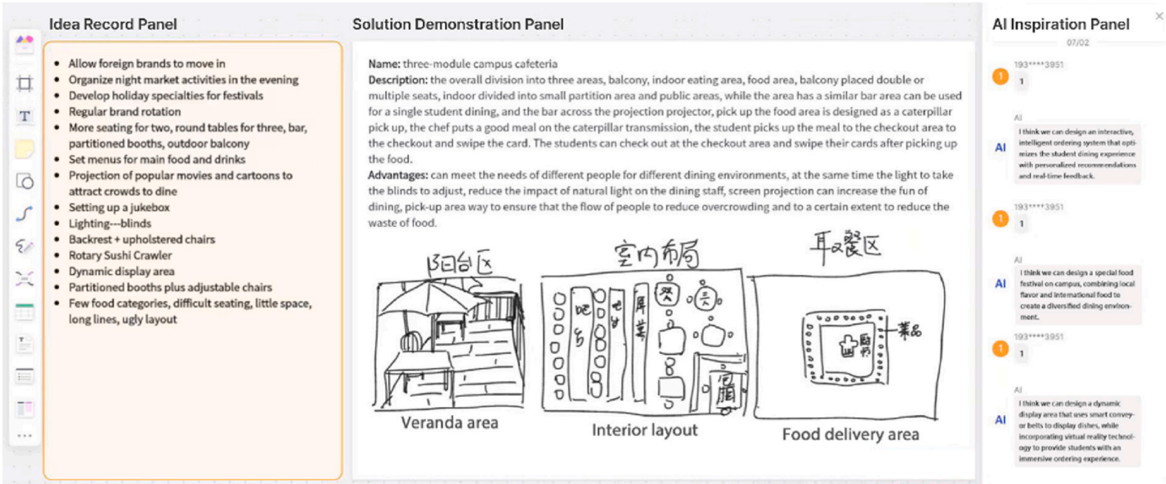

Fig. 3. Experimental interactive platform. The idea record panel enables participants to record and organize ideas in the brainstorming phase; the solution demonstration panel enables participants to develop an idea in the solution development phase; the AI inspiration panel provides AI-generated content in the brainstorming phase.

brainstorming studies to identify patterns of ideas in a temporal sequence (van der Lugt, 2000; Kan and Gero, 2008), and the link ratio was computed based on the constructed linkography to indicate cohesiveness among ideas. To construct linkographies for each team, two researchers coded the ideas of each team (extracted from the idea record panel and refined by audio recordings) based on the Linkography codebook (van der Lugt, 2000). The link ratio was then calculated with the LiNKODER software (Pourmohamadi and Gero, 2011). In addition, we also calculated the **horizonlink entropy** based on the constructed linkographies to capture the opportunities relating to cohesiveness (Kan et al., 2007).

Convergence between members was measured by the Index of Convergence (IOC) based on behavior analysis. IOC assessed the extent to which group members combine their ideas with others and was used to measure convergence between members in previous studies (Larey and Paulus, 1999; Lu et al., 2019, 2020). In addition, **AI content adoption** was the extent to which participants adopted AI-generated content in their alternative idea list. We calculated it by adapting the link density index (LDI) of the linkographs mentioned above. Similar approaches have been used earlier to measure design fixation (Perttula and Sipilä, 2007).

3.5.2. *Affective TESs*

Team emotion was evaluated by averaging team members' self-reported emotions. Each member's emotion was measured by the nine-point three-item Self-Assessment Manikin questionnaire (Bradley and Lang, 1994). SAM is a non-verbal pictorial questionnaire consisting of three rows of pictograms. It assesses an individual's emotions in three dimensions: arousal, valence, and dominance. A higher valence score reflects a higher level of happiness. The team emotion is calculated as the mean score of the two participants' emotions.

Team cohesion was measured using the Cohesion Assessment Manikin (CAM) scale developed by Bonny (2018). It consisted of five rows of seven-point pictograms with interpretive descriptions to visualize five team cohesion components: drawn-together, committed, pride, social, and future. This scale demonstrated substantial reliability in this study (Cronbach's alpha = 0.818).

Team climate was assessed using the Team Climate Inventory (Loo and Loewen, 2002), a 14-item five-point Likert scale comprising four dimensions: vision, participative safety, task orientation, and support for innovation. These dimensions reflect team members' shared understanding of goals, psychological safety, focus on performance, and openness to innovation (Simonton et al., 1992; West and Anderson, 1996). The scale exhibited strong reliability in this study (Cronbach's alpha = 0.846).

In addition, since we controlled extraversion when analyzing the effects on affective TESs, **extraversion** was also measured by a two-item five-point Likert scale from a Chinese version of the big five personality inventory from Li, 2013. In this study, the internal reliability was acceptable (Cronbach's alpha = 0.562) for the two-item scale.

3.5.3. *Performance*

Divergent performance was assessed by fluency (Guilford, 1956), calculated using the LDI method (Perttula and Sipilä, 2007). In this method, we reduced the weights of supplementary and modification ideas to 0.3 and 0.7 to fit the divergent context. A higher fluency score indicates a richer generation of novel idea combinations.

Objective performance was evaluated based on the final design solutions. Two independent experts, blind to the experimental conditions, rated the solutions with sketches on three dimensions: innovation (the uniqueness and originality), practicability (problem-solving capacity and feasibility), and completeness (refinement and concreteness). Scoring criteria are shown in Appendix B. The values of Inter-rater reliability were acceptable (ICC: innovation = 0.87, practicability = 0.66, completeness = 0.84; all p values < 0.01).

Perceived performance was measured using a four-item five-point scale adapted from Wang et al. (2016). Sample items include "How creative do you consider your team to be?" and "How well does your team produce new ideas?" (1 = "Poorly", 5 = "Very much"). The scale demonstrated substantial reliability in this study (Cronbach's alpha = 0.861).

Satisfaction was measured using a three-item five-point scale adapted from Van Der Vegt et al. (2001). Sample items include "Overall, I am satisfied with my work in this team." (1 = "Poorly", 5 = "Very much"). The scale demonstrated high reliability in this study (Cronbach's alpha = 0.954).

3.5.4. *Post-task interview*

To verify the manipulation of AI content strategies and understand participants' preferences, attitudes, and expectations, we conducted a post-experiment semi-structured interview with the following questions. (1) Did the participants notice the differences between the two AI content strategies? (2) Which AI strategy offered a better, more inspiring experience? (3) After we presented the other AI participation style, how did the participants expect it would affect the collaborative ideation, and which style did they prefer?

3.6. Procedures of the student experiment

Based on pilot experiments with four participants, we established the following procedure, as shown in Fig. 4. First, the two participants signed the informed consent form, completed a pre-test questionnaire (Q1: demographics and personality), and received instructions and platform training. Then, the researcher started video recording, and the participants completed two counterbalanced trials. Each trial consisted of a 20-min brainstorming (divergent) phase and a 10-min solution development (convergent) phase. After each trial, participants filled out a post-test questionnaire (Q2: TESs and perceived performance). Finally, after the second trial, the researcher briefly interviewed two participants together. The experiment lasted 80–90 min.

3.7. Data analysis of the student experiment

We conducted the mixed-design ANOVA to assess the effects of AI participation style (between subjects) and AI content strategy (within subjects) on multiple dependent variables. In addition, as the extraversion of teammates affected affective TESs by changing social interaction and members' perceptions (Buchanan, 1998; Kickul and Neuman, 2000), we conducted ANCOVA to control its influence on affective TESs. Effect sizes were measured by partial eta squared (η^2), and powers of ANOVA were calculated for (marginally) significant effects. For significant interaction effects in ANOVA, we further analyzed simple main effects.

We used Partial Least Squares Structural Equation Modeling (PLS-SEM) to explore relationships between TESs and performance. The goodness-of-fit criteria of variables were measured using R^2, and the significance of path coefficients was assessed using bootstrapping analysis. The model included six exogenous variables (emotional arousal, emotional dominance, team cohesion, team climate, IOC, and horizonlink entropy) and four endogenous variables (perceived performance, satisfaction, fluency, and the score of the solution). Emotional valence and knowledge sharing were excluded due to their high correlations with team cohesion (Pearson's $r = 0.58$) and team climate (Pearson's $r = 0.57$), respectively. These analyses were mainly performed using R-4.3.1, with PLS-SEM analyzed by the 'SEMinR' package, and ANOVA conducted via the 'BruceR' package. The power analysis for ANOVA was conducted using G*Power 3.1 software.

3.8. Interviews with industrial professionals

3.8.1. Interview participants

We recruited seven full-time employees to validate our findings. Three were female and four were male, aged between 25 and 35 ($M = 30.71$, $SD = 9.91$). As shown in Table 1, all the participants had substantial work experience (2–13 years). They all had group brainstorming experience, and they frequently used AI tools to assist creative work.

Table 1
Background information of validation interview participants.

ID	Age	Gender	Major	Position	Working experience (years)
P1	30	Male	Product Design	UX&Product Designer	8
P2	28	Female	Interaction Design	Project Manager	3.5
P3	35	Male	Digital media art	Motion Designer	13
P4	26	Male	Industrial Design	Industrial Designer	2
P5	33	Female	Mechanical Engineering	Senior Product Manager	8
P6	33	Male	Graphic Design	UX Designer	11
P7	30	Female	Industrial Design	UI Designer	5

3.8.2. Interview design and data analysis

Participants were interviewed individually in person. First, we introduced the aim of this study and explained all the variables, including the AI features, TESs, and team performance. Then, the participant was asked to predict the relationships among all the variables based on their working experiences and explain the reasons for his/her prediction. Next, we introduced the settings and the major results of the student experiment. Finally, the participant evaluated these experiment results (e.g., "Do you agree with the conclusion that 'Depth-first AI promotes cognitive convergence'? Could you provide reasons or personal examples to support your view?"). Each interview lasted approximately 40 min. All interviews were recorded with participants' consent. The recordings were transcribed and analyzed by the affinity diagram method.

4. Results

4.1. The effect of AI design features on TESs

Table 2 shows the ANOVA results of cognitive TESs. The AI content strategy significantly affected **convergence between ideas**, measured by **link ratio** ($F(1,24) = 21.187$, $p < 0.001$, $\eta^2 = 0.469$, power >0.90). Collaborating with depth-first AI ($M = 0.716$, $SD = 0.267$) induced more idea links than with breadth-first AI ($M = 1.217$, $SD = 0.491$). The content strategy also significantly affected **horizonlink entropy** ($F(1,24) = 9.786$, $p = 0.005$, $\eta^2 = 0.289$, power >0.90). Breadth-first AI ($M = 4.122$, $SD = 1.817$) led to lower horizonlink entropy than the depth-first AI ($M = 2.766$, $SD = 0.967$).

The AI content strategy also significantly affected **convergence between members**, measured by **IOC** ($F(1,24) = 17.210$, $p < 0.001$, $\eta^2 = 0.418$, power >0.90). Breadth-first AI ($M = 0.007$, $SD = 0.004$) led to higher IOC than the depth-first AI ($M = 0.013$, $SD = 0.006$). Moreover, content strategy influenced **AI content adoption** ($F(1,24) = 95.869$, $p < 0.001$, $\eta^2 = 0.800$, power >0.90). Breath-first content strategy ($M =$

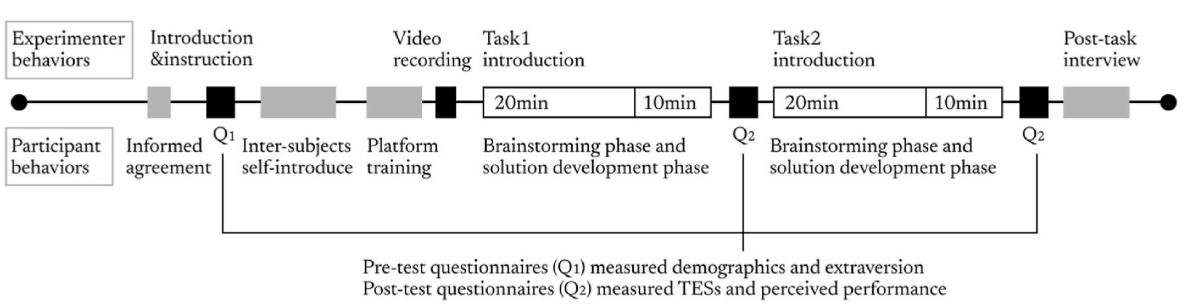

Fig. 4. Procedures of the student experiment. The figure shows the timeline of the experimental procedure with key actions. Above the timeline are the experimenter's behaviors, and below the timeline are the participants' behaviors.

Table 2
ANOVA summary table of cognitive TESs.

Dependent variable	Independent variable	Level	Mean	SD	F	p	η2
Knowledge sharing	Content strategy	Breadth-first	4.438	0.280	0.858	0.364	0.035
		Depth-first	4.385	0.335			
	Participation style	Active	4.470	0.294	1.220	0.280	0.048
		Passive	4.353	0.313			
	Content strategy × Participation style				0.232	0.634	0.010
IOC (convergence between members)	Content strategy	Breadth-first	0.007	0.004	17.210	<0.001***	0.418
		Depth-first	0.013	0.006			
	Participation style	Active	0.011	0.007	2.294	0.143	0.087
		Passive	0.009	0.005			
	Content strategy × Participation style				0.008	0.928	0.000
Link ratio (convergence between ideas)	Content strategy	Breadth-first	0.761	0.267	9.768	0.005**	0.289
		Depth-first	1.217	0.491			
	Participation style	Active	0.972	0.364	0.535	0.472	0.022
		Passive	1.006	0.536			
	Content strategy × Participation style				0.242	0.627	0.010
Horizonlink entropy	Content strategy	Breadth-first	2.766	0.967	9.768	0.005**	0.289
		Depth-first	4.122	1.817			
	Participation style	Active	3.304	1.172	0.535	0.472	0.022
		Passive	3.584	1.945			
	Content strategy × Participation style				0.242	0.627	0.010
AI content adoption	Content strategy	Breadth-first	0.225	0.099	95.869	<0.001***	0.800
		Depth-first	0.037	0.030			
	Participation style	Active	0.139	0.116	0.443	0.512	0.018
		Passive	0.124	0.125			
	Content strategy × Participation style				0.477	0.497	0.019

p < 0.1 (*), indicating significance (or marginally significant); p < 0.01 (**), indicating high significance; p < 0.001 (***), indicating very high significance.

0.225, SD = 0.099) led to higher AI content adoption than depth-first content strategy (M = 0.037, SD = 0.030). The results showed no difference in knowledge sharing between content strategies and participation styles of AI (all p > 0.1).

Table 3 shows the ANCOVA results of affective TESs. First, AI content strategies marginally influenced participants' **emotional valence** (F(1,23) = 4.072, p = 0.055, $\eta^2 = 0.15$), but the statistical power was low (0.66). Depth-first content (M = 8.308, SD = 0.663) evoked higher emotional valence than the breadth-first content (M = 7.692, SD = 0.778, p = 0.050) when the AI participation style was passive. Second, AI content strategies and participation styles had a significant interaction effect on **emotional dominance** (F(1,23) = 4.072, p = 0.037, $\eta^2 =$ 0.163)**.** The simple main effects analysis suggested no significant difference between breadth-first and depth-first content when AI participated actively. However, when AI participated passively, the depth-first content evoked higher emotional dominance (M = 7.885, SD = 0.916) than the breadth-first content (M = 7.269, SD = 0.971, p = 0.048). Third, AI participation styles affected **team cohesion** slightly (F(1,23) = 3.753, p = 0.065, η2 = 0.14, power = 0.62). Active participant style (M = 5.492, SD = 0.519) significantly increased team cohesion than the passive participant style (M = 5.069, SD = 0.626, p = 0.019) under the breadth-first condition. In addition, the results showed no difference in the emotional arousal and team climate (all p > 0.1).

Table 3
ANCOVA summary table of affective TESs.

Dependent variable	Independent variable	Level	Mean	SD	F	p	η^2
Emotional valence	Content strategy	Breadth-first	7.615	0.931	4.072	0.055*	0.150
		Depth-first	8.058	0.804			
	Participation style	Active	7.673	0.979	1.015	0.324	0.042
		Passive	8.000	0.775			
	Content strategy × Participation style				0.460	0.367	0.035
Emotional arousal	Content strategy	Breadth-first	6.962	1.029	0.398	0.534	0.017
		Depth-first	6.846	1.369			
	Participation style	Active	6.827	1.191	0.005	0.946	0.000
		Passive	6.981	1.229			
	Content strategy × Participation style				0.986	0.331	0.041
Emotional dominance	Content strategy	Breadth-first	7.231	0.886	0.681	0.418	0.029
		Depth-first	7.423	1.155			
	Participation style	Active	7.077	1.027	2.174	0.154	0.086
		Passive	7.577	0.977			
	Content strategy × Participation style				4.478	0.045*	0.163
Team cohesion	Content strategy	Breadth-first	5.281	0.603	0.240	0.629	0.010
		Depth-first	5.231	0.614			
	Participation style	Active	5.415	0.536	3.753	0.065*	0.140
		Passive	5.096	0.635			
	Content strategy × Participation style				1.438	0.243	0.059
Team climate	Content strategy	Breadth-first	4.380	0.211	1.286	0.269	0.053
		Depth-first	4.330	0.294			
	Participation style	Active	4.361	0.287	0.103	0.751	0.004
		Passive	4.349	0.224			
	Content strategy × Participation style				0.000	0.991	0.000

p < 0.1 (*), indicating significance (or marginally significant); p < 0.01 (**), indicating high significance; p < 0.001 (***), indicating very high significance.

4.2. The effect of AI design features on creative performance

As shown in Table 4, AI content strategies affected the **fluency** (divergent performance) in the divergent phase ($F(1,24) = 20.045$, $p < 0.001$, $\eta^2 = 0.455$, power >0.90). Breath-first AI ($M = 17.385$, $SD = 6.001$) resulted in higher fluency than depth-first AI ($M = 11.346$, $SD = 3.947$). In addition, AI content strategies and participation styles had an interaction effect on the **score of the design solution** (objective performance, $F(1,24) = 4.27$, $p = 0.050$, $\eta^2 = 0.151$). The simple main effects analysis suggested no significant difference between breadth-first and depth-first content when AI participated actively. However, when AI participated passively, the depth-first AI resulted in a slightly higher solution score ($M = 74.821$, $SD = 11.838$) than the breadth-first AI ($M = 71.808$, $SD = 9.163$, $p = 0.093$). AI content strategies affected the **practicality of solution** ($F(1,24) = 9.881$, $p = 0.004$, $\eta^2 = 0.292$, power >0.90) and **completeness of solution** ($F(1,24) = 4.879$, $p = 0.044$, $\eta^2 = 0.159$, power $= 0.70$). Breath-first AI ($M = 76.865$, $SD = 7.552$) resulted in higher practicality scores than depth-first AI ($M = 71.5$, $SD = 10.678$). However, depth-first AI ($M = 77.250$, $SD = 8.388$) led to higher completeness of the final solution than breadth-first AI ($M = 70.712$, $SD = 4.879$).

4.3. TESs as predictors of creative performance

The PLS-SEM model (as shown in Fig. 5) revealed that perceived performance was predicted by team climate ($\beta = 0.564$, $|t| > 2.58$, 95 % BCCI = (0.283, 0.855), $f^2 = 0.370$) and emotional arousal ($\beta = 0.194$, $|t| > 1.96$, 95 % BCCI = (0.034, 0.368), $f^2 = 0.084$), explaining 60.8 % of the variance in perceived performance ($R^2 = 0.608$). Satisfaction was predicted by team climate ($\beta = 0.532$, $|t| > 2.58$, 95 % BCCI = (0.171, 0.792), $f^2 = 0.245$), explaining 49.5 % of the variance in satisfaction ($R^2 = 0.495$). Fluency (divergent performance) was significantly predicted by IOC (convergence between members, $\beta = -0.565$, $|t| > 3.786$, 95 % BCCI = (−0.761, −0.396), $f^2 = 0.440$), and team cohesion ($\beta = 0.271$, $|t| > 1.96$, 95 % BCCI = (0.025, 0.550), $f^2 = 0.058$), explaining 36.9 % of the variance in fluency (divergent performance, $R^2 = 0.369$). The score of solution (objective performance) was significantly predicted by IOC ($\beta = -0.356$, $|t| > 2.58$, 95 % BCCI = (−0.597, −0.143), $f^2 = 0.147$), explaining 25.3 % of the variance in objective performance ($R^2 = 0.253$).

4.4. Interviews with industrial professionals

Using the affinity diagram method, we extracted 92 labels reflecting participants' views. Among these labels, 27 addressed participants' experiences of using AI in their creative work, 51 focused on participants' evaluations of the experiment results, 12 highlighted the distinguished features of team-AI collaboration and the expectations for AI, and 2 presented the differences between students and professionals.

Regarding the experience with AI, creative professionals viewed current AI as a practical support in workflow to accelerate the design process, but not a replacement for human creativity. They used AI to collect and organize information and generate pictures for inspiration. P6 stated, "*AI can help us aggregate a large amount of information quickly in the early design process, and this information may inspire us.*" However, most participants also emphasized its creative limitations, as P5 noted, "*AI lacks creativity, so it is hard to directly generate innovative work; that is why humans still make key design decisions and deliver the final solutions.*" In addition, when inspiration was blocked, some participants turned to AI for emotional relief. For example, P4 shared, "*Using AI when inspiration is exhausted can effectively alleviate design anxiety*," highlighting AI's role in regulating emotions during creative blocks.

Table 4
ANOVA summary table of team performance.

Dependent variable	Independent variable	Level	Mean	SD	F	p	η^2
Satisfaction	Content strategy	Breadth-first	4.712	0.315	1.444	0.241	0.057
		Depth-first	4.628	0.465			
	Participation style	Active	4.609	0.494	0.759	0.392	0.031
		Passive	4.731	0.259			
	Content strategy × Participation style				1.444	0.241	0.057
Perceived performance	Content strategy	Breadth-first	4.277	0.299	0.416	0.525	0.017
		Depth-first	4.324	0.372			
	Participation style	Active	4.269	0.395	0.312	0.581	0.013
		Passive	4.332	0.267			
	Content strategy × Participation style				0.324	0.575	0.013
Fluency (divergent performance)	Content strategy	Breadth-first	17.385	6.001	20.045	<0.001***	0.455
		Depth-first	11.346	3.947			
	Participation style	Active	13.558	4.879	1.184	0.287	0.047
		Passive	15.173	6.736			
	Content strategy × Participation style				0.029	0.866	0.001
Solution score (objective performance)	Content strategy	Breadth-first	73.744	8.431	0.165	0.688	0.007
		Depth-first	73.006	9.073			
	Participation style	Active	73.436	6.614	0.002	0.967	0.000
		Passive	73.314	10.485			
	Content strategy × Participation style				4.270	0.050*	0.151
Completeness of solution	Content strategy	Breadth-first	70.712	4.879	4.523	0.044*	0.159
		Depth-first	77.250	8.388			
	Participation style	Active	73.500	10.624	0.069	0.795	0.003
		Passive	74.462	14.165			
	Content strategy × Participation style				1.268	0.271	0.050
Practicability of solution	Content strategy	Breadth-first	76.865	7.552	9.881	0.004*	0.292
		Depth-first	71.500	10.678			
	Participation style	Active	72.846	9.448	0.693	0.413	0.028
		Passive	75.519	9.646			
	Content strategy × Participation style				1.508	0.231	0.059
Innovation of solution	Content strategy	Breadth-first	73.654	13.714	1.013	0.324	0.040
		Depth-first	70.269	18.062			
	Participation style	Active	73.962	14.259	0.574	0.456	0.023
		Passive	69.962	17.568			
	Content strategy × Participation style				2.865	0.103	0.107

$p < 0.1$ (*), indicating significance (or marginally significant); $p < 0.01$ (**), indicating high significance; $p < 0.001$ (***), indicating very high significance.

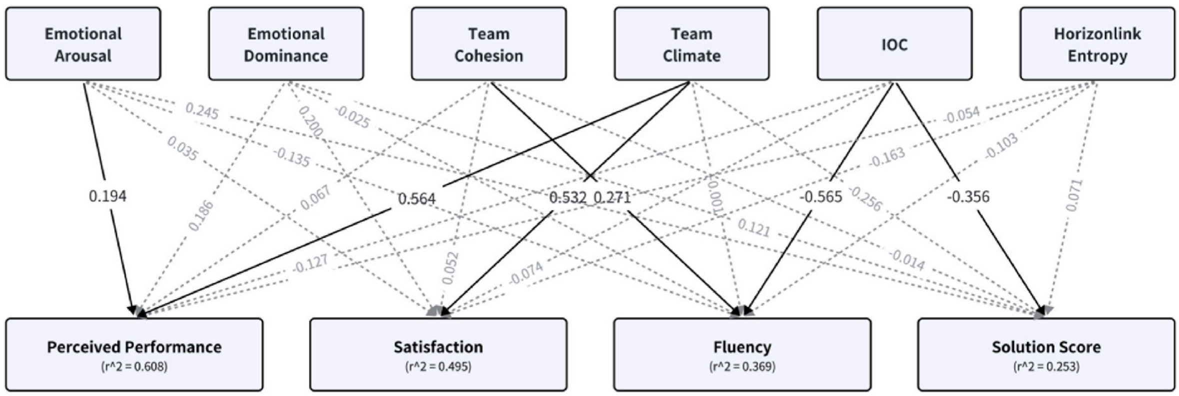

Fig. 5. The PLS-SEM model of TESs and team performance. Black and solid arrows represent significant pathways, and grey and dashed arrows signify non-significant pathways. IOC denotes the index of convergence, capturing the degree of convergence among team members. Horizonlink entropy reflects the diversity of the link structure in the creative process. Fluency indicates divergent performance, and the solution score represents objective performance.

Regarding the evaluation of the experiment results, professionals agreed that most findings are applicable to industrial settings. For example, all participants strongly agreed that the breadth-first AI could increase fluency and the diversity of solutions by reducing cognitive convergence in ideation, and that AI's content strategies potentially modulated the rhythm of the human creative process. However, two professionals questioned the findings of AI's direct impact on team emotions. P6 said, "*I feel happier when AI provides useful content, regardless of whether it follows a breadth-first or a depth-first strategy,*" and P5 noted, "*Interactions with human team members influence my emotions far more than AI does.*" It suggests that AI's emotional effects can be indirect and contingent, shaped by other factors such as the quality of AI output and individual sensitivity. In addition, P5 expressed doubts about proactive AI's impact, suggesting that it would depend heavily on the quality of AI-generated content.

The participants also highlighted the differences between human-AI and team-AI interactions in ideation. First, AI's strong performance can be more confidence-shaking in teams. As P3 noted: "*Compared to working alone with AI, seeing AI outperform us in a team setting can undermine our sense of contribution.*" Second, four participants stressed the value of human-human relationships and expected AI to recognize them, yet noted that current AI lacks this capacity. P3 expressed concern: "*AI does not understand the historical background among team members, so when it jumps in during a stalled discussion, even with good intent, AI can break the flow and damage my goodwill toward it.*" Similarly, P5 suggested AI to recognize tacit cues: *"AI needs to understand the social rules and perceive the non-verbal cues conveyed between humans to achieve better collaboration. There is still a gap between human intelligence and AI."* Third, participants hoped to build a long-term rapport with an AI agent. P7 emphasized: "*In enterprise projects, AI should not just participate in brainstorming. It needs to grow with the team, build trust, share knowledge over time, and become a bridge connecting team members that strengthens team cohesion and emotional climate.*"

Regarding the applicability of student experiment findings to the industry, participants suggested that early-stage ideation is similar across experience levels. Specifically, P5 distinguished the concept between idea generation and product innovation, stating: *"Innovation requires more accumulated experience and knowledge, which means AI must match professional designers in both expertise and collaboration."* Nonetheless, the early-stage ideation process in both educational and industrial contexts is similar, indicating the theoretical and practical value of the experiment findings, supported by P2: *"The main gap between student designers and professionals lies in industry experience. Student ideas sometimes could lack feasibility, but are often highly creative, which still makes them valuable for studying creativity."*

5. Discussion

5.1. Findings

Table 5 summarizes the major findings, their corresponding research questions (RQs), and the supporting evidence obtained through the experiment and interviews with professionals. The following subsections will explore each finding grouped by RQs, focusing on the underlying mechanisms and connections to prior literature.

5.1.1. AI design features affected team emergent states: depth-first strategies enhanced convergence

Both the student experiment and the interviews with professionals suggested that **depth-first strategies strongly promoted both convergence between ideas and members**. This finding was supported by the significance and the high powers (larger than 0.95) of ANOVA as well as the interviews with professionals, as P7 further noted that: "*Depth-first AI may provide more related and useful information, and help our discussions focus.*" Previous studies suggest that diverse knowledge generally promotes information sharing, cognitive consensus, and shared mental models (Mohammed and Dumville, 2001), but may also increase conflict (Cronin and Weingart, 2007; Mello and Delise, 2015; Paletz and Schunn, 2010). When teams have insufficient time to collaborate (especially when newly formed), they can hardly resolve the conflicts triggered by the diverse knowledge. This explains why, instead of breadth-first AI, depth-first AI with lower content diversity promoted cognitive convergence in our short-term experiment.

The experiment also suggested three trends about how AI design features affect TES, which required further verification. **First, depth-first strategies may enhance positive emotions** ($p = 0.055$, power $= 0.66$). As suggested by the post-task interviews with students, a possible reason was that participants felt acknowledged and understood when depth-first AI presented ideas similar to participants' own. It aligns with previous studies that social recognition boosts self-confidence (Rees and Freeman, 2007), AI adoption (Chong et al., 2022), and creative behaviors (Beghetto et al., 2021). Some student participants even viewed breadth-first AI as off-task and irrelevant, which could disrupt their thought processes. On the contrary, other student participants felt that depth-first AI "copied" their ideas and did not contribute to brainstorming. Similarly, professionals preferred the breadth-first AI's creativity and expertise. These different preferences of AI content strategies could result from individual differences or different understandings of the task goals (Flathmann et al., 2023), which need further investigation.

Second, passive depth-first AI yielded the highest emotional dominance ($p = 0.045$). The passive AI increased participants' sense of control, consistent with previous research (Hauptman et al., 2024).

Table 5
Summary of key findings and supporting evidence.

No.	Findings	Answering RQ[a]	ANOVA significance	ANOVA power	Interviews with professional
1	Depth-first strategies strongly promoted both convergence among ideas and members.	RQ1	Significant	All the powers >0.90	Supported
2	Trends: (1) Depth-first strategies enhanced positive emotions. (2) Passive depth-first AI resulted in the highest emotional dominance. (3) AI's active participation enhanced team cohesion.	RQ1	Marginally significant	>0.60 (0.66 for valence and 0.62 for cohesion)	Not fully supported
3	Breadth-first AI increased fluency and solution practicability.	RQ2	Significant	>0.90	Supported
4	Depth-first AI promoted solution completeness.	RQ2	Significant	0.70	Supported
5	Interactive effects: Active and breadth-first AI resulted in the highest final solution scores	RQ2	Significant	N.A.	Supported
6	Cognitive TESs[b] predict objective performance and affective TESs predict subjective outcomes	RQ3	Partially supported	N.A.	Supported

[a] RQ: Research questions
[b] TESs: Team Emergent States

Furthermore, this feeling was amplified by the depth-first content, which made participants feel acknowledged. Such recognition and perceived control have been found to enhance satisfaction (Turner et al., 2020). However, this finding was not fully supported by the interviews with professionals and required further investigation.

Third, AI's active participation enhanced team cohesion ($p = 0.065$, power = 0.62), with breadth-first active AI yielding the highest levels. Active idea-sharing may stimulate members' engagement as suggested in previous studies (P. B. Paulus and Brown, 2007; P. B. Paulus and Dzindolet, 1993), and increased motivation is linked to greater team cohesion (Gu et al., 2011). Moreover, active members directly facilitate emotional contagion (Linnenbrink-Garcia et al., 2011; Rhee et al., 2020), potentially strengthening emotional bonds within the team. However, as the effect size is small, this finding remains preliminary and requires further validation.

5.1.2. Breadth- and depth-first content strategies differently enhanced creative performance

Creative performance was affected by AI content strategies more strongly than AI participation styles. First, we found **breadth-first AI enhanced idea fluency and solution practicability**, which is particularly valuable in early design stages (Guilford, 1956; Y. Liu et al., 2024). This was strongly supported by both the student experiment (all p values < 0.05 and powers >0.90) and the interviews with professionals. The reason was that the breadth-first AI introduced novel information and knowledge to team members, and this novel information can enhance creativity as suggested by a substantial body of prior research (Oldham and Da Silva, 2015; Mathuki and Zhang, 2022; X. Huang et al., 2014; Hou et al., 2021; Sung and Choi, 2019).

Second, **depth-first AI promoted solution completeness**. This finding was supported by both the significance of ANOVA and the interviews with professionals, but the power was only 0.70, suggesting further verification. Together with the first finding, it suggests a complementary role of AI strategies: breadth-first AI is more effective in early ideation, while depth-first AI is preferred in later design stages. It aligned with previous empirical research on human teams, which shows that users prefer explorative and wide content in early phases and focus on more relevant and narrowed topics later (Y. Liu et al., 2024; Zhang et al., 2022; Mannucci and Yong, 2018).

Third, we found an interactive effect of content strategies and participation styles: active and breadth-first AI resulted in the highest final solution scores. This interactive effect was supported by both ANOVA and interviews with professionals. A possible reason was that AI was engaged solely in the brainstorming phases of this experiment, where breadth-first strategies were more effective, as mentioned above. Furthermore, this effect was amplified by AI's active participation and more engagement.

5.1.3. TESs predict performance: cognitive TESs for objective performance and affective TESs for subjective outcomes

Both the experiment and the interview suggest that **cognitive TESs tend to predict objective performance, whereas affective TESs tend to predict subjective outcomes**. On the one hand, we found convergence between members negatively associated with objective performance, including fluency and solution score. Previous studies revealed dual effects of cognitive convergence: enhancing team coordination and design quality (Levesque et al., 2001; Hinsz et al., 1997; Dong et al., 2004; Kodama and Kimura, 2020; Tiwana, 2012), yet risking design fixation and reduced creativity (Meslec et al., 2020; Kohn, 2009; Rietzschel et al., 2006). Our PLS-SEM model supported its detrimental role, possibly because the simple brainstorming tasks in our experiment required less knowledge integration. Notably, ANOVA results revealed that depth-first AI increased both convergence and solution completeness, suggesting convergence may enhance refinement in later stages, in line with previous research (Dong et al., 2004).

On the other hand, affective TESs primarily affected subjective outcomes. Team climate emerged as the strongest predictor of both perceived performance ($\beta = 0.564$) and satisfaction ($\beta = 0.532$), reflecting its role in shaping a collaborative atmosphere in line with prior research (Zhu et al., 2018; G. Chen et al., 2013; Hülsheger et al., 2009; Gaggioli et al., 2015). Emotional arousal and team cohesion also positively predicted the objective and subjective performance, respectively, supporting previous studies (Martindale and Greenough, 1973; Agnoli et al., 2019; Craig and Kelly, 1999; Joo et al., 2012; Reiter-Palmon et al., 2021).

Overall, the PLS-SEM results provide preliminary evidence for distinct predictive patterns of cognitive and affective TESs on creative performance, which is further verified by the interviews with professionals. However, due to the limited sample size, these results should be interpreted as exploratory. Future research should validate these patterns with larger samples and investigate the mediating role of TESs in how AI design features influence creative performance.

5.2. Implications

5.2.1. Theoretical implications

These findings advance the understanding of team-AI collaborative ideation by revealing how AI design features affect creative performance through team emergent states. The findings extend associative theories of creativity and the social-cognitive framework (Mednick, 1962; Malaga, 2000; Beaty and Kenett, 2023; Paletz and Schunn, 2010) from human teams to hybrid human-AI contexts, demonstrating that AI-generated content can serve as semantic stimuli that trigger associative thinking. Moreover, we found a trend that active AI increased team cohesion and passive AI amplified emotional dominance. These findings tentatively aligned with research on human team dynamics (Linnenbrink-Garcia et al., 2011; Rhee et al., 2020; P. B. Paulus and Brown, 2007; P. B. Paulus and Dzindolet, 1993; Gu et al., 2011; Hauptman et al., 2024). However, given the marginal significance, low statistical power, and the mixed opinions from professionals, these effects should be interpreted as preliminary and require further investigation.

Furthermore, team emergent states (TESs, particularly cognitive convergence, team emotion, and team cohesion) potentially mediated the effects of AI design features on creative performance, aligning with previous research on human team collaboration (C.-C. Huang, 2009; Ilgen et al., 2005; Kleanthous, 2024). This reframes AI not merely as an idea generator, but as a socio-cognitive regulator in design teams. Given the limited empirical studies on how AI shapes team dynamics, our findings provide critical insights into the design and understanding of team-AI collaborative ideation.

5.2.2. Design implications

The findings suggest the following design implications for generative AI in collaborative ideation. First, AI should adapt its content strategies based on the creative process (or the maturity of ideas) and TESs. Breadth-first strategies (providing diverse, novel ideas) could support divergent thinking in early stages, while depth-first strategies (refining existing ideas) could help complete solutions in later phases. This aligns with previous recommendations for balancing exploration and exploitation in collective creativity (Gonthier and Besançon, 2024; Leimeister, 2010). Furthermore, these positive effects of the different content strategies can be amplified by AI's active participation. Nevertheless, human designers need to keep leading ideation processes since excessive active AI may diminish human involvement and reduce creativity (Boers et al., 2025; Hauptman et al., 2024).

Second, AI participation style should be context-sensitive and team-aware. While active AI may enhance team cohesion and passive AI may increase perceived control, our exploratory results suggest these effects are subtle and context-dependent. Therefore, AI should perceive collaborative context across multiple modalities and adjust its level of activeness based on TESs. Furthermore, recent NLP tools make it feasible to monitor TESs, such as cognitive convergence, from conversational data (Hauptman et al., 2024; Peng et al., 2024; Schleith et al., 2022; Yu et al., 2025). Future AI systems could use such data to adapt AI's participation styles in real time.

5.3. Limitations

This study has the following conceptual and methodological limitations. Conceptually, some affective TESs (e.g., team climate) require a long time to develop in real teams (Gersick, 1988; Koopmann et al., 2016) and thus are hard to capture in short-term experiments. In addition, some confounding factors (such as cognitive styles and AI expertise) were not controlled in the experiment, as suggested by the interviewed professionals later. Methodologically, most TESs were measured by post-task questionnaires, which could not capture the dynamics of TESs as effectively as probe-based methods. To control confounding factors, we restricted AI content and some interaction functions of the platform, which could be unnatural to participants. The experiment recruited a limited number of students, which may have reduced the statistical power for some ANOVA results. Professionals were interviewed but did not participate in the experiment. Future research is needed to validate these findings in real industrial settings.

In addition, our findings may be influenced by the interactional asymmetry between humans and AI. Participants often focused more on their human teammates and sometimes ignored messages from AI. Possible reasons were the modality differences of our experiment (face-to-face for humans and text-based for AI) and humans' tendencies to ignore AI's contributions (Rayan et al., 2024), which could stem from speciesism toward AI (A. Chen et al., 2025). This interesting phenomenon requires further exploration in further studies.

6. Conclusion

This study conducted controlled student experiments and in-depth interviews with professionals to examine the impact of AI content strategies and participation styles on team-AI collaborative ideation. We found depth-first strategies fostered stronger convergence among ideas and members and further enhanced solution completeness, whereas breadth-first AI increased divergent performance and solution practicability. AI design features have the potential to influence affective TESs, but the effects remain complex and require further investigation. Furthermore, cognitive TESs tend to predict objective performance, whereas affective TESs tend to predict subjective outcomes. This study reveals how the design of generative AI affects team-AI collaborative ideation from the perspective of TESs and suggests designing generative AI to dynamically adjust to TESs and the creative process.

CRediT authorship contribution statement

Xi Xiao: Writing – original draft, Visualization, Software, Investigation, Formal analysis, Data curation. **Yue Chen:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Can Liu:** Writing – review & editing, Visualization, Validation.

Availability of data

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethical compliance statement

All the procedures were performed in compliance with relevant laws and institutional guidelines and have been approved by the Ethics Committee of East China University of Science and Technology (Approval No. ECUST-2024-r010, Date: May 1, 2024).

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Implementation of AI Manipulation

Content strategy was manipulated based on the semantic similarity between AI-generated content and previously discussed ideas in a team, which has been used in previous studies (Chan et al., 2017; Green, 2016; Y. Liu et al., 2024; Wise and Kenett, 2024). In the breadth-first condition, the novelty is calculated by the semantic similarity between AI-generated ideas and human-generated ideas. We generated 200 novel ideas for each task as our idea database with the help of ChatGPT in advance (prompt: please give me 20 creative solutions to address the disparities in schedules among roommates through the design of shared spaces & enhance the attractiveness of the campus cafeteria with various dining options). To quantify the novelty of AI-generated ideas, we utilized a 384-dimensional dense vector space sentence transformer model[1] to calculate the semantic similarity developed by Hugging Face (W. Wang et al., 2020). A smaller semantic similarity value indicates that the AI-generated idea is more novel.

During the experiment, the experimenter computed the semantic similarity instantly between the ideas in the database and all human-generated ideas in Python to choose the most novel idea. The code in Python firstly excluded AI-generated ideas with one or more semantic similarities greater than 0.8 with any human-generated ideas, then averaged the semantic similarity of each remaining AI-generated idea with all current human-generated ideas, and selected the smallest value as the statement of AI. In manipulation, the wizard should update the human-generated ideas in the Python file, then run the code to filter the most novel idea in the database, and show the idea to the participants by sending a message in the AI inspiration panel. All operations can be completed within 30 s.

In the depth-first condition, the statement of AI is generated by ChatGPT in real-time using a template prompt. In manipulation, the wizard should send the current topic discussed by participants into ChatGPT using a template prompt (Prompt: You are a professional designer, the design task is [the description of the task], the topic of discussion is [the current discussed idea], please generate a more detailed and reasonable creative design concept, avoid the same words as the discussion topic, start with "I think we can design", in one sentence and briefly describe in 50 words). After the generation, the wizard copies and pastes the answer from ChatGPT and sends it to the AI inspiration panel.

Participation styles controlled the timing of the AI's participation by modifying the interaction mechanism between the human and AI. In active conditions, AI proactively and actively participates in discussions without human command. Detailed rules were defined to ensure the operability and objectivity of the experiment. The AI can only speak if two conditions are met: the first condition is that no participant is currently speaking, the second condition is that more than 2 min have passed since the last AI participation, or the human has independently generated two ideas in sequence. These rules aim to control the participation of AI to simulate the turn-taking of the human team in brainstorming. Our 2 pilot experiments illustrated that these rules were effective. In passive conditions, AI only participates when humans ask it for help. In manipulation, the wizard needs to monitor human behaviors at all times, and once the participant enters the 'Generate' command, the wizard needs to generate the corresponding content of AI and send it to participants in a short time.

Appendix B

Scoring criteria.

Scores	Innovation	Practicability	Completeness
0∼55	The solution is based on the existing design with 1 or 2 points of adjustment or improvement, and these parts of the improvement are not significantly innovative. It is just a simple optimization of the existing design. (e.g., design of food ordering APP, single compartment)	The scenario does not solve the problems present in the scenario, the technology on which the scenario relies is completely infeasible, it results in a large waste of resources (e.g., space), it is only applicable to a single scenario, and it is very economically expensive to implement. (e.g., space design in a specific scenario)	Very early abstract concepts that do not take into account any of the details of the process of realizing the solution, or design solutions that cannot be well understood through schematics and descriptive text.
55∼70	The program introduces novel elements or approaches in certain aspects, and these innovations (1–2) are relatively rare in the scenario, but may not be fully mature or commonly applied. (e.g., cafeteria app that allows you to view seating or navigate, improved bedside light fixture curtains, adjustments to the spatial layout of the dormitory, etc.)	The program solves the problems present in the scenario, the technology on which the program is based will be feasible in the coming years and the economic cost of implementation is acceptable. (e.g., materials with adjustable light transmission)	The most important design points have been clearly stated and expressed (e.g., spatial layout, division of functional areas, etc.), and the design scheme begins to consider the detailed completion of the program.
70∼85	Provides a distinctive solution, which has significant innovations or more than 2 rare innovations in design thinking, technology application or user experience, which are rare in the scenario, and the innovations have high originality and influence, and can lead the industry trend. (e.g., sleep isolation warehouse, noise visualization reminder device, etc., food punch card APP)	The solution effectively solves the problem in the scenario, the technology on which the solution relies is achievable (but not widely used), and the functionality is reasonably practical; the solution is flexible, can be applied to multiple scenarios, and has a sustained impact. (e.g., food delivery robots, multi-functional partitioning)	The program can be clearly known; it has a certain amount of implementation details, the technology and means of implementing the functions are considered (e.g., soundproofing, lifting tables, user interface), but the details are still not perfect.
85∼100	The solution revolutionizes the existing design paradigm, introduces a completely new concept or technology, and has a revolutionary impact on the industry or market. The innovation point is highly original and disruptive, capable of redefining the product or service, bringing unprecedented experience to the user, with great market potential and transformative power. (e.g., multi-functional entertaining bar canteen space, meta-universe canteen, etc.)	The program can effectively solve the problems in the scenario, the technology on which the program relies is easy to implement and less dependent on the technology, the functions are necessary and practical; the program has good flexibility, can be applied to all scenarios, is environmentally friendly, and has a sustained impact. (e.g., food ordering APP applet)	The solution is very close to its final form, with detailed planning and comprehensive analysis, including details of the user interface, operating procedures and implementation of the hardware products. (e.g., drawings depicting the structural details of the lifting table)

[1] https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2.

Data availability

Data will be made available on request.

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