2. Navigating Human-AI Collaboration: The Emerging Role of Technical Communicators as AI Facilitators

Amber Hedquist
Arizona State University

Mark A. Hannah
Arizona State University

Heidi Willers
Utah State University

Abstract: This study reports on the experiences and responsibilities of an AI Facilitator: a member of a collaborative team responsible for integrating AI in research workflows. Outlining the responsibilities of an AI Facilitator demonstrates the substantive role that a technical communicator (TCer) can play in managing and shaping human-AI interactions. A TCer assumed the role of AI Facilitator during a qualitative coding process with a three-person team. The dialogue between the facilitator and the AI model, consisting of 422 interactions, was analyzed to understand the AI Facilitator's role. Thominet et al.'s framework for conversational roles with AI (manager, teacher, colleague, and advocate) was utilized to explore how the roles informed the AI Facilitator's responsibilities. By employing quasi-coding, dialogue with collaborators, and reflective memos, the research team identified distinct features of each role. Across the interactions, TCers initiated their work as managers but frequently evolved to assume additional responsibilities, such as enculturating the AI, creating space for conversation, and leveraging AI's capacity for pattern recognition. This study affirms the centrality of managerial oversight in human-AI collaboration, while highlighting how TCers can expand their facilitative roles to support such collaborations.

Keywords: Collaboration, Artificial Intelligence (AI)

This study focuses on how technical communicators (TCers) can leverage their expertise in facilitation to support human-AI collaboration. In contexts such as community-engaged research and organizational communications, researchers and scholars in technical and professional communication and also rhetoric have facilitated dialogue (e.g., Moore & Elliott, 2016), access to resources (e.g., Gottschalk-Druschke, 2022; Hartline, 2023), interpersonal relationships (e.g., Hannah & Lam, 2023; Redish, 2010) and communication with users (e.g., Ceraso, 2013; Cleary & Flammia, 2012). In each of these contexts, the TCer operates as an

DOI: https://doi.org/10.37514/TPC-B.2026.2869.2.02

intermediary responsible for negotiating tensions (Ceraso, 2013) and assembling people to achieve common goals (Redish, 2010). As the TC discipline begins to assess AI's potential role in teaming contexts (Carradini, 2024), it is important to understand how their expertise as intermediaries adds value to collaborative work with AI, but more importantly, how the application of such expertise creates work conditions that call into question TCers' disciplinary and ethical responsibilities in AI integration.

Thus far, human-AI collaborations have been described in contexts of work, writing, and research; however, the human's role in these interactions has narrowly focused on overseeing the accuracy of the AI. For instance, interdisciplinary scholars have investigated the ways that AI can support collaborative research by assisting coding (Omizo, 2024; Thominet et al., 2024), data analysis (DeJeu, 2024), and writing (Babl & Babl, 2023). While accuracy is important when collaborating with AI, it is insufficient as a basis for evaluating and theorizing the relational dynamics of researchers' work with AI in research contexts. This study assesses how TCers not only manage AI towards accuracy but also how they guide its integration in ways that support the rhetorical, relational, and ethical demands of collaboration.

In this chapter, we refer to the expanded intermediary role as "AI Facilitator": a member of a collaborative team responsible for the rhetorical, relational, and ethical integration of AI into team processes. Our case study builds upon Luke Thominet et al.'s (2024) work on conversational roles with AI as a framework for human-AI research collaboration. Specifically, we report on how a TCer simultaneously enacted Thominet et al.'s conversational roles of manager, teacher, colleague, and advocate when supporting AI integration in a collaborative research context. By providing examples of how the TCer enacted these roles, we develop an initial conceptualization of an AI Facilitator, its responsibilities, and the connection between AI facilitation and disciplinary goals.

Literature Review

In this section, we describe how AI is integrated in TC work and explore the roles that TCers enact to support AI collaboration. Specifically, we document the discipline's tendency to highlight TCers' work managing AI systems that prioritizes accuracy and output quality. While noting the significance of this work as foundational in this emerging line of research, we also highlight a growing disciplinary interest in developing ethical critiques of AI that move beyond accuracy concerns and confronts the ethical and relational dimensions of TCers' interaction(s) with AI.

Working with AI: Assessing Accuracy and Ethics

At present, AI models cannot operate independently (Johnson-Eilola et al., 2024; Mallette, 2024). Rather, AI is seen as a non-competitive collaborator

(Johnson-Eilola et al., 2024) and early work has outlined where human oversight is necessary in support of TC work tasks. Generally, this phenomenon is described as 'human-in-the-loop' collaborations, wherein humans insert themselves into AI systems to "assess and modify AI-generated content toward nuance and quality" (Verhulsdonck et al., 2024, p. 62). In the workplace, TCers operate as the human in the loop to actively support the training and implementation of AI as a workplace tool. Their work in these instances often is described in managerial terms, i.e., as ensuring an AI model's accuracy. Underlying this concern with accuracy is TC practitioners and researchers' general lack of trust in AI models to "communicate effectively with users (or evolve) on [their] own" (Hocutt et al., 2022, p. 128), which thus necessitates continuous human involvement and collaboration throughout the AI's lifecycle. As an example, TC practitioners in user experience (UX) and content management are increasingly asked to develop AI models, such as chatbots, that can provide context-rich information to users (Hocutt et al., 2022; Porter, 2017). In this role of "botmaker" (Porter, 2017, p. 186), TCers are responsible for training and managing the AI models to produce accurate information and thereby achieve a positive user experience. While important in documenting an early role for TCers in the AI landscape, the tendency in work like this to focus on accuracy limits TCers' ability to imagine more expansive roles that work beyond the pragmatic and managerial.

Anticipating the need to think beyond accuracy, some scholars have urged the field to remain critical of the ethical implications that accompany AI integration (Bender et al., 2021; Johnson-Eilola et al., 2024; Lauer et al., 2018; Sano-Franchini, 2025). For instance, valuing accuracy might obscure important questions about what is being optimized, for whom, and at what cost (Sano-Franchini, 2025). Often, researchers highlighted AI's capacity for bias (Bender et al., 2021) and misinformation (Sano-Franchini & Carpenter, 2023). These concerns often stem from AI being a "black box": a metaphor for systems that take an input and return an output without exposing the algorithmic logic or decision-making processes that facilitate them (Lauer et al., 2018, p. 405). Without understanding this underlying logic and its influence on their managerial work, TCers risk facilitating systems that reinforce harmful patterns or biases. To mitigate these risks, employers are encouraged to establish clear AI policies and incorporate active human involvement throughout an organization's decision-making processes (refer to Kong & Ding, 2024, p. 33).

Concerns with accuracy and ethical assessment further intersect with questions of authorship and voice in the writing process. There is a sustained debate about how to determine when an AI model is assisting writing versus overtaking the writer's unique voice (Cardon et al., 2023). This debate centers on issues such as reduced critical thinking and authenticity (Cardon et al., 2023, p. 247). These concerns have prompted teachers and educational institutions to develop strategies for how to guide students through responsible AI use. Responding to this need, Ehren Helmut Pflugfelder and Joshua Reeves (2024) offered a framework that teaches students how to approach AI-assisted writing with a "critical, authorial, rhetorical, and educational" mindset (p. 419). Their work stresses the importance of engaging with AI critically, with attention to its incapacity for rhetorical nuance. Students are therefore encouraged to maintain rhetorical awareness and authorial control while working with AI. While useful for suggesting that thoughtful use is ethical use, this approach tends to equate criticality with ethical responsibility. Such frameworks might conflate ethical responsibility with preserving authorship and accuracy, leaving little space to discuss broader ethical implications such as access, power, and bias in AI-assisted writing.

Researching with AI: Assisting Analysis

AI has been evaluated as a research assistant capable of handling tasks such as data analysis and data visualization. In qualitative coding contexts, for instance, AI has demonstrated proficiency in locating "concrete, descriptive themes" but struggles to locate more "subtle, interpretative" themes (Morgan, 2023, p. 1) and make decisions based on shared norms or tacit knowledge (Hedquist, 2024, p. 267). Similarly, AI models can produce results that are 'hallucinations' or otherwise baffling, e.g., unrelated to the specified context (Omizo, 2024). Due to these inconsistencies—whether they be a hallucination or missing knowledge—TCers consistently have to verify accuracy and interrogate how outputs are shaped, the assumptions they reflect, and their implications. Particularly in qualitative data analysis, there is a risk of reinforcing reductive narratives or overlooking participant experiences.

Recently, scholars such as Thominet et al. (2024) have deepened our understanding about the multi-faceted roles TCers can adopt when working with AI assistants in research. Recognizing that AI can be a powerful collaborator in qualitative research practices due to its ability to potentially "broaden access to automated textual analysis" (p. 397). Thominet et al. (2024) found that researchers can affect an AI's behavior through adopting a particular kind of conversational frame. Specifically, they describe four conversational frameworks for working with AI: as manager, teacher, colleague, and advocate. Significant for our purposes in this chapter, this framing expands the relational dimension of human-AI collaboration. That is, rather than exclusively managing AI, TCers engage with AI through adaptive and co-constructive interaction that extends their work beyond concerns with accuracy.

Building on this foundation, we designed our case study to shift the focus away from accuracy and management issues towards the broader concerns called for in the discipline's scholarship. We see these concerns as implicated in the teacher, advocate, and colleague roles described by Thominet et al. (2024) and wanted to develop understanding about how those roles are activated and evolve in AI research collaborations. Using a qualitative coding experience as our example, we posit facilitation as a form of TC expertise that can ethically support the relational and rhetorical work of collaboration. By outlining the TCers' responsibilities as an AI Facilitator before, during, and after our qualitative coding work, we illustrate how TCers can broadly contribute to meaning-making, coordination, and ethical responsiveness in human-AI interaction. In doing so, we offer a set of skills and vocabulary that can help TCers make a case (Hannah & Arreguin, 2017; Willers, 2025) for their role in ethically and effectively leveraging AI in collaborative research.

Methodology

This case study examines how a three-member research team operationalized an 'AI Facilitator' while collaborating with a custom AI model during a qualitative research project. In the original study, the team collaborated with a university student coalition dedicated to improving accessibility and disability etiquette on campus. To support the coalition's advocacy goals, the researchers interviewed students about their experiences and analyzed the interview transcripts (Hedquist et al., 2024). The team's goal in this work was to develop themes that could inform the coalition's future advocacy campaigns on their campus. During the analysis process, the team configured a custom AI bot (known as a 'GPT') to help analyze the interviews. Specifically, the AI supported the research team's codebook development and transcript coding. To sustain the team's interaction with the AI bot during this work, one researcher was designated as the AI Facilitator and was responsible for managing how the AI was integrated into the research workflow.

Over the course of several months, the research team coded the interview transcripts and met regularly via Zoom to review progress, refine the codebook, and discuss emerging patterns. Each team member, including the AI, independently coded transcripts and participated in coding discussions. The AI Facilitator was responsible for guiding the AI's participation in these activities, which involved asking the AI to complete tasks, posing questions to the AI, and translating the AI's input back to the team. In previous work (Hedquist et al., 2024), we focused on the broader process of integrating AI into qualitative coding. In the present case study, we focus instead on the interactions between the AI and the Facilitator, namely how the AI Facilitator prompted, responded to, and adapted to the AI throughout the collaboration.

Because the AI Facilitator role was emergent and evolved throughout the collaboration process, we developed a mixed methods approach, including transcript analysis, team dialogue, and reflective memos. By examining the data collected across the full arc of the collaboration, we identified patterns and practices that helped define the responsibilities and impact associated with the AI Facilitator role in collaborative research.

Textual Analysis: Reviewing the Dialogue

One of our objects of analysis was the dialogue between the AI Facilitator and the AI. Using the ChatGPT software, we were able to download the full dialogue that the AI Facilitator had with the AI, which included conversations about the codebook, line-by-line coding, and discussions about revising codes. The dialogue included 422 messages.

To analyze the dialogue, we quasi-coded the messages using Thominet et al.'s (2024) framework for conversation roles with AI, which they refer to as 'GAI.' We used Thominet et al.'s (2022) definitions to guide our analysis:

- **Manager:** "the researcher carefully observes and verifies GAI's work to ensure consistency" (p. 404).
- **Teacher:** "the researcher seeks to teach GAI about theories, research methods, or qualities of the data to improve its outputs" (p. 406).
- **Colleague:** "the researcher seeks to understand data better by openly discussing it with GAI. Rather than expecting GAI to replace the researcher's work, colleagues expect meaning and knowledge to be produced through the chat conversation" (p. 405).
- **Advocate:** "the researcher works with GAI to improve the user experience of texts similar to those being studied. In this way, advocates expect GAI to provide useful insights into how specific users might understand and use the texts in a dataset" (p. 407).

We reviewed the transcript to find examples of each role, marking when and how the Facilitator enacted different roles across the phases of the collaboration.

Dialogue with Collaborators: Reflecting as a Team

To better understand the evolving nature of the AI Facilitator role, the research team spent a portion of each coding session reflecting on and discussing how facilitation practices were evolving. Early in the collaboration, team members described the Facilitator as a "scribal" figure—someone who relayed information from human researchers to the AI without shaping the interaction. However, as the project progressed, the team began to recognize that the Facilitator's role involved far more than transcription.

Notes were taken during these reflective discussions to document emerging ideas and shifts in how the team understood the Facilitator's contributions and responsibilities. Reflection prompted important revelations; for instance, during the coding process, one of the collaborators noted that the facilitator is, in many ways, the voice of the AI. Thus, timing when and how that voice appears in the collaboration took on special significance. This reflection—among others—was documented in reflective notes that we analyzed later, alongside reflective memos that were written specifically by the AI Facilitator.

Reflective Memos: Reflecting as Facilitator

In addition to team meetings, the AI Facilitator engaged in structured reflection by maintaining reflective memos throughout the coding process. During and after coding sessions with the GPT, the Facilitator documented her observations, challenges, and evolving strategies for integrating the AI. Unlike the team reflections, these memos provided a first-person account of the Facilitator's experience and offered insight into the moment-to-moment decision-making involved in facilitating human-AI interaction. These memos served as data sources for identifying tensions, adjustments, and patterns that helped shape the definition of the Facilitator role.

Results

This section presents our analysis of how the Facilitator role was enacted across the qualitative coding process. Drawing on Thominet et al.'s (2024) framework of conversational roles—manager, teacher, colleague, and advocate—we describe the Facilitator's interactions with the AI to explore the range of responsibilities involved in these roles when facilitating human-AI collaboration.

We restate each role definition at the beginning of its respective subsection to guide the reader and contextualize our findings. After defining each role, we then offer examples that illustrate how the role was enacted throughout the coding process. This approach helps us trace how the Facilitator's responsibilities evolved over time and how role adoption varied across phases of the collaboration.

Facilitating as Manager: Assessing Accuracy and Comprehension

Thominet et al. (2024) describe the managerial role as one in which the researcher "carefully observes and verifies GAI's work to ensure consistency" (p. 404). In our study, the AI Facilitator enacted this role when assessing alignment with the uploaded data, closely monitoring the AI's memory, and overseeing the accuracy of the outputs.

One responsibility of the AI facilitator in this role was checking the AI's access to and comprehension of the data in the interview transcripts. While coding statement seven of the second transcript, the AI suggested multiple codes when the human coders did not have any. After asking the AI to cite evidence from the statement, we realized it was coding the wrong statement. The Facilitator responded, stating "I don't think you are looking at the right statement. The text you pulled for statement seven (lines 37–43), is from line 126." The AI continued to code the wrong statement until the Facilitator prompted the AI by stating, "this line starts with '100%.' Try again." This strategy was effective, and the AI was able to locate statement seven successfully. While this led to the identification of the correct line, the Facilitator learned that they would need to tell the AI which statement was being analyzed and provide the first word of the statement.

A second responsibility involved managing the AI's memory and tracking its use of previous conversations during the coding process. Often, the Facilitator asked the AI to complete a task or make a decision based on information stated earlier in the conversation as a means to gauge the AI's capacity for recalling information. After the first transcript, the Facilitator gave the AI instructions on how to create a table about agreement between coders (what to include in the rows, columns, and so forth). During subsequent requests, the Facilitator asked "Can you do what you did last time? Where you create the table? Do you remember the elements of the table?" The AI responded in the affirmative and created the table accordingly. Had the AI not remembered, the Facilitator would have been alerted to a lapse in memory that could affect other elements of the collaboration, such as coding decisions or enculturated norms. As a result, the Facilitator's role was essential for overseeing the accuracy and consistent memory of the AI, which were foci that continued throughout the collaboration.

The final managerial responsibility involved scrutinizing the AI's outputs to assess its accuracy. For example, as just noted, the AI was asked to create tables that summarized agreement levels among collaborators. Here, the Facilitator manually verified the calculations by counting the agreements and disagreements between collaborators from the transcript. As the AI's results were correct, this confirmation process increased the research team's confidence in the AI's performance and calculations. This practice of validating outputs was especially important given the risk of AI models hallucinating or producing inaccurate results (Omizo, 2024)—a phenomena we noticed in the AI's inconsistencies with pulling the correct statements. Those inconsistencies were significant because they signaled a need for more verification and oversight, which ultimately encouraged us to check that the AI cited the source material in each of its discussion points. The Facilitator's role here included anticipating and guarding against such errors, emphasizing that managing AI requires active oversight.

Together, these responsibilities align with the managerial oversight described in early research. However, the responsibilities also involved evaluating if outputs were usable and contextually appropriate for the team's goals. In these ways, managerial facilitation in this case study became a matter not only of attending to data access, memory, and rhetorical implications of potential inaccuracies but also protecting the quality and credibility of the data analysis process.

Facilitating as Teacher: Structuring and Iterating the Learning Process

According to Thominet et al. (2024), the teacher role emerges when the researcher "seeks to teach GAI about theories, research methods, or qualities of the data to improve its outputs" (p. 406). In our collaboration, the AI Facilitator took on this role by shaping the AI's knowledge base, providing iterative feedback, and filling gaps in knowledge.

When configuring the AI, the AI Facilitator was responsible for training the AI on discipline-specific literature. First, the Facilitator collaborated with the research team to curate texts in five content areas, including widely cited coding manuals, such as *The Coding Manual for Qualitative Researchers,* and foundational literature in technical communication relevant to our research such as the *Routledge Handbook of Disability Studies,* which were uploaded as TXT files. Before configuration, the AI's knowledge base was limited to the Internet with a knowledge cutoff date of January 2022. Therefore, the Facilitator played an important role in anticipating potential knowledge that the AI might need in order to code from a similar perspective to that of the human team. By accounting for this disciplinary knowledge at the beginning, the Facilitator pre-emptively filled knowledge gaps resulting from the technology's content limitations.

A second teaching responsibility involved adding local or tacit knowledge when appropriate to support the AI's coding. While these teaching moments arose out of managerial checks for accuracy, they revealed opportunities to assess and address gaps in the AI's knowledge. For example, we noticed an important knowledge gap when we coded an interviewee's discussion of tabling on campus. At Southwestern University, tabling is a significant community activity where student groups and organizations set up tables in a major campus hub to meet and recruit new student members. As such, we coded this as 'community' and the AI did not. Once we explained the context in more detail, the AI was persuaded. If these instances are not interrogated, then the research team might assume that the AI does not think the phenomenon is significant or relevant. However, if the AI is informed about tacit or local knowledge, the research team can better understand and integrate its perspectives. In this sense, AI Facilitators engage in building shared language (Hannah & Saidy, 2014), which requires attention to knowledge gaps and enculturation opportunities (Hannah et al., 2024). Attending to dimensions of enculturation can help the AI substantially contribute to the collaboration as a disciplinary peer while simultaneously being mindful of important moments to pause, reflect, and iterate.

In addition to providing local knowledge, the AI Facilitator often had to enculturate the AI into the group to help the AI operate within the norms and expectations of the team. Throughout the coding process, the Facilitator encouraged the AI to refine its outputs, adjusting response length, tone, or framing based on the group's expectations. For instance, the Facilitator noticed that the AI continued to list recommendations for next steps rather than discussing specific codes and tensions as the team had developed as a practice. Recognizing this tendency, the Facilitator prompted the AI to discontinue including recommendations for next steps in its responses, which led to more productive and nuanced discussions within the team. In no longer listing next steps, the AI better aligned with the team's expectations. This attention to instructing the AI about collaborative norms continued when the Facilitator enacted the colleague role.

Facilitating as Colleague: Creating Space for Contribution

Thominet et al. (2024) describe the colleague role as one where "the researcher seeks to understand data better by openly discussing it with GAI. Rather than expecting GAI to replace the researcher's work, colleagues expect meaning and knowledge to be produced through the chat conversation" (p. 405). The AI Facilitator adopted this role by engaging the AI in moments of interpretation, pausing the conversation to facilitate AI input, and spending time dissecting the AI's contributions.

Establishing the AI as a peer contributor began during the configuration stage by assigning it the role of a qualitative researcher and continued throughout the coding process as the Facilitator worked to reduce the AI's deference and encourage substantial collaboration. While configuring the AI's backend instructions, the Facilitator added the instructions that the AI's purpose is "analyzing text as a qualitative researcher in the field of Technical and Professional Communication." Then, before coding, the AI was told that it was "a collaborator" and all team members would be coding interviews. Despite these efforts, the AI was deferential early on, in the sense that it rarely pushed back on the decisions of the human coders; similarly, the AI rarely explained its answers and was quick to agree with the human team members. Recognizing these deferential tendencies, the Facilitator experimented with different prompting strategies. Prompts such as "why didn't you code anything for statement 6?" were largely ineffective; the AI was quick to re-code the statement, rather than to explain its decision-making. However, prompts such as "Why did you originally code for education?" led to more detailed answers from the AI which in this case study included, "I originally coded for 'Education' in Statement 5 because I might have interpreted the participant's discussion of their diagnosis and understanding of their differences as part of an educational journey or process." This justification helped us understand the textual basis for the AI's coding decision. In turn, we could more aptly consider its contributions as a colleague through discussing the merits of the AI's rationale alongside competing rationales from other team members. This example reveals the importance of trying different prompting strategies to overcome deference and integrate AI effectively. Achieving these substantive responses was made possible through the Facilitator's prompting adaptations.

Throughout the process, the AI Facilitator was responsible for helping the team maintain a pace suitable to fully integrating the AI. Often, the coding process involved dialogue wherein researchers built upon the ideas and contributions of their colleagues. Lacking the capacity for in-time contributions to the team dialogue, the AI's comments and suggestions did not fit seamlessly into the team's dialogue style. Specifically, the AI Facilitator had to continually pause the conversation to inform the AI about shifts and/or updates in the conversation. In these moments of pause, the Facilitator would inform the AI and ask for its contribution and reactions. In one instance, the human coders were talking about a difficulty with the concept of 'role,' which the Facilitator summarized in a message to the AI as, "Do you think this line in isolation should be coded as role? We are hesitant because Amber thinks she was reading into the context too much when she coded with role." In response, the AI explained that the "brevity and ambiguity" of the statement would not warrant coding the statement for 'role.' While the pause disrupted the steady flow of human dialogue and dampened the excitement that emerged through new coding insights or working through difficulties, it was a formative moment for drawing in the AI as an entity or object that the researchers work with rather than isolating it as a tool that did work for the researchers. By securing and maintaining a slower pace, the Facilitator was able to incorporate the AI as a substantive contributor to the research team's dynamic conversations.

As emphasized in Thominet et al.'s (2024) definition, colleagues expect the AI to contribute to meaning-making, which the Facilitator prioritized when the AI coded differently from the human researchers. Rather than dismissing these differences as errors, which might happen if the AI was viewed as a tool or passive assistant, the Facilitator treated them as opportunities for more reflection. In one instance, the team was coding a statement about language use. No one coded for 'community' except Amber, and she was struggling to articulate how she saw the code operating in context. Since the AI also coded for 'community,' the Facilitator asked for its justification. In response, the AI stated that "community is emphasized because the participant is discussing how the debates and perspectives on language use are shaped and shared within the community." This explanation reminded the team of their original definition, particularly its emphasis on the social. As a result, all coders agreed to apply the 'community' codes in this instance, and in subsequent statements, thereby shifting their interpretive lens to look for similar discussions around language and community. This instance highlighted the important role of the Facilitator in calling attention to the AI's contributions and exploring its justification. Without this intervention, the AI's divergent coding may have been undervalued. The Facilitator's attentiveness reinforced the team's commitment to integrating the AI as a colleague and meaningfully incorporating its contributions in the coding process. While treating the AI as a colleague helped the team's interpretive process, the Facilitator also assumed an advocate role, which helped surface patterns that could support the project's overall goals of investigating disability etiquette and supporting the coalition.

Facilitating as Advocate: Harnessing AI's Pattern Recognition

In the advocate role, Thominet et al. (2024) explain that the researcher "works with GAI to improve the user experience of texts similar to those being studied. In this way, advocates expect GAI to provide useful insights into how specific users might understand and use the texts in a dataset" (p. 407). In an example of this type of facilitation, Thominet et al. describe how a study team member used AI to "identify some patterns relevant to the populations she sought to assist" (p. 409). Our team was utilizing AI in a similar manner as we wanted to incorporate AI into our efforts to define disability etiquette, develop themes, and provide the insights to the coalition to support their campaigns about disability etiquette.

Before engaging the AI in conversations about key themes or patterns in the interviews, the Facilitator was responsible for informing the AI about the study and its objectives as it relates to the coalition's goals. Specifically, the Facilitator explained the project's history, scope, and ideal deliverables prior to the coding process. The Facilitator outlined these dimensions of the collaboration early on, through statements such as "We are all coding interviews with [Southwest University] students from the [coalition]. The interviewees are all students with disabilities who are reflecting on their thoughts and experiences related to disability etiquette." By framing the data as coming from a specific community, the Facilitator helped the AI contextualize the material beyond the coding process. This groundwork enabled the AI to engage more meaningfully in later prompts, particularly those asking it to identify patterns that could inform how the coalition understood and shared reflections on disability etiquette on campus. Overall, the Facilitator supported the AI's knowledge acquisition as an initial step toward leveraging the AI's pattern recognition and dialogic interactions as the team worked to parse through complex concepts.

The student coalition asked the research team to help define disability etiquette, a concept they found to be important and difficult to define; therefore, the task of pulling key themes from the transcript and developing actionable insights was difficult. In these moments of difficulty, the Facilitator asked the AI to help the team think through conceptual tensions. In one such example, the team was struggling to parse through definitional differences between the codes 'normativity' and 'ethics,' which would have important implications for how we defined disability etiquette and proposed solutions for the coalition. The Facilitator asked the AI, "We see normativity and ethics as being very similar. Here, it seems like the speaker is suggesting that asking about language preferences is ethical, and therefore should be the norm. How do we decide what is leading in this case?" In response, the AI justified how 'ethics' was the leading code (the code with the most emphasis) because the interviewee seemed to equate language preferences as "fundamentally an ethical issue." This response helped the team clarify the conceptual distinction between the two codes and better articulate the ethical dimensions of disability etiquette. Importantly, it allowed the team to frame the issue in a way that aligned with the coalition's goals. By integrating the AI in these important, conceptually difficult discussions geared toward future deliverables, the Facilitator helped the team develop analytically clear and useful outputs.

After tracing how the AI Facilitator enacted each role, we recognize that each role involves significant responsibilities throughout the collaboration. To make them accessible for readers, Table 2.1 outlines the responsibilities associated with each role, as well as an applied example to contextualize how each responsibility might be enacted.

The enactment of these roles reveals how an AI Facilitator can balance rhetorically complex decision-making and support the practical demands of collaborative human-AI teams. The following section builds on these insights by examining how the Facilitator pivots between roles to sustain interaction.

Table 2.1. Roles, Responsibilities, and Applied Examples of AI Facilitation

AI Facilitator Role	Key Responsibilities	Applied Example
Manager	Oversees that the AI's knowledge base and source materials are comprehensive and accessible.	Conduct pre-project assessments of AI systems to confirm that all necessary data sources are uploaded and legible.
	Continually monitors the AI's memory capacity.	Check that the AI can recall conversations from early in a collaboration.
	Verifies AI outputs for accuracy and ties outputs to data sources.	Use AI for generating data summaries or reports and verify accuracy to assess the reliability of outputs.
Teacher	Guides AI learning by selecting relevant training materials.	Meet with multiple stakeholders to gather perspectives on what should be included in the AI's training.
	Provides iterative feedback to improve AI performance.	Establish feedback loops with AI systems, such as explaining which of its outputs were helpful for collaboration and why.
	Fills knowledge gaps, such as those related to disciplinary knowledge or norms.	Create a workflow wherein the AI is continually asked to recall prior conversations and concepts.
Colleague	Treats AI as a knowledge contributor, not just a tool.	Make space for including the AI during conversations, rather than using an AI model as a means for starting or book-ending a conversation.
	Controls the pace of the conversation to ensure the AI is included.	Ask colleagues to pause their conversation to allow time for the AI to be updated.
	Spends time asking for the AI to justify its decisions to contribute to meaning-making.	Ask AI to justify its coding decisions to explore how its meaning-making processes differ from other team members.
Advocate	Leverages AI's pattern recognition to uncover insights.	Utilize AI for advanced data analysis tasks like identifying trends in customer feedback or predicting user behavior in product development.
	Aligns AI contributions with broader organizational goals.	Use AI to support advocacy efforts by identifying underrepresented issues or communities based on analysis of large datasets.

Discussion

This section illustrates how AI Facilitation often centers on managerial concerns and then pivots to one of the other conversational roles (teacher, colleague, or advocate). To illuminate these pivots, we organize the following discussion around how and why the TCer transitions between roles. Tracing these pivots clarifies the responsibilities and rhetorical skills that an AI Facilitator demonstrates in collaborative work. In addition to clarifying the role, these pivots speak to the complex relational work involved in sustaining human-AI collaboration.

Manager to Teacher: Filling Knowledge Gaps

One of the earliest pivots the Facilitator made was from manager to teacher in instances where the AI needed to be enculturated into the team through a better understanding of group norms and shared language. Enculturation is the "process of learning our own culture" (St.Amant, 2016, p. 7) and in collaborative teams, this involves developing shared norms and understandings of language and processes. As collaborators who have worked together several times, we had a rhythm to our work process that we had cultivated over time. Therefore, it was a bit jarring in instances where the AI, for instance, used a lot of pleasantries. In response to one piece of feedback, the AI stated, "Thank you for emphasizing the importance of critical engagement and assertiveness in our collaboration. I appreciate your guidance and will ensure to provide thoughtful, independent analysis moving forward." This statement was not inaccurate; however, the Facilitator recognized an opportunity to help the AI enculturate into the team. To do so, the Facilitator stated, "please do away with the pleasantries." In doing so, the AI focused its responses more on the task at hand, which aligned with the group's working expectations. This foundational instruction helped set expectations for the AI's role in the group; however, the Facilitator intervened at a more granular level when it was evident that the AI needed more information about the coding process itself.

Beyond group norms, the Facilitator shifted focus at times from verifying outputs to explaining how the AI could be more aligned with the team's coding process and expectations. In multiple instances, the AI stated its recommended codes without justifying their relevance or situating the codes in the text. In one moment, the Facilitator seized the opportunity to clarify expectations, explaining "What in the text made you code normativity? Again, we need this information. Think out loud. This makes you a good collaborator." Similar to the enculturation example above, the Facilitator focused less on accuracy and more on the AI's alignment with the group's workflow and expectations. These teaching moments helped the AI begin to participate more meaningfully in the work. Therefore, the Facilitator continued to look for gaps in conceptual knowledge as opportunities to support the AI's involvement.

Filling in the AI's local knowledge gaps not only supported more accurate analysis but also helped the Facilitator improve the AI's enculturation into the team's shared understanding and knowledge. Since the interviewees were all students, there were several instances where campus-specific-phenomena were discussed. In one example, a student mentioned being an online student and all human coders coded the instance as 'community.' When the AI did not include this code, the Facilitator determined that the omission could be due to a lack of tacit knowledge about the campus community. Thus, the Facilitator stated, "We realize that you were unaware that the institution where these students go to school has a 100% online option. These students operate in a different community, so we coded as a community. Do you agree?" The AI responded that the knowledge clarified the context, and it agreed that 'community' should be a code. In this example, as with the prior examples in the teacher section, enculturation is made possible in instances where the Facilitator moves beyond accuracy to fill knowledge gaps. Teaching played a foundational role in the AI's performance and the Facilitator jumped into this role intermittently, when necessary. Unlike the teacher role, pivoting from manager to colleague required more attention and consistency.

Manager to Colleague: Creating Space for Pause

The pivot from manager to colleague began when the Facilitator slowed the pace of collaboration to create space for the AI's contributions. Pausing thus required the Facilitator to resist the urge to move quickly and efficiently, instead taking the time to ask follow-up questions and provide the AI time to respond. In one instance, the Facilitator asked "Why do you suddenly agree with putting in agency? Please elaborate. Here is where longer answers are appreciated to better understand your thinking." The team learned that the AI was focusing on dissemination and emotions within the participant's experiences, which helped the team understand its decision-making process. Taking the time to dive into the AI's contributions signals how the AI was valued as a meaning-making member of the collaboration.

Part of this pivot to colleague involved taking the time to restructure expectations to best situate the AI for meaningful and substantial collaboration. At times, this involved positively reinforcing the AI's behaviors that were supporting the collaboration. In one exchange, the AI indicated which codes were 'emphasized' in a statement and which were secondary (or, as the AI termed them, 'relevant'). The Facilitator responded with the following, "We would also like to note that in statement 3 your discussion of relevance versus emphasis is really important and was really helpful…please keep doing this." Here, the Facilitator recognized the AI's contributions and gave it the space and vocabulary to continue being an effective collaborator. Though time intensive, taking the time to confirm the AI's positive communication styles helped the team treat the AI as a colleague and benefit from its contributions and meaning-making.

In many instances, creating space afforded the AI opportunities to contribute while helping the team leverage the AI's insights. In particular, the Facilitator valued incorporating the AI in moments of conceptual disagreement. For instance, the human coders continued to struggle creating distinctions between the definitions for 'knowledge' and 'awareness.' In light of this difficulty, the Facilitator communicated to the AI that "Amber coded as knowledge and Mark coded as awareness. Heidi thinks it might be an overreading. We would like your input." In response, the AI argued for neither—instead, arguing that ethics was the primary code. We were impressed by the AI's unique contribution here that we ultimately adopted. The contribution spurred new dialogue that helped us think through the interviewee's experiences and situate it within the broader context and help the coalition define and frame disability etiquette on its campus.

Manager to Advocate: Embracing Anticipatory Thinking

The move from manager to advocate began when the Facilitator pivoted from equipping the AI with a disciplinary knowledge base to preparing the AI to align its decision-making with the coalition's project-specific goals. Specifically, in pivoting toward the advocate role, the priority shifted to helping the AI see the coalition's stakeholders as end users. For instance, the Facilitator explained an important change in our codebook that anticipated the project's deliverables. We informed the AI that we would remove 'etiquette' as a code, explaining that "it does not make sense to have 'etiquette' be a code. We want to think of each code in our codebook as representative of a different component of disability etiquette." This decision was geared toward our plan to present the coalition with a framework or set of themes for understanding disability etiquette on campus. Providing this rationale helped the AI align its future decisions with the coalition's purpose of raising awareness about disability etiquette on its campus. Ultimately, this anticipatory thinking encouraged the team to see the AI not as a tool but as a partner in shaping and uncovering findings that could support the community-engaged research goals with the coalition.

The pivot toward anticipatory thinking was particularly important when the Facilitator prompted the AI to help the team think through key concepts that would inform how disability etiquette was communicated to the coalition. We were mindful of the coalition's goals throughout the project, and we were particularly attuned to the fact that closely related concepts—such as 'normativity' and 'ethics'—would be difficult to distinguish. Additionally, after interviewing the coalition's members, we knew that the themes associated with 'normativity' and 'ethics' would be key components in how disability etiquette was framed and defined. As we worked through the transcripts, disagreements emerged. During a disagreement about one statement—where the interviewee reflected on capitalizing the 'D' in disabled—only Mark coded for 'ethics.' To explore this difference, and inform the AI that there was disagreement, the Facilitator informed the AI and asked, "For statement 35, none of us saw ethics but Mark did. What do you think about this?" In response, the AI disagreed with Mark and situated 'normativity' and 'community' as the more relevant codes. The AI explained why it did not code for 'ethics' and made the argument that the perspective on language was grounded in social dynamics and should be considered a normativity concern. By offering an alternative and justifying its coding, the AI helped the team clarify the conceptual boundary between 'ethics' and 'normativity,' which would later shape how disability etiquette was framed and defined when communicating results to the coalition.

Limitations

This study presents findings from an exploratory case study in an effort to articulate the emergent concept of the AI Facilitator role and has three main limitations. First, our collaborative group has worked together previously, which may have influenced the success of facilitation. For example, we did not run into significant issues with human-to-human norming or challenges related to collaborative workflows. Future studies might investigate how an AI Facilitator can be operationalized in a new team, which would require balancing both AI integration and facilitating new interpersonal relationships and expectations.

Secondly, our team shared an interest in exploring AI integration in research practice. While this alignment supported a productive and exploratory environment, it also created conditions that may not reflect the realities of other collaborative settings. We recognize that our shared interests may not reflect the range of perspectives or hesitations about AI in broader contexts. In these instances, AI Facilitators may need to spend more time engaging collaborators, listening to concerns, and adapting processes in a way that reflects every collaborator's values. An outcome of this process may be that AI is not included in the collaboration, which would be an appropriate outcome given the pressing concerns and ethical implications of AI work.

Lastly, though this paper focused on defining an emergent concept, we acknowledge that AI integration raises important ethical questions, including algorithmic biases. While we briefly discussed these concerns when appropriate, future work can further examine how ethical considerations can and should inform facilitation practices with AI and future technologies.

Conclusion

This study demonstrates how AI facilitation can involve moving beyond accuracy and attending to the relational and rhetorical dimensions of human-AI collaboration. By pivoting from a managerial role to the roles of teacher, colleague, and advocate, AI Facilitators enable the AI to participate more meaningfully in the co-construction of knowledge. These pivots reflect the adaptive, rhetorical work required to sustain collaborative engagement, highlighting a growing opportunity for TCers to apply and expand their expertise in AI-enabled spaces.

Acknowledgments

This project was supported by Arizona State University's 2024 AI Innovation Challenge: a collaboration between ASU and OpenAI. The authors thank ASU and OpenAI for their support and resources.

References

Babl, Franz E, & Babl, Maximilian P. (2023). Generative artificial intelligence: Can ChatGPT write a quality abstract? *Emergency Medicine Australasia*, *35*(5), 809–811. https://doi.org/10.1111/1742-6723.14233

Bender, Emily M., Gebru, Timnit, McMillan-Major, Angelina, & Shmitchell, Shmargaret. (2021, March). On the dangers of stochastic parrots: Can language models be too big?. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency* (pp. 610–623). https://doi.org/10.1145/3442188.3445922

Cardon, Peter, Fleischmann, Carolin, Aritz, Jolanta, Logemann, Minna, & Heidewald, Jeanette. (2023). The challenges and opportunities of AI-assisted writing: developing AI literacy for the AI age. *Business and Professional Communication Quarterly*, *86*(3), 257–295. https://doi.org/10.1177/23294906231176517

Carlson, Erin B., & Caretta, Martina A. (2021). Legitimizing situated knowledge in rural communities through storytelling around gas pipelines and environmental risk. *Technical Communication*, *68*(4), 40–55.

Ceraso, Antonio. (2013). How can technical communicators plan for users? In J, Johnson-Eilola & S. Selber (Eds.), *Solving problems in technical communication* (pp. 237–261). The University of Chicago Press.

Carradini, Stephen. (2024). On the current moment in AI: Introduction to special issue on effects of artificial intelligence tools in technical communication pedagogy, practice, and research, part 1. *Journal of Business and Technical Communication*, *38*(3), 187–198. https://doi.org/10.1177/10506519241239638

Cleary, Yvonne, & Flammia, Madelyn. (2012). Preparing technical communication students to function as user advocates in a self-service society. *Journal of Technical Writing and Communication*, *42*(3), 305–322. https://doi.org/10.2190/TW.42.3.g

DeJeu, Emily B. (2024). Using generative AI to facilitate data analysis and visualization: a case study of Olympic athletes. *Journal of Business and Technical Communication*, *38*(3), 225–241. https://doi.org/10.1177/10506519241239923

Gottschalk-Druschke, Caroline. (2022). From access to refusal: remaking university-community collaboration. *Community Literacy Journal*, *17*(1). n.p. https://doi.org/10.25148/CLJ.17.1.010656

Hannah, Mark A., & Arreguin, Alex. (2017). Cultivating conditions for access: A case for "case-making" in graduate student preparation for interdisciplinary research. *Journal of Technical Writing and Communication*, *47*(2), 172–193. https://doi.org/10.1177/0047281617692070

Hannah, Mark A., & Lam, Chris. (2023). Functional flexibility: cultivating a culture of adaptability for the work of professional writing. In L. Anderson (Ed.), *Rewriting Work* (pp. 141–158). The WAC Clearinghouse; University Press of Colorado. https://doi.org/10.37514/TPC-B.2023.2128.2.06

Hannah, Mark A., & Saidy, Christina. (2014). Locating the terms of engagement: shared language development in secondary to postsecondary writing transitions. *College Composition and Communication*, *66*(1), 120–144.
Hannah, Mark A., Caputo, Courtney, Deen, Lily, Hedquist, Amber, Salgado, Catherine, Shah, Seher, Cruiser, Laura, Fluty, Chris, Lane, Tom, Rebe, Tristan, & Sutrisno, Dwi Bl. (2024). Thinking with keywords: Investigating the role and nature of professionalism keywords in TPC enculturation. *Technical Communication Quarterly*, *33*(3), 342–357. https://doi.org/10.1080/10572252.2024.2340434
Hartline, Megan F. (2023). The hidden labor of sustaining community partnerships. *Communication Design Quarterly*, *11*(2), 44–49. https://doi.org/10.1145/3592356.3592362
Hedquist, Amber, Willers, Heidi, & Hannah, Mark A. (2024). Discipline-driven AI: training a GPT to qualitatively code for technical and professional communication research. *Proceedings of the 42nd ACM International Conference on Design of Communication*, 266–268. https://doi.org/10.1145/3641237.3691686
Hocutt, Daniel, Ranade, Nupoor, & Verhulsdonck, Gustav. (2022). Localizing content: the roles of technical & professional communicators and machine learning in personalized chatbot responses. *Technical Communication*, *69*(4), 114–131. https://doi.org/10.55177/tc148396
Johnson-Eilola, Johndan, Selber, Stuart A., & York, Eric J. (2024). Can artificial intelligence robots write effective instructions? *Journal of Business and Technical Communication*, *38*(3), 199–212. https://doi.org/10.1177/10506519241239641
Kong, Yequing, & Ding, Huiling. (2024). Tools, potential, and pitfalls of social media screening: social profiling in the era of AI-assisted recruiting. *Journal of Business and Technical Communication*, *38*(1), 33–65. https://doi.org/10.1177/10506519231199478
Lauer, Claire, & Brumberger, Eva. (2016). Technical communication as user experience in a broadening industry landscape. *Technical Communication*, *63*(3), 248–264.
Lauer, Claire, Brumberger, Eva, & Beveridge, Aaron. (2018). Hand collecting and coding versus data-driven methods in technical and professional communication research. *IEEE Transactions on Professional Communication*, *61*(4), 389–408. https://doi.org/10.1109/TPC.2018.2870632
Mallette, Jennifer C. (2024). Preparing future technical editors for an artificial intelligence-enabled workplace. *Journal of Business and Technical Communication*, *38*(3), 289–302. https://doi.org/10.1177/10506519241239950
Moore, Kristen R., & Elliott, Timothy J. (2016). From participatory design to a listening infrastructure: A case of urban planning and participation. *Journal of Business and Technical Communication*, *30*(1), 59–84. https://doi.org/10.1177/1050651915602294
Morgan, David L. (2023). Exploring the use of artificial intelligence for qualitative data analysis: The case of ChatGPT. *International Journal of Qualitative Methods*, *22*. n.p. https://doi.org/10.1177/16094069231211248
Omizo, Ryan M. (2024). Automating research in business and technical communication: large language models as qualitative coders. *Journal of Business and Technical Communication*, *38*(3), 242–265. https://doi.org/10.1177/10506519241239927
Pflugfelder, Ehren. H., & Reeves, Joshua. (2024). Surveillance work in (and) teaching technical writing with AI. *Journal of Technical Writing and Communication*, *54*(4), 419–438. https://doi.org/10.1177/00472816241260028
Porter, James E. (2017). Professional communication as phatic: From classical eunoia to personal artificial intelligence. *Business and Professional Communication Quarterly*, *80*(2), 174–193. https://doi.org/10.1177/2329490616671708

Redish, Janice. (2010). Technical communication and usability: intertwined strands and mutual influences. *IEEE Transactions on Professional Communication*, *53*(3), 191–201. https://doi.org/10.1109/TPC.2010.2052861

Sano-Franchini, Jennifer, & Carpenter, Kaytely. (2023). Critical digital interface analysis and social justice. *Technical Communication*, *70*(4), 1–7.

Sano-Franchini, Jennifer. (2025, May 21). *Recognizing AI hype masquerading as research*. Refusing Generative AI in Writing Studies. https://refusinggenai.wordpress.com/2025/05/21/recognizing-ai-hype-masquerading-as-research/

St.Amant, Kirk. (2016). Introduction to the special issue: Cultural considerations for communication design: Integrating ideas of culture, communication, and context into user experience design. *Communication Design Quarterly Review*, *4*(1), 6–22.

Thominet, Luke, Amorim, Jacqueline, Acosta, Kristine, & Sohan, Vanessa K. (2024). Role play: Conversational roles as a framework for reflexive practice in AI-assisted qualitative research. *Journal of Technical Writing and Communication*, *54*(4), 396–418. https://doi.org/10.1177/00472816241260044

Verhulsdonck, Gustav, Weible, Jennifer, Stambler, Danielle M., Howard, Tharon, & Tham, Jason. (2024). Incorporating human judgment in AI-assisted content development: The HEAT heuristic. *Technical Communication*, *71*(3), 60–72. https://doi.org/10.55177/tc286621

Wertz, Olivia M., Workman, Kandi, & Carlson, Erin B. (2023). Seeking out the stakeholders: building coalitions to address cultural (in)equity through arts-based, community-engaged research. *Communication Design Quarterly*, *11*(2), 18–27. https://doi.org/10.1145/3592356.3592359

Willers, Heidi. (2025). Lessons from a "scholar on fire" for a world on fire: A framework to position technical and professional communication scholars for policy impact. *Journal of Technical Writing and Communication*, *55*(1), 31–57. https://doi.org/10.1177/00472816231210224