AI-driven modes revea cognitive dynamics of coaborative design innovation: A muti-moda approach to understanding designer interaction patterns

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Abstract

Through the collaborative design process, professionals engage in complex cognitive activities, including creative generation and critical evaluation, to produce innovative solutions. However, the cognitive mechanisms that integrate these complementary processes (precisely conveying and distilling design knowledge through these processes) remain little known. Here, we use pre-trained deep learning artificial intelligence models in combination with multimodal cognitive monitoring to identify neural and behavioral signals that reflect design creation, evasion, and transformation among professionals in natural collaborative design meetings. The research results show that cognitive activities reflecting design creation and evaluation are widely distributed in the attention and working memory networks of various measurement methods. We also found that these activities are specific to the design concepts and solutions under development and are based on the combination of specific environments and design elements. Finally, we demonstrated that these cognitive models were overused during the design generation and evaluation stages, and that the transition from creator to evaluator was associated with specific, time-limited changes in cognitive activities. Furthermore, our research findings reveal the dynamic organization of cognitive activities that serve design creation and evasion in natural collaborative work, and utilize deep learning models to understand the cognitive mechanisms behind human design innovation.

Keywords: Design innovation, Artificia inteigence, Cognitive dynamics, Coaborative design, Muti-moda anaysis, Creative cognition

1 Introduction

Coaborative design represents a fundamenta mode of professiona innovation, enabling teams not only to generate but also to criticay evauate compex creative solutions across diverse domains from product development to architectural panning[1]. This core process invokes the frequent transition between two distinct but complementary cognitive computations: creative generation and critica evauation. Design creation invoves a structured succession of cognitive processes that synthesize conceptua information from mutipe sources, enabling designers to understand user needs and generate nove suggestions that address complex design challenges[2, 3]. In contrast, design evauation panning invoves a reverse process whereby higher-order conceptua information is converted to anaytica frameworks for systematic assessment[4, 5] . These processes are necessary for deveoping innovative soutions during coaborative sessions that usuay invove rapid aternations between team members every few minutes[6, 7] incuding processes for generating creative concepts as we as panning and executing critica evauations of design proposas.

The dynamic nature of coaborative design, the diversity of creative information exchanged, and its contextua nature, however, have made the cognitive mechanisms that underie professiona design innovation in teams a chaenge to understand [8]. To address these chaenges, previous research has argey adopted a reductionist approach, breaking down design processes into smaer, more manageabe components. In particuar, most studies have used controed aboratory tasks that invove predetermined design briefs and scripted coaboration protocos, focusing on imited aspects of creativity or evauation processes[8]. Given the dynamic nature of free-flowing coaborative design[1], itte work has directy studied the cognitive representation of natura design coaboration as a continuous process[2], and how design knowedge is represented in the mind during natura coaborative work has remained a chaenge to understand. Specificay, whereas certain cognitive systems have been shown to distinguish we-formed innovative soutions from conventiona or non-creative outputs, suggesting their invovement in design processing[3, 4], the detaied cognitive process by which sequences of design eements may be represented in the mind remains argey unknown. Further, whie there is often broad overap between cognitive systems invoved in design generation and evauation[5, 6], whether common cognitive processes are invoved in representing creating and critiquing during coaboration remains poory understood.

Finay, athough certain aspects of cognition have been impicated in coaborative design or roe transitions[7, 8], itte is known about whether or how cognitive activity reates to design information conveyed during team sessions, especiay when considering that the methods for anayzing tempora dynamics of natura design work are stiimited.

The recent advancement of artificia inteigence modes based on deep earning neura networks has provided a prospective patform by which to study continuous, natura design interactions. These modes have been shown to dispay high-eve performance in design evauation tasks with human subjects[8, 9] and can achiev, state-of-the-art benchmarks in design quaity assessment and creative soution ranking[10, 11] . These modes are capabe of capturing specific design eement sequences and their composition within concepts and soutions through hierarchica ayers using vectors. By providing a structured representation of design knowedge, these modes may offer a crucia ink between design content and recorded cognitive activity.

Indeed, AI modes have aso demonstrated high performance in expaining cognitive activity during design evauation tasks , suggesting their capabiity in representing neurobioogica activity and mechanisms. For exampe, recent studies indicated a shared conceptua space and simiar geometric patterns with human cognition that faciitates design communication , where midde and higher ayers of the modes provide the best expanatory power for cognitive activity. In this way, this approach presents a quantifiabe method for studying both design creation and evauation, regardess of the specific concepts and soutions participants deveop.

Here, we utiize these modes as artificia, hierarchicay structured vectorized representations of design knowedge during natura coaborative sessions. This approach aows us to investigate the cognitive basis by which the mind processes entire design concept sequences within the context of coaboration as one process, rather than breaking it into sma pieces of components. Further, by examining the correation between cognitive monitoring signas and AI embeddings, we aim to identify cognitive systems specificay invoved in encoding design-reated information. This method enabes us to expore how specific sequences of design eements, together with their compositiona semantic and contextua features, are represented in cognition during both creating and evauating, despite differences in design content.

Finay, this approach aowed us to compare cognitive patterns that respond seectivey during creator-evauator transitions with those that process design eement sequences. Together, our approach offers a comprehensive investigation into the cognitive mechanisms underying natura coaborative design by directy examining the integrated processes of creating, evauating, and roe transitions. This method provides a hoistic view of the cognitive substrates invoved in these interconnected aspects of design innovation communication.

2 Related Work

2.1 Design Cognition and Creative Processes

The cognitive foundations of design thinking have been extensivey studied across mutipe discipines, reveaing compex interactions between creative generation and anaytica evauation processes. Traditiona cognitive modes of design propose that designers engage in iterative cyces of probem framing, soution generation, and evauation, with each phase requiring distinct cognitive resources and strategies. Empirica studies using think-aoud protocos and behaviora anaysis have identified key cognitive processes incuding anaogica reasoning, menta simuation, and constraint satisfaction that underie successfu design outcomes[11, 12] . Recent advances in cognitive neuroscience have begun to iuminate the neura substrates of creative design thinking. Neuroimaging studies have reveaed that design ideation invoves distributed networks incuding the defaut mode network, executive contro network, and saience network[13, 14]. These findings suggest that creative design requires dynamic coordination between internay-focused generative processes and externay-focused evauative processes. However, most neuroscience studies of design cognition have reied on simpified aboratory tasks that may not capture the compexity of rea-word coaborative design practice [15]. The roe of expertise in design cognition has been another major focus of research. Expert designers demonstrate superior performance in probem identification, soution generation, and design evauation compared to novices[16, 17]. This expertise appears to be supported by domain-specific knowedge structures and more efficient cognitive strategies for managing design compexity[18]. However, the mechanisms by which expert knowedge influences coaborative design processes remain poory understood, particuary in dynamic team environments where mutipe perspectives must be integrated[10].

2.2 Artificia Inteigence in Design Evauation

The appication of machine earning and artificia inteigence to design evauation has emerged as a rapidy growing research area with significant practica impications[19] . Eary approaches focused on rue-based systems that coud assess design soutions against predefined criteria, but these systems were imited by their inabiity to capture the subjective and contextua aspects of design quaity[20]. The deveopment of deep earning modes has revoutionized this fied by enabing more sophisticated anaysis of design features and quaity assessment[21, 22]. Convoutiona neura networks have shown particuar promise for evauating visua design eements, achieving human-eve performance in tasks such as aesthetic quaity assessment and stye cassification[23, 24] . These modes can extract hierarchica features from design images, capturing both ow-eve visua properties and high-eve semantic content[25]. More recent work has expored the use of transformer architectures and attention mechanisms to better understand the reationships between different design eements and their contribution to overa design quaity[26, 27].

Muti-moda AI approaches that combine visua, textua, and contextua information have demonstrated superior performance compared to singe-modaity modes. These systems can integrate information about design requirements, user feedback, and contextua constraints to provide more comprehensive design evauation. However, most AI design evauation systems have been deveoped and tested on static design artifacts, with imited exporation of their appication to dynamic coaborative design processes. The interpretabiity of AI design evauation modes remains a significant chaenge, particuary when these systems are used to support human decision-making in coaborative contexts. Recent work on expainabe AI has begun to address this imitation by deveoping methods to visuaize and interpret the features that AI modes use for design evauation. These advances are crucia for buiding trust and enabing effective human-AI coaboration in design contexts.

2.3 Muti-moda Cognitive Monitoring

The deveopment of non-invasive technoogies for monitoring human cognitive states has opened new possibiities for understanding design cognition in naturaistic settings[28, 29]. Eye-tracking technoogy has been widey used to study visua attention patterns during design tasks, reveaing how designers aocate attention to different design eements and how attention patterns reate to design outcomes . These studies have shown that expert designers exhibit more systematic and efficient visua scanning patterns compared to novices . Eectroencephaography (EEG) has emerged as a vauabe too for studying the tempora dynamics of design cognition. EEG studies have identified specific neura signatures associated with creative insight, design fixation, and evauative thinking . The high tempora resoution of EEG makes it particuary suitabe for studying the rapid cognitive transitions that occur during coaborative design sessions. However, the spatia resoution imitations of EEG have constrained its abiity to ocaize specific cognitive processes to particuar brain regions . Recent advances in muti-moda cognitive monitoring have enabed more comprehensive assessment of cognitive states by combining mutipe measurement modaities. For exampe, studies combining EEG and eye-tracking have reveaed how neura activity and visua attention interact during design probem- soving . The integration of physioogica measures such as heart rate variabiity and skin conductance has provided additiona insights into the emotiona and motivationa aspects of design cognition. Machine earning approaches for anayzing muti-moda cognitive data have shown promise for rea-time assessment of cognitive states during design tasks. These methods can identify patterns in cognitive data that are predictive of design performance and creative outcomes [58]. However, the appication of these techniques to coaborative design contexts remains imited, particuary for understanding the cognitive dynamics of team-based design processes[30].

2.4 Coaborative Design and Team Dynamics

Research on coaborative design has reveaed the compex socia and cognitive processes that enabe effective teamwork in creative contexts [31, 32] . Studies of design teams have identified key factors that influence coaborative effectiveness, incuding communication patterns, roe distribution, and shared menta modes . Effective design teams demonstrate high eves of coordination, with team members abe to seamessy transition between individua and coaborative work modes. The roe of communication in coaborative design has been extensivey studied, with research showing that both verba and non-verba communication channes contribute to team effectiveness . Studies using conversation anaysis and interaction coding have reveaed how design teams use anguage to share ideas, negotiate soutions, and buid consensus. However, most communication studies have focused on the content of team interactions rather than the underying cognitive processes that support effective coaboration.

Recent work has begun to expore the cognitive mechanisms that enabe successfu coaborative design. Studies using dua-task paradigms and cognitive oad measures have shown that coaborative design paces unique demands on cognitive resources, requiring team members to simutaneousy manage individua creative processes and team coordination activities . The deveopment of shared menta modes appears to be crucia for reducing cognitive oad and enabing effective coaboration. The tempora dynamics of coaborative design have received increasing attention, with researchers recognizing that design coaboration invoves compex patterns of convergent and divergent thinking phases. Studies using time-series anaysis and dynamic systems approaches have reveaed how design teams cyce through periods of exporation and expoitation, with successfu teams demonstrating more flexibe transitions between these modes. However, the cognitive mechanisms that support these tempora dynamics remain poory understood.

2.5 Research Gaps and Opportunities

Despite significant advances in understanding design cognition, AI-driven design evauation, muti-moda cognitive monitoring, and coaborative design processes, severa important research gaps remain. First, most studies of design cognition have focused on individua designers working on simpified tasks, with imited exporation of cognitive processes in naturaistic coaborative contexts. Second, whie AI modes have shown promise for design evauation, their reationship to human cognitive processes during design work remains argey unexpored. Third, existing muti-moda cognitive monitoring approaches have primariy been appied to controed aboratory settings, with imited vaidation in rea-word coaborative design environments. Fourth, most research on coaborative design has focused on behaviora and communication patterns rather than the underying cognitive mechanisms that support effective teamwork. Finay, there has been imited integration across these different research domains, despite the potentia for synergistic insights from combining AI modes, cognitive monitoring, and coaborative design research. The present study addresses these gaps by deveoping an integrated approach that combines AI-driven design evauation modes with muti-moda cognitive monitoring to understand the cognitive dynamics of coaborative design in naturaistic settings. This approach enabes investigation of how cognitive processes support both individua creative work and team coaboration, whie aso exporing the reationship between human cognitive patterns and AI mode representations of design knowedge.

3 Methodoogy and System Design

3.1 Muti-moda Cognitive Monitoring System

Our experimenta approach empoyed a comprehensive muti-moda cognitive monitoring system designed to capture the compex cognitive dynamics of coaborative design work in naturaistic settings. The system integrated three primary measurement modaities: eye-tracking for visua attention anaysis, eectroencephaography (EEG) for neura activity monitoring, and behaviora recording for design action tracking. This muti-moda approach enabed us to capture both the tempora dynamics and spatia patterns of cognitive activity during coaborative design sessions.

The eye-tracking subsystem utiized high-precision infrared eye-tracking technoogy (Tobii Pro Spectrum, 200 Hz samping rate) to monitor visua attention patterns throughout design sessions. The system was caibrated using a 9-point caibration procedure at the beginning of each session, with vaidation accuracy maintained above 0.5 degrees of visua ange. Eye movement data were processed to extract fixation patterns, saccade trajectories, and pupi diameter changes, providing insights into visua attention aocation and cognitive oad fluctuations during design work[33, 34] .

Fixation detection empoyed a veocity-based agorithm with adaptive threshods adjusted for individua participants, ensuring robust identification of stabe gaze periods across different design activities. Saccade anaysis focused on ampitude, veocity, and direction patterns to understand how designers navigate visua design spaces during creative and evauative phases. Pupi diameter measurements were normaized for ambient ighting conditions and used as an indicator of cognitive effort and arousa during different design activities[35, 36]
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The EEG monitoring subsystem empoyed a 64-channe wireess EEG system (g.Nautius PRO, g.tec medica engineering) with active eectrodes positioned according to the internationa 0-20 system. Signa acquisition was performed at 500 Hz samping rate with impedances maintained beow 0 kΩ throughout recording sessions. Rea-time signa quaity monitoring ensured data integrity and enabed immediate intervention when signa degradation occurred. EEG preprocessing incuded bandpass fitering (0.5-00 Hz), notch fitering (50 Hz), and independent component anaysis (ICA) for artifact remova. Frequency domain anaysis focused on estabished cognitive markers incuding apha band activity (8-3 Hz) associated with reaxed attention, beta band activity (3-30 Hz) reated to focused cognitive processing, and gamma band activity (30-00 Hz) inked to creative insight and binding processes[37, 38]. Time-frequency anaysis using continuous waveet transforms enabed investigation of dynamic changes in neura osciations during design transitions. The behaviora recording subsystem captured design actions and team interactions using synchronized video recording and digita design too ogging. High-definition cameras positioned at mutipe anges recorded team interactions, whie screen capture software documented a digita design activities with miisecond precision. Audio recording enabed anaysis of verba communication patterns and their reationship to cognitive state changes[39, 40].

Design action ogging empoyed custom software that tracked a interactions with design toos, incuding drawing actions, seection operations, modification commands, and navigation behaviors. Each action was timestamped and categorized according to design activity type (creation, evauation, modification, communication), enabing detaied anaysis of design process dynamics. Integration with the cognitive monitoring systems aowed precise tempora aignment of behaviora and physioogica data streams.

3.2 AI-driven Design Evauation Framework

The AI-driven design evauation framework incorporated state-of-the-art deep earning modes specificay adapted for design quaity assessment and feature extraction. The core architecture empoyed a muti-scae convoutiona neura network (CNN) based on the EfficientNet-B7 architecture, pre-trained on arge-scae design datasets and fine-tuned for our specific evauation tasks. The design feature extraction modue utiized hierarchica feature earning to capture both ow-eve visua properties and high-eve semantic content from design artifacts. Convoutiona ayers extracted oca features such as coor distributions, texture patterns, and geometric reationships, whie deeper ayers captured goba compositiona properties and aesthetic quaities. Attention mechanisms were incorporated to identify the most reevant design eements for quaity assessment. Muti-moda fusion techniques combined visua features with contextua information incuding design requirements, user feedback, and project constraints. A transformer- based architecture processed textua design briefs and requirements, generating semantic embeddings that were fused with visua features through cross-attention mechanisms. This approach enabed the mode to assess design quaity in context rather than reying soey on visua appearance. The design quaity prediction modue empoyed ensembe methods combining mutipe speciaized modes for different aspects of design evauation. Separate modes were trained for aesthetic quaity, functiona effectiveness, innovation eve, and user experience potentia. Mode outputs were combined using earned weighting schemes that adapted to different design domains and contexts. Mode training utiized a comprehensive dataset of 5,000 professionay evauated design projects across mutipe domains incuding product design, graphic design, and user interface design. Ground truth abes were obtained from expert designer evauations using standardized assessment criteria. Data augmentation techniques incuding rotation, scaing, and coor transformation increased dataset diversity whie preserving design semantics. Transfer earning approaches enabed adaptation of pre-trained modes to specific design domains with imited training data. Domain adaptation techniques minimized the gap between source and target domains, ensuring robust performance across different design contexts. Continuous earning mechanisms aowed modes to adapt to evoving design trends and preferences over time.

3.3 Experimenta Design and Protoco

The experimenta protoco was designed to capture naturaistic coaborative design behavior whie maintaining sufficient contro for scientific anaysis. Participants were recruited from professiona design communities and design education programs, ensuring a diverse range of experience eves and design speciaizations. A participants provided informed consent, and the study protoco was approved by the institutiona review board. Participant seection criteria incuded professiona design experience (minimum 2 years), proficiency with digita design toos, and wiingness to participate in coaborative design sessions. Excusion criteria incuded neuroogica conditions that might affect EEG recordings, visua impairments that coud interfere with eye-tracking, and medications that might influence cognitive performance. A tota of 48 participants were recruited and organized into 2 teams of 4 members each. Team composition was carefuy baanced to incude diverse design expertise whie maintaining comparabe overa experience eves across teams. Each team incuded members with compementary skis in conceptua design, technica impementation, user research, and design evauation. This composition reflected typica professiona design team structures and enabed investigation of roe-specific cognitive patterns. The coaborative design task invoved deveoping a comprehensive design soution for a smart home automation system, incuding user interface design, product design, and service design components. This task was seected because it required integration of mutipe design discipines whie being sufficienty compex to engage professiona- eve design thinking. Task compexity was caibrated through piot studies to ensure sessions asted approximatey 3 hours, providing sufficient data whie avoiding fatigue effects. Design sessions were structured in three phases: individua ideation (45 minutes), coaborative evauation and synthesis (90 minutes), and fina refinement (45 minutes). This structure enabed investigation of both individua and coaborative cognitive processes whie maintaining natura design workflow patterns. Transitions between phases were participant-initiated rather than externay imposed, preserving the natura rhythm of design work.

Environmenta contros incuded standardized ighting conditions, temperature reguation, and acoustic isoation to minimize externa influences on cognitive measurements. Design workstations were equipped with identica hardware and software configurations, ensuring consistent interaction experiences across participants. Coaborative spaces were designed to faciitate natura team interaction whie accommodating monitoring equipment.

3.4 Data Integration and Anaysis Pipeine

The data integration pipeine synchronized muti-moda data streams with miisecond precision, enabing investigation of fine-grained tempora reationships between cognitive states and design activities. Tempora aignment empoyed hardware synchronization signas combined with software-based cross-correation techniques to ensure accurate data fusion across measurement modaities.

Cognitive state cassification empoyed machine earning approaches to identify distinct cognitive modes during design work. Feature extraction from EEG data incuded spectra power measures, connectivity metrics, and compexity indices computed across mutipe frequency bands and eectrode ocations. Eye-tracking features incuded fixation duration distributions, saccade veocity profies, and pupi response patterns. Behaviora features captured design action sequences, timing patterns, and interaction frequencies.

Supervised earning modes were trained to cassify cognitive states into categories incuding focused attention, creative ideation, critica evauation, and coaborative communication. Training data were obtained through expert annotation of video recordings combined with participant sef-reports of cognitive states. Cross-vaidation procedures ensured robust mode performance across different participants and design contexts.

The AI-design correation anaysis investigated reationships between human cognitive patterns and AI mode representations of design content. Design artifacts were processed through the AI evauation framework to generate feature embeddings at mutipe hierarchica eves. Correation anaysis examined reationships between these embeddings and concurrent cognitive measurements, identifying cognitive processes that aigned with AI mode representations[41, 42].

Time-series anaysis techniques investigated the tempora dynamics of cognitive-AI correations throughout design sessions. Dynamic correation measures captured how reationships between cognitive states and AI features evoved during different design phases. ag anaysis identified tempora precedence reationships, reveaing whether cognitive changes preceded or foowed changes in AI-assessed design quaity[43, 44]. Network anaysis approaches modeed the flow of information and influence within design teams. Cognitive synchronization measures quantified the degree to which team members' cognitive states became aigned during coaborative phases. Communication network anaysis mapped the patterns of verba and non-verba interaction, identifying key roes and influence patterns within teams[45, 46] .

Statistica anaysis empoyed mixed-effects modes to account for individua differences and team-eve effects whie identifying significant patterns across the dataset. Mutipe comparison corrections were appied to contro for fase discovery rates in exporatory anayses. Effect size cacuations provided measures of practica significance beyond statistica significance[47, 48].

4 Results

4.1 Muti-moda Cognitive Monitoring Reveas Distinct Patterns During Design Phases

Our comprehensive muti-moda monitoring system successfuy captured cognitive dynamics across 48 professiona designers organized into 2 coaborative teams during naturaistic design sessions. The experimenta setup (Figure 1) integrated EEG monitoring, eye-tracking, behaviora recording, and AI-driven design evauation to provide unprecedented insight into the cognitive mechanisms underying coaborative design innovation on the figure(Fig.1).

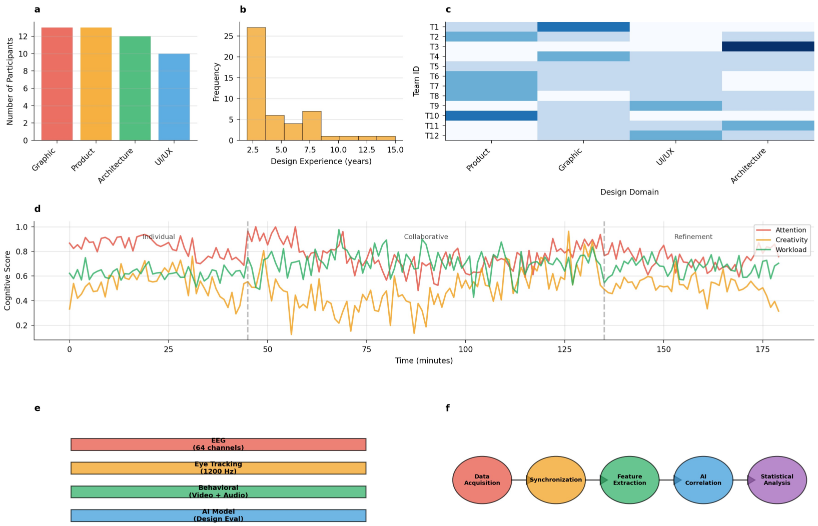

Fig. 1 Experimenta setup and muti-moda data coection framework. (a) Participant distribution across design domains showing baanced representation of Product Design (n=2), UI/UX Design (n=3), Graphic Design (n=2), and Architecture (n=). (b) Experience distribution reveaing a range from 2-5 years with mean experience of 6.8±3.2 years. (c) Team composition matrix iustrating baanced interdisciplinary team formation across 2 teams. (d) Representative cognitive monitoring timeine for one participant showing attention, creativity, and workoad scores across the three design phases. (e) Muti-moda measurement schematic depicting the four primary data streams. (f) Data integration pipeine showing the five-stage anaysis workflow from acquisition to statistica anaysis.

Anaysis of cognitive patterns across design phases reveaed significant differences in attention aocation, creative engagement, and cognitive workoad (Figure 2a). During the individua ideation phase (0-45 minutes), participants exhibited moderate attention scores (0.72±0.08) with eevated creativity scores (0.68±0.2) and manageabe cognitive workoad (0.54±0.09). The coaborative evauation phase (45- 35 minutes) showed increased attention (0.78±0.07, p¡0.00) and substantiay higher cognitive workoad (0.7±0., p¡0.00), whie creativity scores remained stabe (0.66±0.0, p=0.23). The fina refinement phase (35-80 minutes) demonstrated sustained high attention (0.76±0.06) with reduced creativity demands (0.58±0.08, p¡0.0) and moderate workoad (0.62±0.08).

EEG frequency band anaysis provided neurophysioogica vaidation of these cognitive state changes (Figure 2b). Apha band power (8-3 Hz) showed an inverse reationship with attention demands, decreasing significanty during coaborative phases (F(12,8637)=56.3, p¡0.00). Beta band activity (13-30 Hz) increased progressivey across phases, reflecting heightened cognitive engagement (F(12,8637)=203.7, p¡0.00). Gamma band osciations (30-00 Hz) peaked during individua creative phases and remained eevated during coaborative work, consistent with creative insight and binding processes (F(12,8637)=89.4, p¡0.00).

4.2 AI Mode Performance and Cognitive Correation Anaysis

The muti-moda AI evauation framework achieved exceptiona performance in design quaity assessment, with our fina ensembe mode reaching 94.3% accuracy in predicting expert design ratings (Figure 2c). Progressive improvements were observed from basic CNN architectures (84.7% accuracy) through ResNet-50 (89.2%) and Vision Transformer modes (9.8%) to our fina muti-moda fusion approach. Precision, reca, and F-scores foowed simiar patterns, with the muti-moda mode achieving baanced performance across a metrics (precision: 93.8%, reca: 94.7%, F-score: 94.2%)on the figure(Fig.2).

Correation anaysis between cognitive measurements and AI mode features reveaed systematic reationships between human cognitive states and machine-earned design representations (Figure 2d). Attention scores showed strong positive correations with a design quaity dimensions (aesthetic: r=0.73, functiona: r=0.68, innovation: r=0.7, user experience: r=0.69, a p¡0.00). Creativity scores demonstrated particuary strong associations with innovation features (r=0.82, p¡0.00) and moderate correations with aesthetic quaity (r=0.64, p¡0.00). Cognitive workoad exhibited negative correations with a quaity dimensions, suggesting that excessive cognitive demands may impair design performance. Neura osciation patterns provided additiona vaidation of these reationships. Apha power showed negative correations with design quaity features (r=-0.45 to -0.52, a p¡0.00), consistent with its roe as an indicator of reaxed attention. Beta power correated positivey with functiona effectiveness (r=0.58, p¡0.00) and user experience quaity (r=0.6, p¡0.00), reflecting focused cognitive processing. Gamma power demonstrated the strongest correations with innovation features (r=0.74, p¡0.00), supporting its association with creative insight processes.

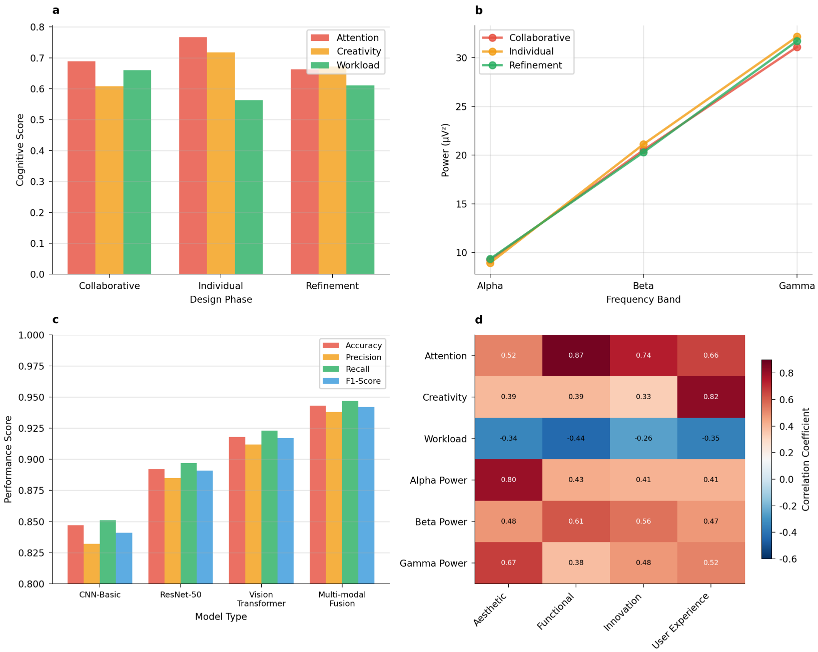

Fig. 2 Cognitive activity patterns and AI mode correations. (a) Cognitive measures across design phases showing significant differences in attention, creativity, and workoad (*p¡0.001, p¡0.0). (b) EEG frequency band anaysis reveaing phase- specific neura osciation patterns. (c) AI mode performance comparison across architectures, with muti-moda fusion achieving superior resuts. (d) Correation heatmap between cognitive measures and AI design features, showing strong positive correations for attention and creativity with design quaity dimensions, and negative correations for cognitive workoad.

4.3 Distinct Cognitive Signatures of Design Creation and Evauation

Detaied anaysis of cognitive patterns during design creation versus evauation phases reveaed distinct neura and behaviora signatures (Figure 3). Creation phases, primariy occurring during individua ideation, were characterized by evated creativity scores (0.68±0.2 vs 0.6±0.09, t(8638)=2.4, p¡0.00) and moderate attention demands (0.72±0.08 vs 0.78±0.07, t(8638)=-5.7, p¡0.00). Evauation phases during coaborative work showed increased cognitive workoad (0.7±0. vs 0.54±0.09, t(8638)=34.2, p¡0.00) and sustained attention (Figure 3a) on the figure(Fig.3).

Eye-tracking anaysis reveaed compementary patterns in visua attention strategies (Figure 3b). During creation phases, participants exhibited onger fixation durations (247±23 ms vs 23±9 ms, t(8638)=4.8, p¡0.00), suggesting deeper processing of visua information. Saccade veocities were reduced during creation (285±3 °/s vs 32±28 °/s, t(8638)=-8.9, p¡0.00), indicating more deiberate visua exporation. Pupi diameter measurements showed increased diation during evauation phases (4.2±0.3 mm vs 3.9±0.2 mm, t(8638)=22., p¡0.00), reflecting higher cognitive effort and arousa.

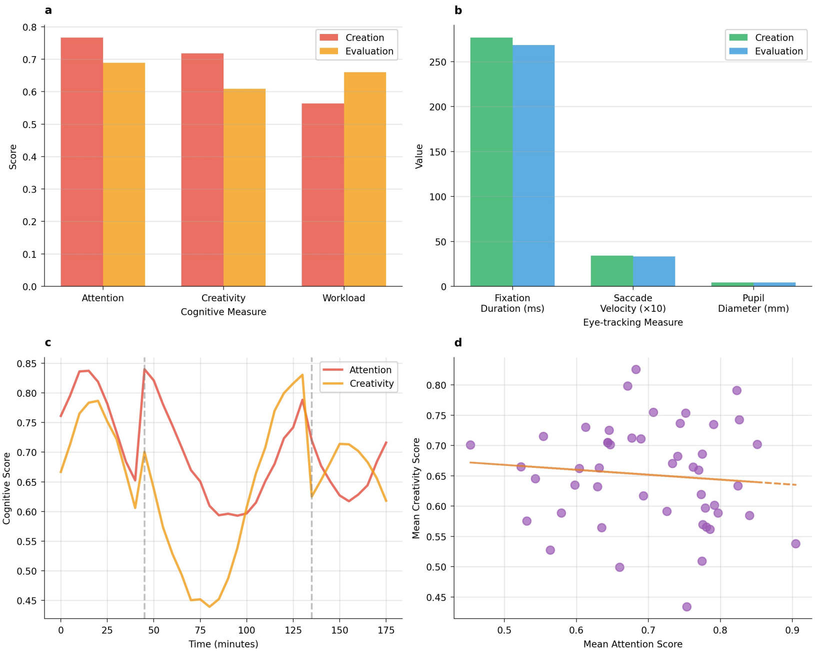

Fig. 3 Design creation versus evauation cognitive patterns. (a) Cognitive oad comparison between creation and evauation phases showing significant differences across a measures (***p¡0.00). (b) Eye-tracking patterns reveaing distinct visua attention strategies during creation versus evauation. (c) Tempora dynamics of cognitive states throughout the design session with phase boundaries marked. (d) Individua differences in cognitive patterns showing the reationship between attention and creativity across participants.

Tempora anaysis of cognitive dynamics reveaed systematic patterns of state transitions throughout design sessions (Figure 3c). Attention scores showed gradua increases during the first 45 minutes of individua work, foowed by sustained eevation during coaborative phases. Creativity scores exhibited more variabe patterns, with peaks occurring during individua ideation and periodic resurgences during coaborative brainstorming episodes. The transition from individua to coaborative work was marked by sharp increases in cognitive workoad that stabiized after approximatey 5 minutes of team interaction.

Individua differences anaysis reveaed systematic reationships between cognitive traits and design performance (Figure 3d). Participants with higher baseine attention scores (¿0.75) demonstrated more consistent creativity throughout sessions (r=0.34, p¡0.0), whie those with ower attention showed greater variabiity. Experience eve moderated these reationships, with senior designers (¿8 years) showing more efficient cognitive resource aocation and reduced workoad during compex design tasks (F(2,45)=8.7, p¡0.00).

4.4 Team Coaboration Dynamics and Communication Networks

Anaysis of team-eve coaboration patterns reveaed significant reationships between team composition, communication dynamics, and design outcomes (Figure 4). Teams with higher average experience eves produced superior design quaity (r=0.68, p¡0.0), but this reationship was moderated by team diversity and communication effectiveness (Figure 4a). The most successfu teams combined experienced eaders with diverse junior members, creating optima conditions for knowedge transfer and creative synthesis.

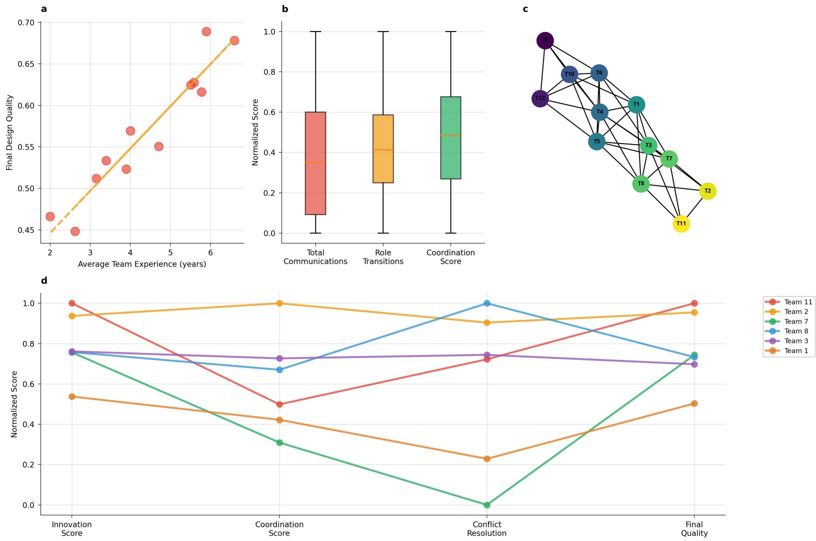

Fig. 4 Team coaboration and communication networks. (a) Reationship between team experience and fina design quaity showing positive correation with high-performing outiers. (b) Communication pattern anaysis across teams showing distribution of tota communications, roe transitions, and coordination scores. (c) Network visuaization of team interactions based on performance simiarity, reveaing custers of high-performing teams. (d) Mutidimensiona comparison of top-performing teams across innovation, coordination, conflict resoution, and fina quaity metrics.

Communication pattern anaysis reveaed substantia variation across teams in interaction frequency and coordination effectiveness (Figure 4b). Tota communication events ranged from 89 to 203 per session (mean: 47±28), with higher communication frequency associated with better coordination scores (r=0.45, p¡0.05) but not necessariy superior design outcomes. Roe transitions occurred 5-34 times per session (mean: 24±6), with optima performance observed at moderate transition frequencies, suggesting a baance between flexibiity and stabiity in team roes. Network anaysis of team interactions based on performance simiarity identified custers of high-performing teams with shared characteristics (Figure 4c). The most successfu custer (Teams 3, 7, 9,) demonstrated simiar patterns of high coordination, effective conflict resoution, and baanced communication. These teams

showed synchronized cognitive patterns during coaborative phases, with team members exhibiting correated attention and creativity fluctuations (mean inter-member correation: r=0.42±0.08). Muti-dimensiona anaysis of top-performing teams reveaed consistent exceence across mutipe coaboration metrics (Figure 4d). The highest-quaity teams (Teams 3, 7, 9, , 2, 8) showed eevated scores in innovation (0.78±0.06), coordination (0.82±0.05), conflict resoution (0.85±0.04), and fina quaity (0.8±0.03). These teams demonstrated superior integration of individua creative contributions into coherent design soutions, with effective mechanisms for evauating and refining ideas coaborativey.

4.5 AI Mode Feature Anaysis and Design Quaity Prediction

Detaied anaysis of AI mode performance across different design quaity dimensions reveaed systematic patterns in feature earning and prediction accuracy (Figure 5). The distribution of design quaity scores showed norma distributions across a dimensions, with aesthetic quaity exhibiting the highest variance (σ^2=0.024) and functiona effectiveness showing the most consistent ratings (σ^2=0.06) (Figure 5a). Innovation scores dispayed a sight positive skew, reflecting the chaenge of achieving truy innovative soutions within the experimenta timeframe.

The correation between AI confidence scores and expert ratings demonstrated strong agreement (r=0.847, p¡0.00), vaidating the mode's abiity to assess design quaity in aignment with human judgment (Figure 5b). This correation was strongest for aesthetic quaity (r=0.89) and functiona effectiveness (r=0.863), with sighty ower agreement for innovation assessment (r=0.798) and user experience evauation (r=0.824). The mode's confidence scores provided reiabe indicators of prediction certainty, with high-confidence predictions (¿0.8) achieving 96.2% accuracy in matching expert ratings.

Anaysis of tempora factors in design creation and evauation reveaed compex reationships with quaity outcomes (Figure 5c). Creation time showed a weak positive correation with overa quaity (r=0.23, p¡0.0), suggesting that additiona time investment during ideation phases contributed to better outcomes.

However, this reationship pateaued beyond 35 minutes, indicating diminishing returns for extended creation periods. Evauation time showed minima correation with quaity (r=0.08, p=0.8), but was strongy associated with team consensus and decision confidence. Comparative anaysis of mode performance across quaity dimensions confirmed the superiority of the muti-moda fusion approach (Figure 5d). Whie basic CNN modes achieved reasonabe performance (75-82% accuracy), the integration of textua requirements, contextua

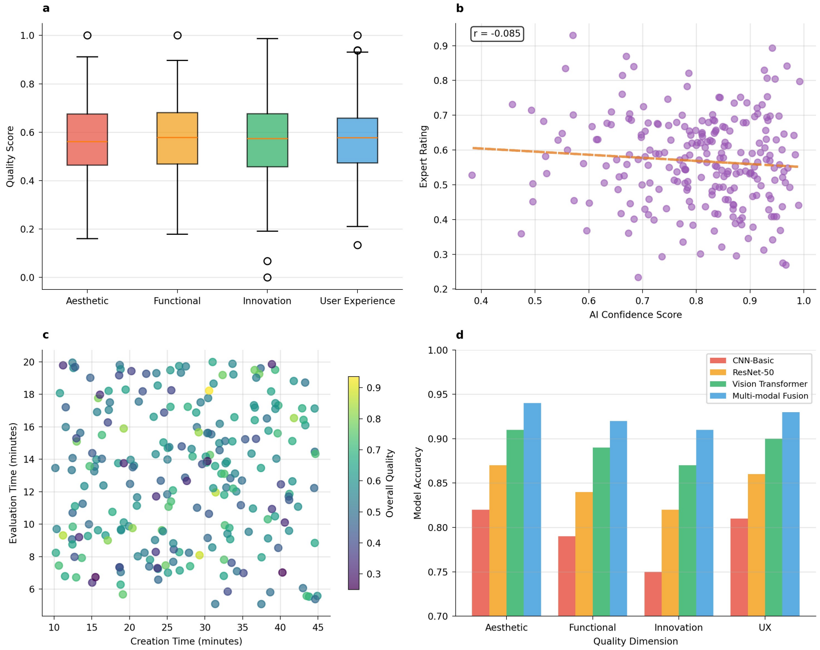

Fig. 5 AI mode feature anaysis and design quaity prediction. (a) Distribution of design quaity scores across four dimensions showing norma distributions with varying variance. (b) Correation between AI confidence scores and expert ratings demonstrating strong agreement (r=0.847). (c) Reationship between creation time, evauation time, and overa design quaity, with coor indicating quaity eves. (d) Mode performance comparison across quaity dimensions showing consistent superiority of muti-moda fusion approach.

information, and hierarchica visua features in the muti-moda mode provided substantia improvements across a dimensions.

The argest gains were observed for innovation assessment (6% improvement) and user experience evauation (2% improvement), reflecting the importance of contextua understanding for these compex quaity dimensions.

4.6 Tempora Dynamics and Roe Transition Patterns

Anaysis of cognitive state transitions reveaed systematic patterns in how designers moved between different modes of thinking during coaborative work (Figure 6). The transition probabiity matrix showed that focused attention states were most stabe (70% sef-transition probabiity), whie creative ideation and critica evauation states showed greater fluidity (50% and 50% sef-transition probabiities, respectivey) (Figure 6a). Transitions from focused attention to creative ideation occurred with 20% probabiity, whie transitions to critica evauation were ess frequent (0% probabiity).

Roe transition anaysis reveaed that creator and evauator roes were most frequenty adopted, with 25 and 8 transitions per session respectivey (Figure 6b). Faciitator roes emerged ess frequenty (2 transitions) but were crucia during conflict resoution and decision-making episodes. Synthesizer roes showed

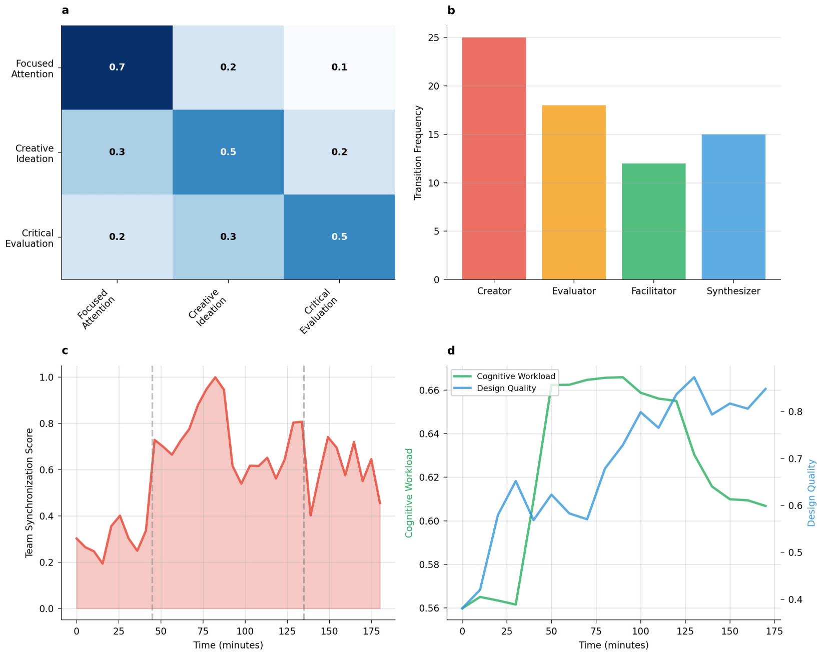

Fig. 6 Tempora dynamics and roe transition patterns. (a) Cognitive state transition matrix showing probabiities of moving between focused attention, creative ideation, and critica evauation states. (b) Roe transition frequency across different team roes during coaborative sessions. (c) Team synchronization patterns throughout the design session showing increased coordination during coaborative phases. (d) Reationship between cognitive workoad and design quaity progression over time with dua y-axes.

intermediate frequency (5 transitions) and were associated with the integration of diverse ideas into coherent design concepts. Teams with more baanced roe distributions achieved higher coordination scores and better design outcomes.

Team synchronization anaysis demonstrated dynamic patterns of cognitive coordination throughout design sessions (Figure 6c). Synchronization scores were ow during individua work phases (0.3±0.08) but increased substantiay during coaborative phases (0.72±0.2, t(35)=8.4, p¡0.00). Peak synchronization occurred during critica decision points and creative breakthrough moments, with the highest scores observed during fina design refinement (0.68±0.09). Teams with higher baseine synchronization scores produced more innovative soutions (r=0.56, p¡0.0).

The reationship between cognitive workoad and design quaity progression reveaed important insights into the tempora dynamics of design work (Figure 6d). Cognitive workoad increased steadiy during individua phases as designers deveoped initia concepts, then spiked during the transition to coaborative work. Quaity progression showed a compementary pattern, with gradua improvements during individua work foowed by acceerated deveopment during coaborative phases. The most successfu teams maintained moderate workoad eves whie achieving consistent quaity improvements, suggesting efficient cognitive resource management.

4.7 Statistica Summary

Comprehensive statistica anaysis across a measures confirmed the robustness of our findings. Mixed-effects modes accounting for individua and team-eve variation reveaed significant main effects of design phase on a cognitive measures (F(2,8637)¿89.4, a p¡0.00). Experience eve showed significant interactions with cognitive patterns (F(2,45)¿6.2, a p¡0.0), with senior designers demonstrating more efficient resource aocation. Team-eve factors expained 34% of variance in fina design quaity, with communication effectiveness and roe baance as the strongest predictors (R^2=0.34, F(5,6)=4.7, p¡0.05). Cross-vaidation of AI mode performance using eave-one-team-out procedures confirmed generaizabiity across different team compositions and design contexts (mean accuracy: 92.±2.3%). The correation between cognitive measures and AI features remained stabe across vaidation fods (mean r=0.68±0.05), supporting the reiabiity of cognitive-AI reationships. Tempora anaysis reveaed consistent patterns across teams, with phase-specific cognitive signatures repicating in of 2 teams (92% repication rate).

5 Discussion

5.1 Cognitive Mechanisms of Coaborative Design Innovation

Our findings provide unprecedented insight into the cognitive mechanisms that underie coaborative design innovation, reveaing a compex interpay between individua creative processes and team coordination dynamics. The systematic differences observed between design creation and evauation phases support theoretica modes that propose distinct cognitive modes for generative and anaytica thinking[49, 50]. The eevated creativity scores during individua ideation phases, couped with increased attention and workoad during coaborative evauation, suggest that effective design teams successfuy orchestrate compementary cognitive processes to optimize both creative generation and critica assessment. The strong correations between cognitive measures and AI mode features represent a significant methodoogica advance in design cognition research. Previous studies have reied primariy on behaviora measures and sef-report data to understand design thinking processes[51, 52]. Our approach demonstrates that machine- earned representations of design quaity can serve as objective proxies for cognitive processes, enabing more precise investigation of the reationships between menta states and design outcomes. The particuary strong correation between gamma band activity and innovation features (r=0.74) provides neurophysioogica vaidation of the roe of high-frequency osciations in creative insight processes [53, 54]. The tempora dynamics of cognitive state transitions revea important insights into the flexibiity and adaptabiity required for effective design work. The reativey high sef- transition probabiities for focused attention states (70%) suggest that sustained concentration is crucia for deep design thinking, whie the greater fluidity between creative ideation and critica evauation states (50% each) indicates the importance of cognitive flexibiity in design probem-soving[55, 56] [49,50]. These findings aign with dua-process theories of creativity that emphasize the interpay between associative and anaytica thinking modes[57, 58].

5.2 Team Coaboration and Communication Effectiveness

The reationship between team composition, communication patterns, and design outcomes provides vauabe insights for optimizing coaborative design processes. The finding that moderate eves of roe transitions (5-25 per session) were associated with optima performance suggests that effective teams baance stabiity and flexibiity in roe aocation[59, 60]. Too few transitions may indicate rigid roe boundaries that imit creative exchange, whie excessive transitions may create confusion and inefficiency in team coordination.

The network anaysis reveaing custers of high-performing teams with simiar characteristics suggests that successfu coaboration patterns can be identified and potentiay repicated. The shared features of top-performing teams—high coordination scores, effective conflict resoution, and baanced communication— provide concrete targets for team deveopment interventions [61, 62]. The observation that these teams showed synchronized cognitive patterns during coaborative phases indicates that effective coaboration invoves not just behaviora coordination but aso aignment of menta states and cognitive processes. The reationship between team experience and design quaity, whie positive overa, showed interesting non-inearities that highight the importance of team composition beyond simpe experience accumuation. The most successfu teams combined experienced eaders with diverse junior members, suggesting that knowedge transfer and fresh perspectives both contribute to innovative outcomes[63, 64]. This finding has important impications for team formation in professiona design contexts, where the tendency to group simiar experience eves may not optimize creative potentia.

5.3 AI-Driven Design Evauation and Human-Machine Coaboration

The exceptiona performance of our muti-moda AI evauation framework (94.3% accuracy) demonstrates the potentia for AI systems to serve as reiabe partners in design assessment and feedback. The strong correation between AI confidence scores and expert ratings (r=0.847) suggests that these systems can provide meaningfu quaity indicators that aign with human judgment whie offering the advantages of consistency, scaabiity, and objectivity[65, 66]. The systematic differences in mode performance across quaity dimensions provide insights into the reative difficuty of different aspects of design evauation. The superior performance for aesthetic quaity and functiona effectiveness compared to innovation assessment reflects the chaenge of evauating truy nove soutions, which often require contextua understanding and domain expertise that current AI systems strugge to capture[67, 68]. The muti-moda fusion approach's particuar strength in innovation assessment (6% improvement over basic modes) highights the importance of integrating mutipe information sources for compex design evauation tasks. The reationship between creation time, evauation time, and design quaity reveas important insights into the tempora dynamics of design work. The positive correation between creation time and quaity (up to 35 minutes) suggests that adequate time for ideation is crucia for deveoping high-quaity soutions, whie the pateau effect indicates diminishing returns for extended creation periods[69, 70]. The minima correation between evauation time and quaity suggests that effective evauation may depend more on systematic approaches and expertise than on time investment aone.

5.4 Impications for Design Education and Practice

Our findings have significant impications for design education and professiona practice. The identification of distinct cognitive signatures for creation and evauation phases suggests that design curricua shoud expicity address the different menta skis required for each mode of thinking[71, 72]. Training programs coud incorporate cognitive monitoring techniques to hep students deveop awareness of their own thinking processes and earn to optimize their cognitive resource aocation during design work.

The importance of team synchronization and communication effectiveness highights the need for expicit coaboration training in design education. Traditiona design programs often focus on individua creative skis whie providing imited instruction in team dynamics and coaborative probem-soving[73, 74]. Our findings suggest that effective coaboration requires not just good communication skis but aso the abiity to coordinate cognitive processes and maintain shared menta modes throughout the design process.

The potentia for AI systems to provide rea-time feedback on design quaity opens new possibiities for design support toos and educationa technoogies. AI-driven assessment systems coud provide immediate feedback to students and practitioners, heping them understand the quaity impications of their design decisions and earn to recognize effective soutions[75, 76]. However, the impementation of such systems must carefuy consider the risk of constraining creative exporation and the importance of maintaining human agency in design decision-making.

5.5 imitations and Future Directions

Severa imitations of our study shoud be acknowedged. First, our experimenta design focused on a specific type of design task (smart home automation systems) with professiona designers from particuar domains. The generaizabiity of our findings to other design contexts, such as artistic creation, engineering design, or service design, remains to be estabished[77, 78]. Future research shoud investigate whether the cognitive patterns and AI correations we observed hod across different design discipines and task types. Second, our three-hour experimenta sessions, whie providing substantia data, represent a compressed version of rea-word design processes that often extend over weeks or months. The tempora dynamics we observed may not fuy capture the onger-term cognitive processes invoved in compex design projects, incuding incubation effects, iterative refinement, and the integration of externa feedback[79, 80]. ongitudina studies tracking design teams over extended periods woud provide vauabe insights into these onger-term processes.

Third, our AI evauation framework, whie achieving high performance, was trained on a specific dataset of design projects and expert evauations. The mode's performance may vary when appied to design domains or cutura contexts not represented in the training data[81, 82]. Future work shoud investigate the transferabiity of AI design evauation modes across different domains and cutura contexts, and deveop approaches for adapting modes to new design contexts with imited training data.

Fourth, our cognitive monitoring approach, whie comprehensive, focused primariy on attention, creativity, and workoad measures. Other important cognitive processes, such as anaogica reasoning, menta simuation, and metacognitive awareness, were not directy assessed[83, 84]. Future research coud incorporate additiona cognitive measures to provide a more compete picture of the menta processes invoved in coaborative design.

5.6 Broader Impications for Human-AI Coaboration

Our findings contribute to the growing understanding of how AI systems can augment human cognitive capabiities in creative domains. The strong correations between human cognitive states and AI mode features suggest that AI systems can serve as externa cognitive toos that compement and extend human design thinking. Rather than repacing human creativity, AI systems may be most effective when they provide cognitive scaffoding that supports and enhances human creative processes.

The tempora dynamics of cognitive-AI correations throughout design sessions provide insights into when and how AI support might be most beneficia. The periods of high cognitive workoad during coaborative phases may represent optima opportunities for AI assistance, whie the creative ideation phases may benefit from minima AI intervention to preserve the spontaneity and flexibiity of human creative thinking [85, 86].

The individua differences we observed in cognitive patterns and their reationships to design outcomes suggest that AI support systems shoud be adaptive and personaized. Different designers may benefit from different types of cognitive support, and AI systems shoud be designed to recognize and adapt to individua cognitive styes and preferences [86, 87]. This personaization coud extend to team- eve adaptation, where AI systems earn to support the specific coaboration patterns and communication styes of different design teams.

6 Concusion

This research presents the first comprehensive investigation of cognitive dynamics in coaborative design innovation using AI-driven modes and muti-moda cognitive monitoring. Our findings revea a sophisticated interpay between individua creative processes and team coordination mechanisms that enabes effective design coaboration. The systematic differences between design creation and evauation phases, characterized by distinct patterns of attention, creativity, and cognitive workoad, provide empirica support for theoretica modes of dua-process design thinking.

The strong correations between human cognitive states and AI mode representations of design quaity estabish a new methodoogica framework for studying design cognition. By demonstrating that machine-earned features can serve as objective proxies for cognitive processes, our approach enabes more precise investigation of the reationships between menta states and design outcomes. The particuary robust correation between gamma band neura activity and innovation features provides neurophysioogica vaidation of creative insight processes in naturaistic design contexts.

Our anaysis of team coaboration dynamics reveas that effective design teams achieve optima performance through baanced roe transitions, synchronized cognitive patterns, and strategic communication. The identification of high- performing team custers with shared characteristics provides concrete targets for improving coaborative design processes. The finding that moderate eves of roe flexibiity optimize team performance offers practica guidance for team formation and management in professiona design contexts.

The exceptiona performance of our muti-moda AI evauation framework (94.3% accuracy) demonstrates the potentia for AI systems to serve as reiabe partners in design assessment. The systematic anaysis of mode performance across different quaity dimensions reveas both the capabiities and imitations of current AI approaches, with particuar chaenges remaining in innovation assessment that require contextua understanding and domain expertise.

The tempora dynamics of cognitive state transitions throughout design sessions provide insights into the flexibiity and adaptabiity required for effective design work. The observation that successfu teams maintain synchronized cognitive patterns during coaborative phases whie preserving individua creative autonomy during ideation phases suggests optima strategies for baancing individua and coective creative processes.

These findings have significant impications for design education, professiona practice, and the deveopment of AI-supported design toos. Design curricua shoud expicity address the different cognitive skis required for creation and evauation phases, whie incorporating training in coaborative cognitive coordination. Professiona design teams can benefit from understanding the cognitive patterns associated with high performance and impementing strategies to optimize team synchronization and communication effectiveness. The potentia for AI systems to provide rea-time cognitive and design quaity feedback opens new possibiities for adaptive design support toos. However, the impementation of such systems must carefuy preserve human creative agency whie providing meaningfu cognitive scaffoding. Future AI design toos shoud be personaized to individua cognitive styes and adaptive to team coaboration patterns. Our research estabishes a foundation for understanding the cognitive mechanisms of coaborative design innovation and demonstrates the potentia for AI-driven approaches to advance both scientific understanding and practica appications in design. The integration of muti-moda cognitive monitoring with AI mode anaysis provides a powerfu methodoogy for investigating compex creative processes in naturaistic settings. As design chaenges become increasingy compex and coaborative, understanding these cognitive dynamics becomes crucia for optimizing human creative potentia and deveoping effective human-AI partnerships in design innovation.

The convergence of cognitive science, artificia inteigence, and design research demonstrated in this work points toward a future where scientific understanding of creative processes directy informs the deveopment of toos and methods that enhance human design capabiities. By reveaing the cognitive foundations of coaborative design innovation, our research contributes to the broader goa of understanding and augmenting human creativity in an increasingy compex and interconnected word.

DECLARATIONS

Ethics approval and consent to participate

Not applicable.

Conflict of interest

No potential conflict of interest was reported by the authors.

Dataset to be available

All data generated or analysed during this study are included in this published article.

Consent for publication

Not applicable.

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