

Improving User Experience with FAICO: Towards a Framework for AI Communication in Human-AI Co-Creativity

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Abstract

How AI communicates with humans is crucial for effective human-AI co-creation. However, many existing co-creative AI tools cannot communicate effectively, limiting their potential as collaborators. This paper introduces our initial design of a Framework for designing AI Communication (FAICO) for co-creative AI based on a systematic review of 107 full-length papers. FAICO presents key aspects of AI communication and their impacts on user experience to guide designing effective AI communication. We then show actionable ways to translate our framework into two practical tools: design cards for designers and a configuration tool for users. The design cards enable designers to consider AI communication strategies that cater to a diverse range of users in co-creative contexts, while the configuration tool empowers users to customize AI communication based on their needs and creative workflows. This paper contributes new insights within the literature on Human-AI Co-Creativity and Human-Computer Interaction, focusing on designing AI communication to enhance user experience.

CCS Concepts

• Human-centered computing → User centered design.

Keywords

Human-AI Co-Creativity, AI Communication, Framework, Co-Creative AI, User Experience

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1 Introduction

Human-AI co-creativity involves humans and AI collaborating in a creative process as partners to produce creative artifacts, ideas or performances [17]. Co-creativity research suggests [54] that when creativity emerges from human-AI interaction, it can surpass contributors' original creativity and intentions as novel ideas arise in

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the process. With the emergence of popular Generative AI (GenAI) systems with co-creative abilities such as ChatGPT [1], DALL-E [2] and Midjourney [3], human-AI co-creativity is making its way into mainstream life. We suggest that the next frontier of co-creative AI needs good **collaborative skills** in addition to algorithmic competence. However, designing co-creative AI has **many challenges** due to the open-ended nature of the interaction between humans and AI in creative contexts [18, 46]. For example, co-creative AI must be able to adapt to spontaneous interaction styles and allow creative products to develop dynamically across different parts of the creative process.

An essential component in human-AI co-creativity is *communication* for the co-regulation of collaborators [9]. In this paper, we define **AI Communication** as where an AI interacts with humans purposefully and directly to convey information [82]. Our focus is specifically on direct communication, excluding indirect communication through sensemaking that occurs through creative contributions. For instance, in a co-creative drawing scenario, AI might provide feedback on users' contributions or proactively suggest design improvements, such as saying, "The house you drew is a little out of proportion. Would you like to fix it, or should I adjust it for you?" The user can choose to incorporate or disregard this suggestion, which distinguishes AI communication from AI's contribution to the creative process, such as drawing a tree next to the user's house. Our definition of AI communication also overlaps with the field explainable AI [32, 50], in particular considering how AI communication can provide additional explanations in co-creative AI contexts [10]. For example, we consider moments where an AI might communicate to people at the moment whilst they interact with the creative product [11].

For effective co-creation, Mamykina et al. [64] suggests that co-creative AI should provide feedback and critique on contributions similar to how human collaborators do in teamwork. When technology effectively communicates with people HCI research has shown that they are perceived as independent *social actors* [72], improving user perception of AI [83]. Therefore, **AI Communication** can be utilized for co-creative AI to be perceived as an equal partner in co-creation [67, 81] and to improve user experience [83]. However, it is challenging to design **AI Communication** due to the complex and dynamic nature of the human-AI partnership [46], which requires conveying intricate processes and suggestions across a range of different types of users [95]. There is a gap in HCI research of tools, such as design frameworks, for effective **AI Communication** in human-AI co-creativity. Motivated by this research gap, this

paper identifies the aspects of AI communication and how these aspects impact user experience through a systematic literature review. Below are the **contributions** of this research:

- A Framework for AI Communication (FAICO) as the first step towards designing and interpreting *AI Communication* in co-creative contexts based on a systematic literature review. FAICO identifies key aspects of *AI Communication* that should be considered for effective co-creation and their influence on user experience.
- Translating FAICO into practical tools such as design cards for AI practitioners and a configuration tool for users, thereby fostering the advancement of human-centered co-creative AI systems.

The paper is organized as follows. We first provide background on communication in human-AI co-creativity, followed by the methodology of our literature review. We then introduce FAICO in section 4 and move to translating FAICO into design cards and configuration tools in Section 5. Lastly, we discuss the implications and future work.

2 Communication in Human-AI Co-Creativity

AI ability alone does not ensure a positive user experience with the AI [59], especially where interaction is essential between humans and AI [94]. **Co-creative AI** systems involve humans and AI collaborating as partners [17] with creativity emerging that surpasses either party's individual creativity [54]. In co-creative settings, effective interaction is crucial [8, 45], e.g. Karimi et al. found an association between human-AI interaction and creativity that emerges from the co-creation [47]. However, there is a scarcity of research focused on the interaction between humans and AI in the field of co-creativity [82]. To address this gap, a few interaction frameworks have been proposed [33, 45, 81]. Notably, Rezwana and Maher [82] introduced the COFI framework for designing and evaluating interaction design in human-AI co-creativity, highlighting communication between humans and AI as a key interaction design component. More recently, the User-Centered Framework for Human-AI Co-Creativity (UCCC) has been proposed, identifying key dimensions for modulating control between users and AI [70]. However, none of these frameworks specifically explore the dimensions of AI communication and their impact on user experience. In this paper, we extend the existing frameworks by focusing on the critical role of AI communication, identifying its key dimensions, and examining how these dimensions influence user experience.

Exploring communication with computer systems has a long history, dating back to when Alan Turing [28] proposed that a machine that communicates indistinguishably to humans might be considered intelligent. For example, a significant challenge in human-AI collaboration is the development of common ground for communication between humans and machines [16]. We take the view that communication is an essential component in human-AI co-creativity for the co-regulation of the collaborators [9, 53]. In human-AI collaboration, *AI Communication* helps the AI agent make decisions in a creative process [9] and supports many aspects of the **user experience** [67]. For example, AI Communication in co-creation can improve user engagement, collaborative experience

and user perception of a co-creative AI [12, 83]. *AI Communication* can also improve social presence and interpersonal trust [5].

Designing human-like communication has been described as an underestimated challenge of machine intelligence [37]. HCI research shows that how users talk in a human-AI conversation is similar to human-human conversation [19]. While it is vital to use human communication and its ideas as a starting point for designing *AI Communication*, it should not impose permanent restrictions on *AI Communication* [34]. For instance, communication between artists is often based on intuition and non-verbal interaction [38], rather than direct explanation-based discussions which are more traditionally seen in non-creative contexts [10]. Identifying the appropriate communication for co-creative AI is thus key to its user experience. For example, elements of communication such as voice elicit human-like responses toward devices [73], which may or may not always be appropriate depending on context. In this paper, we introduce our first steps in creating a framework that could be helpful to guide the design of *AI Communication* in co-creation.

3 Framework Development Methodology: A Systematic Literature Review

In this section, we document the systematic literature review approach we followed as a methodology to identify the key aspects of *AI Communication* and their influence on user experience.

To identify essential aspects of *AI Communication*, we used the ACM Digital Library to connect to conferences where HCI, AI and creativity research is typically published and to build on reviews by others surveying creativity support [29]. We considered documents published from 1995 until 2024 to consider recent articles. We narrowed our search to full-length papers (e.g. not tutorials or posters) to ensure we considered high-quality peer-reviewed studies. We also only considered papers in English that could be understood by both authors.

We used keywords aligned with our research goal for the framework to search for relevant academic publications. We (the paper authors) chose these keywords following several weekly discussions where we reflected upon our own experiences of AI communication as co-creative AI researchers. The first two keywords related directly to communication: "Aspects of Communication" (561 results) and "Factors of Communication" (41 results). The next three related to interaction and communication between AI and Humans: "Human-AI Communication" (47 results), "AI Communication" (117 results) and "Human-AI Interaction" (279 results). The final four related to when the AI might communicate with humans: "Proactive Communication" (90 results), "Reactive Communication" (29 results), "Proactive AI" (19 results) and "Reactive AI" (13 results). From reviewing the abstracts of these papers, we collected 132 papers.

Next, we read the 132 papers, narrowing down the corpus to **107 papers** with relevance to AI Communication. We summarized the discussion on how co-creative AI should communicate information to users and used affinity diagramming on these descriptions [36] to organize the summaries into related groups. Through iterative discussion, we created the first draft of our framework. The framework described below is primarily based on our literature review while

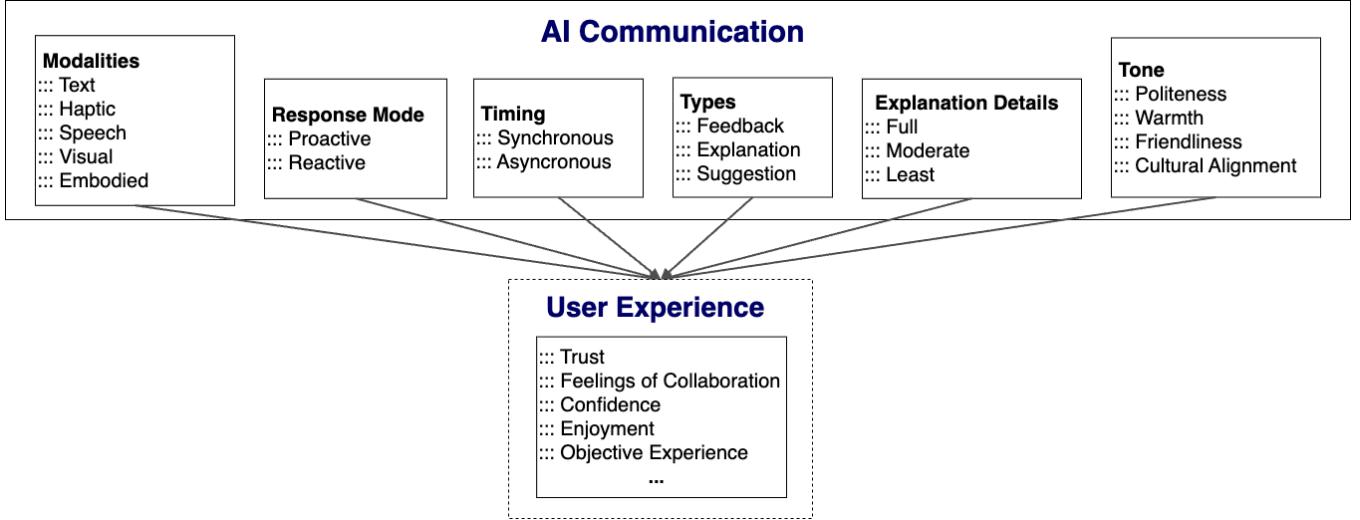


Figure 1: The Framework for AI Communication in Co-Creative Contexts

also integrating relevant insights from additional works outside the scope of the review. The formation and description of FAICO follow a methodology **similar** to that used in other interaction and user-centered frameworks for human-AI co-creation, such as COFI by Rezwna and Maher [82] and UCCC by Moruzzi and Margarido [70].

4 Framework For AI Communication (FAICO)

Figure 1 shows the Framework for AI Communication (FAICO) in the context of human-AI co-creation, introducing **critical aspects** to consider for AI communication and their influence on the **user experience**. The dotted line for user experience (Fig 1) indicates that it is not directly a part of AI Communication but rather comprises aspects influenced by it. Below we discuss each aspect of FAICO and their influence and connections to user experience based on our literature review and related work.

4.1 Modalities

According to FAICO, *Modalities* refers to distinct channels through which AI agents communicate with humans, which is supported by HCI research [48]. Rezwna and Maher outline the classification of modalities for AI to human communication in human-AI co-creation, encompassing text, speech, visuals, haptic, and embodied communication [82]. In our framework, we adopt their classification of modalities for AI Communication.

4.1.1 Connection to User Experience. The literature demonstrates that communication modalities influence user experience. Text-based dialogue plays a key role in helping users perceive the AI's personality [62] and enhances user satisfaction and enjoyment [75]. Speech-based communication has been shown to improve perceived communication quality and trust, often performing better than visual cues in enhancing user experience [102]. Verbal and non-verbal cues allow AI agents to convey their states effectively, which contributes to improved feelings of collaboration and fosters effective human-AI partnerships [4, 12, 87]. Haptics and visual cues

also play an important role, enhancing users' understanding of emotional qualities and fostering a sense of connection [44, 79, 84, 93]. Embodied communication improves the feelings of collaboration with perceived presence compared to text-based communication [56]. Furthermore, multimodal communication, such as combining visuals with verbal interactions, has been found to improve user experience [85]. For instance, the integration of voice, embodied communication, dialogue, and facial expressions provides users with a more accurate perception of AI, improving feelings of collaboration and social presence [71, 87].

The influence of modalities in AI Communication varies between user demographics such as gender [40], age [80], neurodiversity [85], as well as the context in which multimodality is introduced [24]. For example, Vossen et al. [91] found a gender-specific response to embodied communication. To improve the user experience for a diverse population, **multimodal interactions** significantly enhance the performance of AI compared to unimodal interactions [77, 85].

4.2 Response Mode

Response Mode refers to the approach used by an AI agent to initiate or respond to communication during a co-creation. AI can be either *proactive* or *reactive* in terms of how it responds. Proactive AI systems "do not wait for user input but instead actively initiate communication" [89]. On the other hand, when an AI is reactive, it communicates with users when prompted, for example, when clicking a button [69].

4.2.1 Connection to User Experience. Response mode influences user experience in different ways. Proactive AI, while generally favored in social interactions over reactive AI [69], has been perceived as annoying in several studies [89], particularly in contexts where it interrupts users' immersion in creative activities [15] where reactive AI might be preferable. Reactive AI can improve task performance over time and improve perceived usefulness [6, 49]. However, proactive AI can improve perceived trust [43, 51, 101] and encourage

users to be more critical of AI output, which we found connected with human-centered AI guidelines on responsible design [30].

The demographics of users and contexts also affected the different types of timing participants wanted. Pang et al. [76] found that while most mental health app users preferred reactive AI, researchers like doctoral students were more open to proactive AI. Similarly, Meurisch et al. [69] demonstrated that factors such as age, country, gender, and personality traits impact user preferences, with individuals with higher openness favoring proactive AI, while those lower in extraversion preferred reactive communication. Luria and Candy [61] further showed that parents' desired level of AI proactivity varied depending on the situation, emphasizing the importance of context.

4.3 Timing

Timing refers to *when* an AI system communicates with the user, describing whether interactions occur simultaneously or at different times. Timing has been indicated as a crucial aspect of communication in human-AI collaboration [25, 106]. AI Communication can happen either in a *synchronous* (whilst co-creating) or *asynchronous* (outside of working times such as notifications) manner [25].

4.3.1 Connection to User Experience. Timing affects the user experience in many different ways. Synchronous communication is beneficial when immediate feedback and real-time collaboration are necessary [55]. It's particularly useful in improvisational co-creation, such as the studio stage of choreography creation, where AI can engage with users in real-time [58]. Situations requiring a spontaneous and immediate exchange of ideas and feedback from AI can enhance the co-creation process and successful task completion [22]. Asynchronous communication can be useful when users need time for reflection and deeper consideration of AI suggestions [7, 88]. Creative activities that benefit from thoughtful consideration, such as reviewing creative writing or art and producing reflection, asynchronous communication from the AI, could be useful there [58, 98].

Timing influences different user demographics and creative stages differently. Experienced users often prefer asynchronous communication from AI [97], likely because it allows them to maintain an uninterrupted creative flow. Different stages of the creative process may require different timing of AI communication [97]. For example, the ideation stage can benefit from synchronous communication, but the execution stage, where AI works on time-consuming tasks, can use asynchronous communication [42, 57].

4.4 Communication Type

Communication type refers to the type of AI Communication with which AI systems convey information to users based on distinct purposes. The type of communication as one of the major dimensions in AI-mediated communication [34, 35]. According to FAC, types of AI Communication include: *explanation*, *suggestion*, and *feedback*. *Explanation* can be defined as representations of underlying causes that led to a system's output and which reflect decision-making processes. *Feedback* refers to communication in the form of critique, analysis, or assessment of a particular contribution, idea, or artifact. *Suggestion* refers to recommendations or alternatives to the user

contributions during collaborative processes that align with the user's creative objectives.

4.4.1 Connection to User Experience. Research shows that communication type influences various phases of co-creation. Example-based suggestions are effective in the early stages, fostering ideation, while rule-based suggestions are better suited for promoting user understanding [100]. Divergent suggestions are particularly useful during the initial phases to encourage creativity, whereas convergent suggestions are more effective later, helping to refine the co-created product [47]. AI explanations also play a crucial role in shaping user trust. Clear reasoning enhances trustworthiness [68], and social transparency, such as making social contexts visible, improves both trust and decision-making [21]. However, while providing reasoning increases trust, disclosing uncertainty can diminish it [92]. Excessive trust may lead to overreliance on AI, reducing human accuracy [74], a problem further amplified by human-like behaviors, such as hesitations in chatbot responses [105]. Moreover, users tend to value explanations of overall decision-making more than detailed explanations of individual actions, particularly in team settings [103].

Users' responses to AI suggestions are shaped by demographics and task-related factors, including self-confidence, confidence and alignment with the suggestion, and pre-existing beliefs about human versus AI performance [90]. Tailoring AI communication to align with users' cultural backgrounds further enhances interaction effectiveness [104].

4.5 Explanation Details

Explanation details refers to the level of detail that users are given by an AI in co-creation. AI Communication can range from giving *full*, to *moderate*, to the *least* amount of details supported by Moruzzi and Margarido [70].

4.5.1 Connection to User Experience. How much explanation detail is useful seems to vary depending on the co-creative context. There is a balance to be struck between detailed explanations and more ambiguous explanations that offer a moderate understanding of how an AI works whilst still providing an opportunity for serendipity or surprise [10]. For example, in AI music making, whilst AI ambiguity can lead to moments of frustration, it can also be appropriated by musicians [13]. With an AI for co-creative drawing, Oh et al. [75] found that whilst users were more content with drawings based on detailed instructions from a co-creative AI, they also enjoyed its unpredictable nature. Full explanations are often beneficial during ideation stages, helping users understand the AI's intentions [10, 13, 66], whereas less detailed explanations are preferable for in-the-moment interactions, such as reflecting on the AI's output, where additional context may not be necessary [26].

The appropriate level of explanation also depends on user demographics and the stage of the creative process. Explanations should be tailored to the user's AI literacy and expertise [11, 70]. For instance, experienced users may prefer full explanations to access the detailed sequence of actions performed by the AI [107], while non-experts may benefit more from moderate or minimal explanations to avoid overwhelming complexity [70].

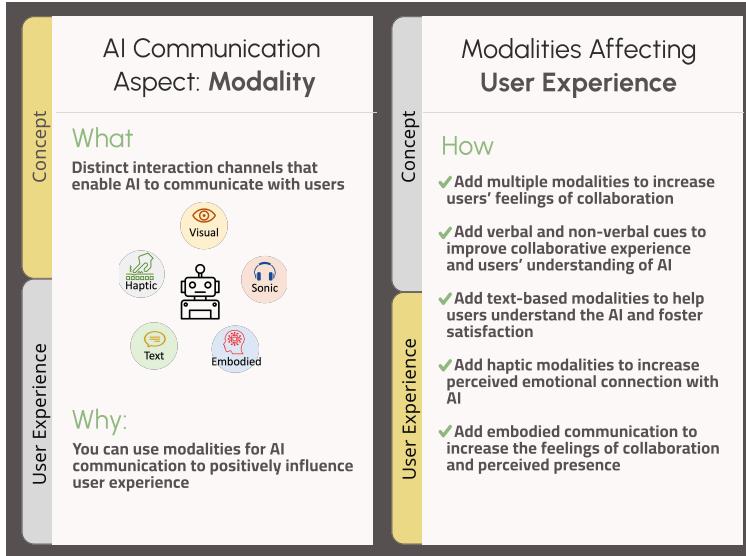


Figure 2: Design Cards

4.6 Tone

Tone refers to qualities of AI Communication that determine whether the expression of the communication conveys a positive emotional intent or not. Tone has been suggested as an aspect that can affect human-AI team performance [52, 63]. In our literature search, we found four influences on the perceived tone of AI Communication - *politeness* (use of considerate, respectful language and behavior following social norms), *warmth* (being approachable and affable in interactions), *friendliness* (ability to foster congenial relationships) and *cultural alignment* (following practices and norms matching the expectations of those involved).

4.6.1 Connection to User Experience. The tone of AI communication significantly impacts user experience. Colley et al. [14] found that when virtual AI avatars in an autonomous vehicle simulation communicated acknowledgment of a user's polite gestures (e.g., waving thank you), the positive perception of the AI increased, demonstrating how respectful behaviors and adherence to cultural norms enhance user experience. Warmth and friendliness also improve user satisfaction and perceptions of AI capability. For instance, Gilad et al. [31] showed that increasing an AI's warmth positively influenced user satisfaction, whereas Poeller et al. [78] found that overly positive messages were sometimes met with skepticism in video game contexts, emphasizing the importance of context in determining the appropriateness of tone. Similarly, AI that responds in a human-like manner with supportive and friendly communication fosters a more engaging and satisfying user experience compared to interactions that lack these qualities [20].

Mascarenhas et al. [65] demonstrated that variations in AI agents' rituals based on cultural behaviors had noticeable effects on users. Likewise, users preferred conversational AI aligned with their cultural norms and were adept at identifying cultural differences in dialogue [23]. Aligning the tone of AI communication with demographic factors such as age, gender, and cultural background can lead to more effective and satisfying interactions [86].

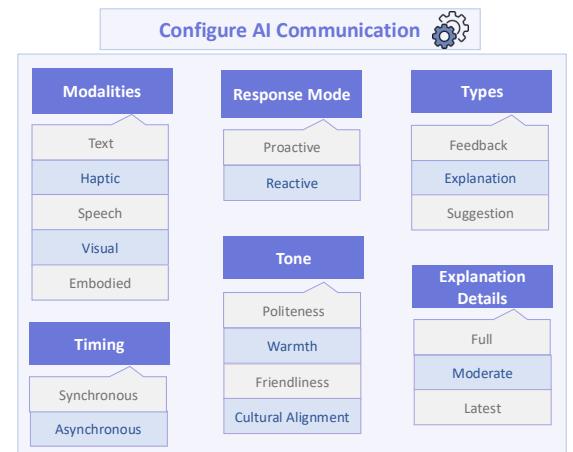


Figure 3: Configuration Tool for Users

5 Framework Applications

This section presents two practical applications of FAICO: Design cards for designers and configuration tools for users.

5.1 Design Cards

We demonstrate an actionable approach to using FAICO for designers by translating it into design cards (Figure 2). Frameworks can be used to guide the design and scaffold of design cards; we offer the example for FAICO here to directly showcase this potential use case. These design cards could be used by AI practitioners to consider how to include effective AI communication in their co-creative AI to improve user experience. Design cards have long been recognized as valuable tools in HCI and design work, appreciated for being “simple, tangible, and easy to manipulate” [60] and an “approachable way to introduce information and sources of inspiration as part of the design process” [96]. Design cards can support designers across various stages of design, including ideation, prototyping, and implementation [39].

We suggest that each design card highlights a specific key component of AI communication from FAICO, explains the aspect, why it is critical to consider in designing AI communication, and how it could influence the user experience. Figure 2 presents a prototypical design card as a proof of concept for developing design cards from FAICO, illustrating how the cards could appear digitally. The card features two tabs: a *Concept* tab describing the corresponding component of the AI Communication framework and a *User Experience* tab detailing how that component impacts different aspects of user experience. In a physical format, the front of each card will include the *Concept* tab, while the back will feature the *User Experience* tab.

Designers can use the design cards for direction and inspiration, helping them enhance user experience through AI communication within their own projects. These cards support designers in exploring the design space of AI communication in co-creation contexts. Additionally, they provide insights into how each component of AI

communication impacts different aspects of user experience, offering actionable suggestions for directly improving user experience outcomes.

5.2 Configuration Tool

This section presents an approach to transforming FAICO into a configuration tool (**Figure 3**) for end-users. With the configuration tool, users can customize and personalize AI communication in their own human-AI collaboration context. The tool can be applied to various co-creative systems, such as design, writing, music composition, or art generation, enabling users to tailor AI communication to their specific needs and preferences. As highlighted in the framework section (section 4), user demographics significantly influence preferences for different aspects of AI communication. Research suggests that users who design their own products using customization toolkits perceived higher value in their creations compared to standard offerings [27]. Allowing users to experience different interface configurations results in interfaces that enhance user engagement and satisfaction [41].

The configuration tool enables users to adjust key communication parameters from FAICO, including modalities, timing, tone, response modes, and communication types, based on their unique requirements and creative objectives. For example, in a co-creative design tool, users could configure the AI to provide synchronous verbal suggestions during brainstorming sessions while opting for asynchronous text-based feedback for refining ideas at a later stage. This flexibility ensures that the AI's communication aligns with the user's workflows and supports their engagement.

6 Discussion and Conclusions

Despite the rapid advancement of generative AI in creative domains, many co-creative AI systems **lack effective AI communication** [82], which limits the user experience [12, 83]. Designing effective human-AI interactions requires identifying key challenges, understanding the unique complexities of AI design, and generating insights to guide future research [99]. This paper presents a novel design framework for designing effective AI Communication (FAICO) to improve user experience in human-AI co-creation. Through a systematic literature review, we designed FAICO to support people in designing and configuring human-centered AI Communication by considering different aspects of AI Communication and their influence on user experience. We then illustrate how FAICO can be practically used through the creation of design cards to help designers consider AI communication in their AI systems. Additionally, we show how FAICO could be utilized as a configuration tool for co-creative AI systems, which users could use to customize and adjust AI communication preferences to align with their own goals.

FAICO can also be used as an evaluation tool to systematically **interpret and assess** the design of AI communication in existing co-creative AI systems. Using FAICO, researchers and practitioners could identify trends, strengths, and gaps in communication design, providing valuable insights into how systems approach communication and highlighting areas for improvement to enhance user experience and future research directions. For instance, FAICO can

reveal whether a system lacks proactive communication capabilities or uses only limited tone and timing preferences. Additionally, FAICO can serve as a benchmarking tool, allowing comparisons between co-creative AI systems' AI communication.

6.1 Limitations & Future Work

FAICO is clearly in the preliminary stage and has room for refinement or extension. Additional aspects of AI communication could be incorporated to address more nuanced design requirements or to cater to emerging, niche co-creative AI domains. FAICO is also based on a systematic literature review, limited to papers from the ACM Digital library, and currently lacks empirical validation; we plan to conduct user studies with designers and users of co-creative AI to evaluate FAICO's effectiveness across diverse co-creative domains. These studies will also explore how AI communication should adapt to various co-creative contexts. Insights from the literature review suggest factors, such as the creative phase, user expertise, and domain-specific practices, influence the optimal design strategies for AI communication. Empirical studies will help better understand the influence of these factors and refine FAICO accordingly.

In addition to validating the framework itself, we plan to evaluate the utility of the design cards presented. By conducting user studies with designers using these cards to develop AI communication, we can assess their effectiveness as a guiding tool for designing human-centered co-creative AI communication and identify opportunities for improvement. Future research can also explore how individual preferences through the configuration tool might influence the user experience to identify more nuanced human-centered design implications.

There is also an opportunity for FAICO to connect more explicitly with the unique challenges of co-creative processes, such as whether different types of communication can spark opportunities for reflection [26] or moments of surprise [10]. In particular, there is a need to explore the trade-offs in AI communication design identified in FAICO and related work – such as how to balance additional multimodal communication elements alongside the risk of overwhelming users and breaking their creative flow [15].

Additionally, we want to identify trends and gaps in the AI communication landscape by analyzing a large corpus of existing co-creative AI systems across various domains. This analysis will provide valuable insights into current practices, highlight best approaches, and uncover gaps in the design of AI communication. The results will guide future research directions and help establish a roadmap for advancing the field of human-AI co-creativity. Overall, this paper lays preliminary groundwork to guide the design of AI communication and to help improving future co-creative AI systems.

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