Fostering Knowledge in Generative AI: Challenges, and Collaborative Learning in Early Development

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The rapid advancement of generative artificial intelligence (GenAI) may outpace organizations' abilities to prepare and offer training materials. Employees may learn on their own, or through collaboration. In this paper, we explore the onboarding experiences of IT employees with generative AI, focusing first on their individual and collaborative learning practices and, second, on the large-scale use of a specific GenAI tool designed for accessing large language models via a visual prompting interface. We conducted a survey with 63 employees and an interview study involving 16 individuals to gain deeper insights into their GenAI collaborative learning practices, including collaborations with peers to address skill gaps and enhance capabilities. We describe the advantages to providing a GenAI human-centered interface tool for testing and intuitive experimentation for accelerating and scaling learning within communities of practice, for communication of results and for knowledge-sharing within small teams and broader social networks.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**; **Collaborative and social computing theory, concepts and paradigms**.

Additional Key Words and Phrases: Work practices, Collaboration, Community, Generative AI, Upskilling

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1 Introduction

Generative AI (GenAI) has changed AI work and required that those who work with it acclimate to a new kind of AI. For example, an expanded set of job roles may be involved in generative AI work, as people can experiment without needing to build the models themselves [28, 33]. Those with less AI experience, but who are expected to integrate generative AI into their work, may need more support to understand and work with generative AI [95, 104]. Even AI experts need to continuously learn about the new developments, due to the novelty around generative AI models [93]. Prior research has also shown the importance of various roles in AI development having enough literacy to understand each other [75]. Our goal was to explore how learning and collaborative work practices have been impacted by the introduction of GenAI.

Our work was inspired by prior work exploring roles and collaboration in AI work prior to the introduction of generative AI [109]. Just as design guidelines for AI developed and changed from 2019 [4] to 2024 [104], we hypothesize that generative AI has changed AI work and learning [12, 19, 37, 49, 70]. Further, we expect that the fast-paced nature of the advancement of generative AI along with the expansion of who can use it has likely impacted the kinds of practices and needs of those who work with generative AI [3, 25, 85, 107]. Since we expect advancements around GenAI to

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continue to change at a fast rate, better understanding practices, needs, and challenges around GenAI work can help us to better support GenAI learning and collaborative work.

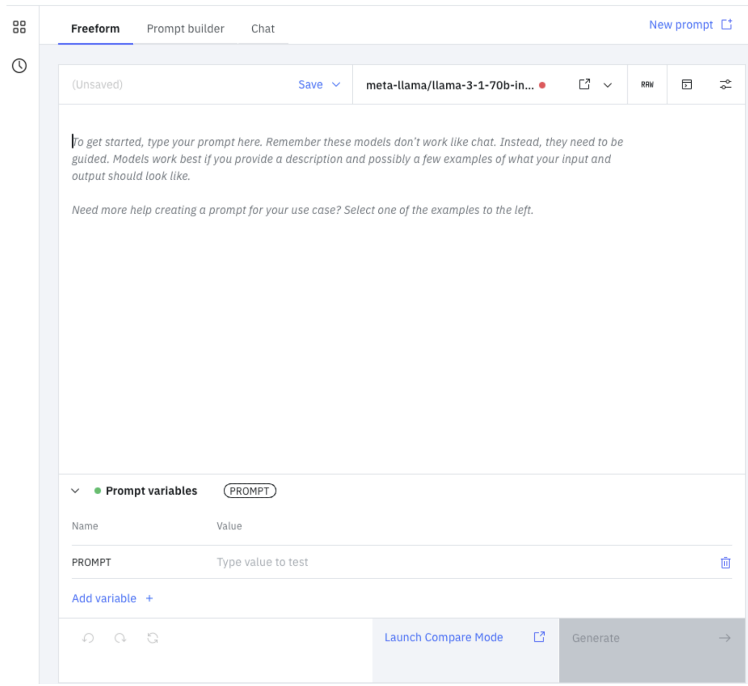


Fig. 1. An example of the Experimental GenAI Platform (EGP) interface.

We explored the collaboration practices employed, community learning practices and challenges around generative AI work, and the perceived value gained from community engagement on an Experimental GenAI Platform (EGP) that was developed by a team in our organization (see Figure 1). The shift to generative AI was disruptive in many ways and caused a race for companies and practitioners alike to get up to speed on the developing AI systems with foundation models. We hypothesized that those who work with generative AI can potentially derive significant value from community engagement, including accelerated development cycles and access to specialized expertise. Community interactions can foster innovation, facilitate peer learning, and provide a support network for addressing challenges in generative AI projects. Through a survey and interview study of employees, our aim was to better understand practices and challenges around generative AI work and collaboration, using tooling generally and as part of a team, and learning about generative AI.

Our research questions are:

- RQ1: What are the collaborative generative AI work practices?
- RQ2: What are the community learning practices and challenges around generative AI work?
- RQ3: How has EGP supported generative AI work and learning practices and what challenges remain?

To answer these questions, we performed a survey with 63 participants and semi-structured interviews with 16 participants. Our survey captured participants' roles, generative AI work, tools, collaborative practices, and how well supported people are in learning about generative AI. Our interviews addressed detailed accounts of these questions and focused on understanding the value of the EGP platform, in the process of learning and working with Generative AI. Our interviews also aimed to capture further detail on collaborative practices and challenges around generative AI work and learning.

Our contributions are: 1) a survey and interview study capturing work, tool, collaboration, and learning practices and challenges in generative AI with a discussion of the unique aspects of generative AI, and 2) design recommendations for better supporting generative AI workers through collaborative tools and practices.

2 Related Work and Background

Our work builds upon and contributes to research around AI, ML, and data science work practices, communities of practice, and adoption and learning of generative AI.

2.1 AI, ML, and Data Science Work Practices

This paper contributes to the understanding of the people and practices around AI, ML, and data science work. We connect our research to these three types of work, as there is overlap in the types of roles and work involved.

Research has investigated work practices and workflows, primarily in data science work, though many apply to AI and ML development work as well [83]. Wang et al. describe a data science workflow in three main steps (preparation, modeling, and deployment). They found that data science work is highly collaborative throughout these steps, particularly during the preparation phase, which includes the ideation stages. This collaboration is mainly focused on generating ideas rather than on coding [103, 109].

Mao et al. report a similar workflow in data science work, including dataset work, research question development, model selection, implementation, evaluation, and summarization [54]. Another study found four main stages of work in an industry-academic data science collaboration: problem understanding, data understanding, experimentation, and MVP (minimum viable product) development [90]. Muller et al. dug into the data work specifically, finding different kinds of data preparation tasks like design and curation [61], while Kross and Guo discovered an “outer loop” of data science work, which involves collaboration with clients beyond the technical work, such as laying groundwork for trust and handling clients’ constraints [42]. Our work contributes to this knowledge through a better understanding of types of generative AI work practices.

The work practices in AI, ML, and data science are inherently collaborative, as most of this kind of work in industry contexts involves teams of workers with a variety of roles [41, 71, 75, 81, 90, 99, 108, 109]. We were particularly inspired by the work of Zhang et al. in understanding how data science workers collaborate, the roles in collaboration, tools, and practices [109]. Our work extends this work to understand the collaborative roles, practices, and challenges around generative AI work and learning. Existing research around the kinds of challenges involved in collaborative data, AI, and ML work has often found that a major hurdle in collaboration for this kind of work is communication [23, 99], often caused by differing expertise among collaborators [1, 5, 65, 71, 75], making it hard to reach a common ground [54]. One study found value in workers they named “intellectual bridges” who have both technical and domain expertise and can support the establishment of common ground [82]. Often, those with less expertise desire and seek out a better understanding about how the technologies work [2, 23, 73].

One way teams handle these challenges in lack of understanding is through educational sessions to improve understanding and reduce communication gaps [75], a practice sometimes called “bridging” work [26, 42]. Another potential solution is project management frameworks specific to the particular needs of AI, ML, or data science work [23, 98]. This prior work indicates a continuing need for learning and literacy in these technologies, even before generative AI. We believed that the rapid influx of novel generative AI methods would increase a need for understanding and collaborative learning across roles, as well as challenges.

Sharing content through tools may be one way to support collaboration and communication within teams [36]. Epperson et al. found a variety of content shared, such as utility libraries, analysis code, template notebooks, and libraries, though there were also obstacles like lack of code modularity and tool compatability [31]. Tooling may be one way to support sharing, such as computational notebooks [20, 101], dataset versioning [7], or platforms for supporting domain knowledge transfer [72]. Yet, various challenges still remain in utilizing tools for collaboration, such as a need for documentation [102] and poor quality code with errors due to the experimental nature of notebooks [71, 77]. Further, data science work involves tacit knowledge that can be hard to capture and transfer [16]. We contribute to research around sharing and collaboration in generative AI development work and how tooling can support collaboration and learning.

2.2 Communities of practice and social learning

2.2.1 Communities of Practice in Software Engineering. Communities of practice in software engineering and design were discussed by Bogdan [9, 10] (software engineering) and by Muller and Carey [63] (design). The broader concepts of communities of practice had been explored earlier by Lave and Wenger [45], and had subsequently been adapted to meet organizational needs [56]. Cox [22] argues that what was initially a project of resistance (e.g., [45]) became absorbed into management practices and management science (e.g., [14, 105] - see also [24]).

Communities of practice have been theorized as sites of social learning [45] and knowledge co-production [105], as well as knowledge preservation [56, 63] and identity construction [44] - particularly Lave and Wenger's concept of legitimate peripheral participation, through which a new member of the community enters as a novice, learns enough to become a full member, and may eventual develop as a leader [9–11]. According to Rothschild et al. [81], the strengths of some communities of practice depend on inclusion of diverse human identities and knowledges.

2.2.2 Process Models for Community-Based Prompt Engineering. We now turn to collaborative support for prompt engineering, "prompt wrangling," [58] or "promptware engineering" [18]. Perhaps because of the emphasis on generative AI as a tool for automation, there seem to be relatively few papers about collaboration in prompt engineering (see below). However, there is a small but growing literature on prompt patterns [87, 88, 106] and on the discovery and solution of prompt problems [27]. In general, these projects are not collaborative in the sense of communities of practice, but rather rely on a single person or team, who publish a set of patterns as a completed resource.

Mahdavi Goloujeh et al. [53][p.1] note that text-to-image prompts "are socially constructed and shaped by the interests and values of diverse groups," partially echoing Sanchez [84]'s observation of the MidJourneys discussions on Discord, as aspects of everyday creative problem-solving during prompt engineering [68]. Following on this insight, and invoking theories of communities of practice, Rodgers and Sako [80] described four types of expertise: professional substantive expertise, technological substantive expertise, human to machine relational expertise, and human-to-human relational expertise in a community of practice. In this way, Rodgers and Sako provided more specific examples of Rothschild et al.'s claim that some communities of practice draw strength from their internal diversity. Muralikumar and McDonald [64] concurred, arguing that a community of practice allows people with diverse skills to educate one another in a third space or hybrid space where multiple disciplines can co-exist equally (e.g., [35, 54, 60].

2.3 Adoption and Learning Generative AI

Recently, there has been a rapid push to learn about generative AI and large language model (LLM) pipelines as a whole. Numerous companies are investing heavily in generative AI, creating a pressing demand for rapid understanding of these technologies, platforms, and strategies for training, safeguarding, and governing projects based on the available LLMs in the market while also advancing research in the field [55, 78, 97]. Speed and performance have become essential requirements, necessitating rapid prototyping to deliver results to clients as quickly as possible in the face of intense competition [29, 50].

Unfortunately, this rapid pace of change in the tech industry has left many developers and practitioners feeling unprepared. The landscape is evolving at an unprecedented rate. This transformation is not just a gradual shift; it's a fast-moving process requiring professionals to adapt and take on additional responsibilities beyond their traditional roles [46, 50, 108]. They may look to new technologies for assistance. New tools for developing generative AI systems are being launched [12, 46, 94], and innovative models and methods [39, 95, 111] are emerging at an unprecedented pace, transitioning from research laboratories to products faster than ever. Clients engage with these technologies using natural language and testing them through prompting engineering techniques [28, 51, 85].

Considering those points, AI practitioners must be prepared to anticipate user inputs and create guardrails to mitigate possible AI risks [40, 52, 74, 110].

The complexities of GenAI pipelines demand collaboration among teams with diverse expertise [79], echoing the challenges seen in traditional AI development and deployment processes [3, 17], which are further heightened with recent advancements [100, 108]. As a result, some companies are seeking to support and expedite the large-scale learning of GenAI technologies to keep pace with this evolution [59]. Key approaches include identifying the transversal and core skills needed for effective AI adoption, providing tailored training and development opportunities such as personalized learning experiences powered by AI, hands-on learning modules, hackathons for collaborative skill-building [21], continuous lifelong learning initiatives and integrating prompt engineering education as a core skill for effective human-AI interaction [38]. However, Clear et al. [21] point out a variability in support, with some organizations lacking formal training, leaving employees to self-learn. Tabarsi et al. [95] identified in their research that early adopters in ML /AI GenAI gain knowledge about generative AI through hands-on experience, self-education, formal resources, and iterative learning supported by LLM explanations and community such as forums, social media, and professional networks.

Learning GenAI can happen in a variety of settings. This research investigates how employees at a multinational corporation learned about Generative AI to perform new organizational required work assignments. It explores both formal training and informal learning methods, highlighting the importance of hands-on experience with a tools and community support. The EGP tool specifically enabled experiential learning and provided broad and timely access to generative AI technologies when they were emerging. The study shows how these elements helped employees work better together and gain GenAI skills more quickly.

3 Methods

We employed a mixed-methods approach combining a survey and semi-structured interviews to study the collaborative work and learning practices of IT employees engaging with GenAI tools, specifically an Experimental GenAI Platform called EGP during its early adoption phase in a large multinational technology company.

3.1 Research Setting

This research was conducted in an international computer and consulting company. The authors were members of the company's research organization, as were many of the users. The company has no formal Institutional Review Board. Instead, all employees take required annual ethics courses. Managers are responsible for conducting ethics review of research. This paper received ethical approval from the company's ethics-review process.

We conducted our research as an internal project. Thereby, all users were company employees, and our sample was accordingly limited (see Limitations, below). Employees were under no pressure to participate, and did so without compensation, in order to contribute to future directions of potential products. Employees consented to our use of their data, under appropriate anonymization and other privacy protocols.

3.2 Experimental GenAI Platform

Both our survey and interview included questions about EGP. EGP was a tool that provided internal company employees access to large language models (LLMs). Due to its' popularity (over 30.000 active users) we were interested in how it supported early GenAI collaborative work and learning practices. EGP was available to workers beginning in November 2022 and was available throughout the survey and interviews we performed.

The EGP had both a user interface as well as an API and SDK (Software Development Kit) for leveraging the LLMs in code. The user interface provided a prompting interface where a user could input a prompt, view the output, and save the prompt. The interface also provided a way to change the parameters of the model and the system prompt, when appropriate. In both versions, there was a set of models available to all users, including both open-source models and internal experimental models. The models available changed over time. The website included documentation about how to use the platform as well as information about the models. The platform had an associated Slack channel, in which users could provide feedback, ask questions to the team who created the platform, report issues, and discuss among the platform users.

In mid-2023, a product version of the EGP was released, which we will refer to as PGP (Product GenAI Platform). All employees had limited free access and some had more extensive access based on their work. Hackathons were run in 2023 and 2024 to encourage experimentation and use of the product.

3.3 Survey

The goal of the survey was to capture generative AI work and collaboration practices. Participants were recruited through invitations in targeted Slack channels and direct messages, employing a purposive sampling approach [15] to attract AI practitioners in channels about EGP GenAI feedback and use.

3.3.1 Survey Design Process. Three researchers were the primary survey designers, who have expertise in Human-Centered AI, generative AI, developer experience, and survey design. We iterated on the questions and question design and got feedback from two other relevant teams on the survey questions and survey goals. The questions were also inspired by previous work about AI practitioners [109]. Then, we piloted the survey with three participants through 60-minute think-aloud sessions, iterated, and finally had three more pilot survey participants before deploying the survey.

3.3.2 Survey Questions. The survey starts with an informed consent form. Next, participants are asked how they have used generative AI- those who have been involved in a project at work that uses generative AI were included. Those who have only experimented with generative AI or used it for work or home tasks were excluded (the survey ended for them). It then asks demographic and background questions, such as their role and length of time working with generative AI, the tools they use, and an example of a project they've worked on to better understand the kind of generative work they do. Then, participants answered questions about collaborative practices, resources they share or seek from others, usage of internal slack channels, and how well they are able to get the help they need. The survey questions are available in Appendix Section A.

3.3.3 Participants. We recruited 63 participants through internal Slack channels focused on generative AI and LLMs at a large international technology company from July 12, 2024 to December 13, 2024. Participants work in various business units, including research (16), software (14), consulting (10), global sales (10), finance and operations (8), infrastructure (4), and marketing and communications (1). While many survey participants have roles in software and development (13) or research (12), we also had participants in a variety of other roles, such as architect (9), data science (6), technical specialist (5), design(4), consulting (4), sales (3), and project management (2). We had participants from the Americas (30), Europe, the Middle East and Africa (21), and Asia Pacific (12). The survey typically took under 20 minutes (75% of participants completed the survey in under 20 minutes, but participants were allowed to leave and come back to the survey, leading to some much longer completion times). Participants volunteered their time to complete the survey during their work day. Responses were required to be completely anonymous according to company policy, limiting us from knowing whether there was overlap in survey and interview participants (discussed below).

3.3.4 Data and Analysis. We use descriptive statistics to analyze the survey results, indicating the kinds of people, practices, tools, and collaborations present in a population of people who work with generative AI. Our interview data provides further insights into the trends we see in our survey.

3.4 Interviews

3.4.1 Interview Design Process. We developed a semi-structured interview protocol based on the research questions of this study. The purpose of the interviews was to gain a deeper understanding of the collaborative nature and nuances involved in the everyday tasks of generative AI development. It included insights into participants' onboarding experiences with Foundational models, including the GenAI development and their usage of platforms and tools that support their work in GenAI development. We piloted the interview protocol with two participants, one researcher and one software engineer working with generative models and applications. Those pilots were essential to clarify the wording of some questions and focus the interview on the examples of work practices supported by technology and teams. In total, 16 practitioners were interviewed, with each interview lasting between 45 and 60 minutes. We ran our interviews in August and September 2024. Participants did not receive any compensation for their participation. Participation was voluntary. Participants gave their permission to use images and audio recordings and could withdraw from the study at any time.

3.4.2 Semi-structured questions. The interview questions were centered around six key topics:

- Participants' current roles and responsibilities within the company, their experience with generative AI (GenAI), and recent projects they have worked on in the GenAI field.
- Tools and technologies they use.
- Enterprise GenAI assets, including the benefits and challenges associated with them.
- Their learning experiences related to GenAI.

- Team collaboration. Specifically in how they supported their teams, exchanged knowledge and tools for communication practices.
- Community tools and support for advancing GenAI knowledge.

Each interview concluded with an open-ended question, allowing participants to share any additional information about their day-to-day work that we had not covered during the interview.

3.4.3 Participants. Participants were recruited using a combination of purposive sampling [15] and snowball sampling approaches [34]. Due to company data restrictions, we were unable to collect statements of interest in the interview from the survey and needed to recruit for the two separately. We recruited volunteer interview participants from Slack channels similar to the survey and by directly messaging individuals that were active in the GenAI and EGP slack channels.

Sixteen participants were interviewed and engaged in various projects for a global IT company, developing and using generative AI platforms in their daily roles. The group comprised six individuals from the research division, four from sales, four from software development teams, and two from finance and operations. Our interview participants also had a variety of roles: research scientist (4), architect (4), manager (2), engineer (2), back-end software developer (1), developer (1), research intern (1), consultant intern (1).

3.4.4 Data and Analysis. We conducted thematic analysis [13, 57, 91] using a similar protocol as in [76]. We first developed a code book with three researchers discussing and resolving any disagreements based on 25% (four transcripts) of the data. This resulted in a total of 32 codes (see Appendix B).

For the remaining thematic coding, researchers worked with an AI coder. We decided to incorporate AI coding into our thematic analysis approach to accelerate data analysis and to explore the approach. The "AI coder" was implemented using a Jupyter notebook based on the prompt in Appendix C. AI coding was done line-by-line by iterating through each interview transcript assigning between one and five codes from the code book. We used llama-3-1-70b-instruct (internally hosted without retraining) as an LLM to perform code assignments on anonymized transcripts. The choice of LLM was driven by doing multiple iterations and experiments with LLMs that were approved for internal use in our company including llama-3-1-70b-instruct, llama-3-405b-instruct, mixtral-8x7b-instruct, and granite-13b-instruct.

Two researchers and the AI coder coded all remaining interview transcripts and recoded the initial four transcripts as needed [47]. Each of these transcripts was coded by one human researcher and the AI coder using the code book as described above. As our codes are not fully overlap-free, sometimes, even when there were differences between human and AI, the differences were very nuanced. The transcripts and codes were checked by a second human researcher, who resolved code conflicts with discussions with the original human researcher when necessary.

4 Results

We answer our three research questions: 1) What are the collaborative generative AI work practices, 2) What are the community learning practices and challenges around generative AI work, and 3) How has EGP supported generative AI work and learning practices and what challenges remain?

4.1 What are the collaborative generative AI work practices?

We aimed to better understand the roles of those working with GenAI, the work they do, and their interactions with EGP.

Survey participants reported a variety of roles in their machine learning/AI work. The most frequently selected primary role was ML/AI engineer/architect, followed by subject matter expert, researcher, and data engineer. Yet, we also had survey participants in less technical roles, like product/project/program management and design. See Figure 2 for the full primary and secondary job roles.

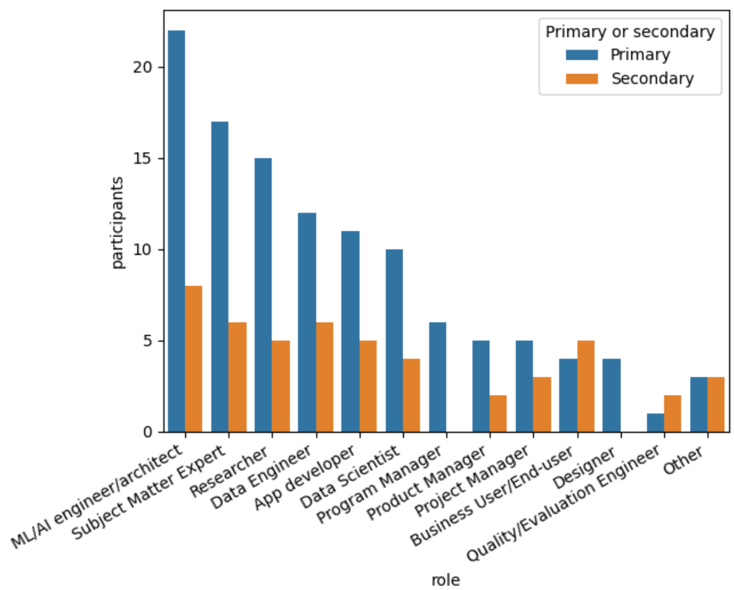


Fig. 2. Number of participants who reported having each primary and secondary role. Participants could choose up to 3 primary roles and 3 secondary roles.

Of the AI development life cycle activities, many survey participants have been involved in prompt engineering (50/63), manual evaluation (42/63), project definition (38/63), and data processing (36/63). Fewer had been involved in pre-training (7/63), monitoring (16/63), and governance and risk management (17/63). We thought we might find patterns in the combinations of activities participants reported as part of their work, but in almost all cases, the combination of activities was unique. All but two participants reported completing multiple activities ($mean = 5.40\ activities, sd = 2.58\ activities$). We asked participants about the levels of collaboration throughout the generative AI development life cycle. We found the most collaboration during project definition, followed by prompt engineering and manual evaluation of outputs (see Figure 3).

We were interested particularly in use of the EGP tool to help us understand the impact of EGP on GenAI learning and work. Many survey participants (39/63) had used EGP. Their usage was split between a prompting UI and the API and SDK for programmatic prompting. For the UI, 21 used it often, 12 used it sometimes, 3 used it once in a while, and 3 had tested or evaluated it. For the API, 17 used it often, 7 used it sometimes, and 1 had tested or evaluated it. Survey participants who hadn't used EGP had used another GenAI tool, either internally or externally. We found that EGP users typically had more experience with GenAI and were more likely to have been involved in a research project than not. EGP users often had more than 2 years of experience (28.21%) or 1-2 years of experience (41.03%) with GenAI, while only 4.17% of non-EGP users had over 2 years of experience and 45.83% had 1-2 years of experience. Relatedly, nearly

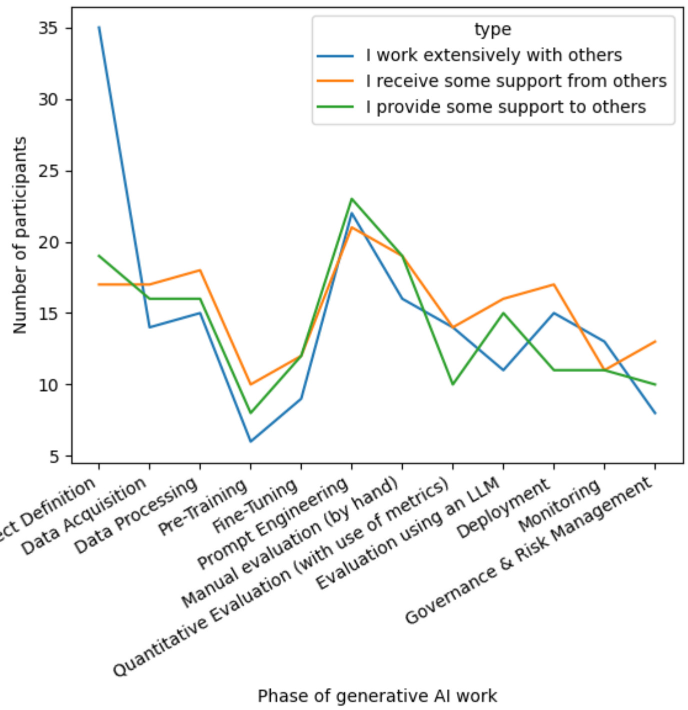


Fig. 3. Number of participants who reported working extensively with others, receiving support, or providing support during the phases of generative AI work.

half (48.72%) of EGP users had been involved in a research project (as opposed to internal or client-facing product work), while only 20.83% of non-EGP users had been involved in a research project.

4.2 What are the community learning practices and challenges around generative AI work?

Overall, survey participants felt moderately well supported and were moderately able to find experts to support them in learning. We asked survey participants how well they feel they are able to find and access information needed and how well they have been able to find experts to collaborate and/or learn GenAI. Most participants felt they were able to find information needed moderately well ($mean = 2.90, std = 1.16$) on a 1-5 scale. They also felt they were able to find needed experts or collaborators moderately well ($mean = 3.05, std = 1.11$). See Figure 4 for boxplots. While it is encouraging that participants feel moderately well supported in learning, we were somewhat surprised to not find more people who felt very well or extremely well supported in finding information or support.

We next discuss interviewees' strategies and challenges in learning GenAI and the associated supporting survey data. Participants talked about three main strategies for learning about generative AI: 1) *learning from the broader community*, 2) *learning within smaller communities*, and 3) *individual learning*. The main learning challenges were the *speed of change* and *information overload.*

4.2.1 Learning from the broader community. Our interview results shed light on learning practices in the broader company community. Many participants talked about the broader community as a space for learning, such as the use of

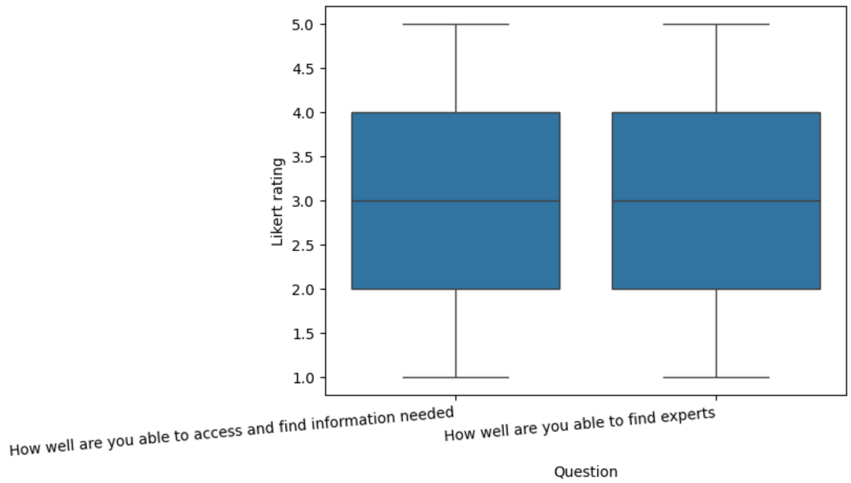
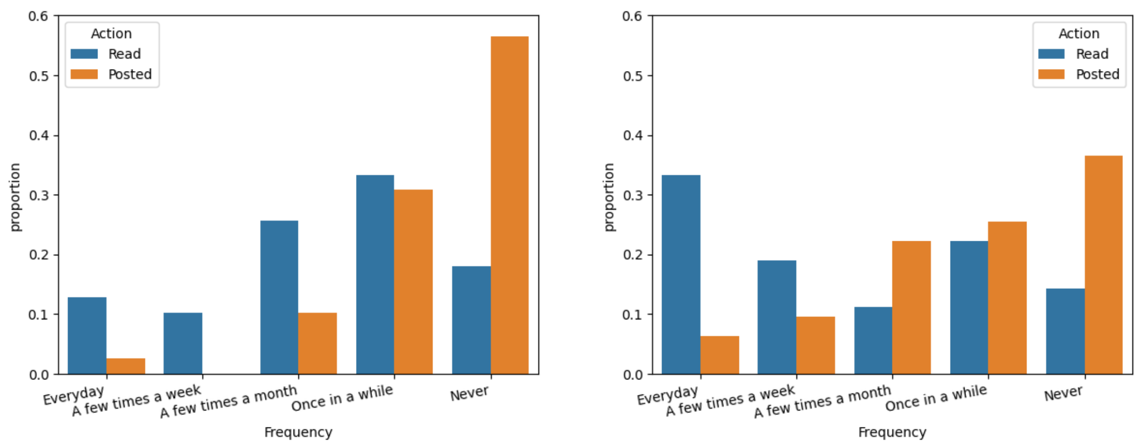


Fig. 4. Boxplots of survey responses for questions: Overall, within the [anonymous company] community, how well are you able to access and find information needed for your generative AI projects or to learn necessary concepts to work with generative AI? and Overall, within the [anonymous company] community, how well are you able to find experts or like-minded people to collaborate with or learn from about generative AI?



(a) Proportion of EGP users who read and/or posted in EGP slack channels.

(b) Proportion of participants who read and/or posted in internal generative AI focused slack channels.

Fig. 5. Proportions of participants who read or posted in Slack channels around EGP (a) and generative AI (b)

generative AI Slack channels, github, or hackathons. Our survey results provide further insight into internal company Slack participation around GenAI for the EGP-specific channel and other GenAI-focused channels. However, they also talked about information overload and the speed of information being challenging. Some also talked about reasons for not participating, like a concern about too many repeated questions in Slack channels.

Our survey captured frequency of reading and posting in EGP and non-EGP slack channels as a way to understand participation in these community spaces around GenAI. Participants often read and participated in non-EGP GenAI slack channels, with 33.33% reading one of these everyday and 19.05% a few times a week. While most did not post daily, nearly two thirds of participants did report participating in these channels at least once in a while (6.35% everyday, 9.52% a few times a week, 22.22% a few times a month, and 25.40% once in a while). Figure 5b shows the proportion of participants who read and posted to non-EGP company generative AI slack channels. For the EGP slack channel, only 12.82% of EGP users read the channel every day and 10.26% read it a few times a week. EGP users posted in the EGP Slack channels even less, with only 2.56% posting everyday and 56.41% never having posted. Approximately a third of participants reporting reading or posting in the channel once in a while. Figure 5a shows the proportion of EGP users who read or posted in the EGP slack channel.

Interview participants talked about the benefits and challenges of slack channels, github, and hackathons for learning. P9 expressed how important community is for learning about GenAI: "I think the GenAI community is the key, like sharing experiences, but through slack channels, through blogs, whatever is there would be the key." P4 said: "But like, that's how I approach any platform. I would want detailed [...] a community around it that you could talk to other users and ask questions. So Slack was invaluable with that. Just to kind of try to find other users with the same error, the same issue as me." Similarly, P2 said"we found that [using the EGP slack channel] was a a good way to get questions answered and get feedback on some of the things we were struggling with." Some participants, such as P9, talked about how this support was especially important in the beginning, when the platform and GenAI was very new.: "At the start, when we started using them, it was a great place to get the information, like if there was, you know some error showing up or something not working going in and seeing if the information is there. That was really helpful at the very start to be very honest" -P9. Participants also talked about GitHub as a larger-scale community resource. For example, P4 used it to search for code that might help them figure out an issue: "My main source, and that's why I mentioned it after was the GitHub because [anonymized] if you're searching for a little piece of code, put those quotation marks and you know you see 3 results from three other users that they're the only ones in [anonymized] that are working on this type of issue and they have the code that you need."

A third larger community learning effort was company-wide hackathons, established to familiarize employees with GenAI. Hackathons were powered by EGP, highlighting its role in the community learning effort. P9 said: "the real learning started during the hackathon last year when you know we didn't know what we were supposed to do. So start learning about GenAI, the possible use cases and [...] the use cases that we can work on for our product." Hackathons support learning through exposure to technologies and engage the larger company community to explore ways to solve problems with GenAI.

Our survey question about sharing and requesting help around particular resources showed that sharing and especially requesting information from the broader company community were overall the least frequent actions (see Figure 6). Some, like P5, talked about making connections through slack and supporting others, this was relatively rare: "I've got friends I've met through slack, people who have messaged me for help with their projects because I post about autogen."

Interviewees also talked about *reasons for not participating* or challenges around using Slack for learning. Some people involved in GenAI development are likely more consumers of information rather than those who would share, such as P10: "With my job role, I don't expect I don't really go there to share a knowledge that was discovered. I kind of assume other folks know that by now." P1 mentioned a lack of time as well as a large amount of channels as reasons for not participating: "Ah, no, to be honest, I haven't done it [participate in EGP channels]. I have a lot of channels." This is related to information overload, which can also make Slack a difficult medium for learning with a topic as large and complex as GenAI. P3 raised the issue of relevancy and that it's hard to find or filter the relevant information when

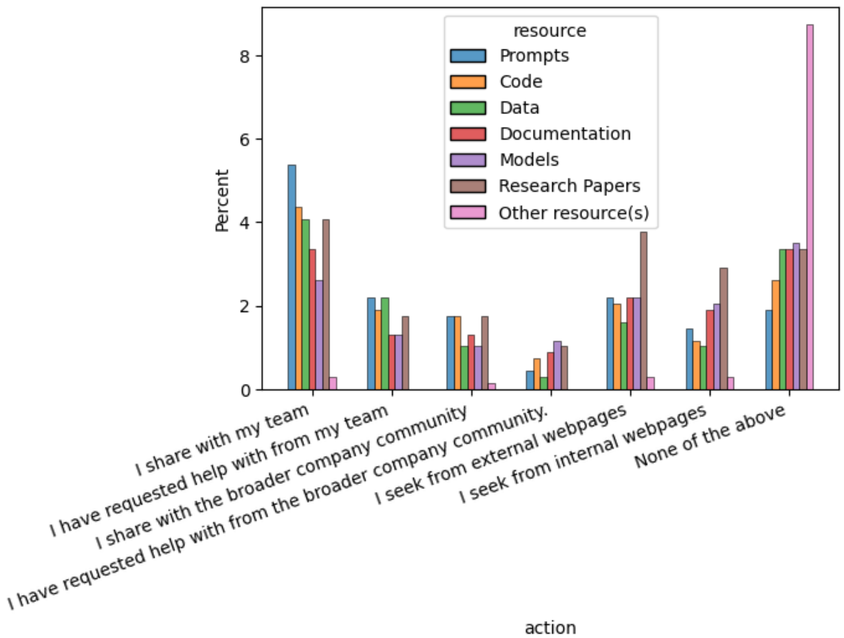


Fig. 6. Histogram with percentages of participants who performed each type of action for the set of resources around generative.

there is so much: "So try and keep up to date with those types of Slack channels across the board is, there's just too many resources to actually plug into and keep up to date with […] Not everything is relevant." Beyond there being too much information, P4 raised the issue that it is not necessarily well organized and ends up spread across many channels: "I think there is a lot. I think the problem is it's spread out into so many channels. So you have to be a member of, you know, 50 channels to be able to get the most information possible or most helpful information." This is likely exacerbated by difficulty searching for information on Slack, as P7 said: "So a lot of the things that people keep asking is already there in slack, right? But the slack search is awful." P9 suggested that categorizing or tagging information would make it a lot easier to find and use, such as " Prompting for summarization for classification for like generation."

4.2.2 Learning in Smaller Communities. The collaborative practices for learning mentioned by participants include forming small communities, such as teams or reading groups, where individuals share knowledge through discussions and resources. P10 highlights the importance to build this culture of collaboration in small teams: "People use small groups like their team, reading groups, or expert connections to learn about generative AI." Other participants also mentioned the importance of social network tools, such as Slack, to foster learning in their teams, like P9 and P7. "So it's a combination of slack like we have a specific calling it, [anonymized] slack channel within the team. So anything around that prompting we did that. We shared it there and plus we had meetings at the start when […] we're doing the prompt engineering work […] we would share our experiences"-P9. For P7, utilizing platforms like Slack for real-time communication allows team members to exchange information quickly and share resources: "Whenever any of us come through a good paper, a good data set, a good evaluation benchmark and so on, that gets posted into the write a channel too.[….] At least like if they are working with me on the same project then I will share the particular repo that we are using to fine tune how we are doing the evaluation [....] Slack is faster, right? Because you don't have to wait, right? And you know that when you text someone, they will see it"-P7. The same participant, P7, also shares the importance of regular communication with structured weekly meetings in collaborative learning environments: "We also have like weekly meetings for the entire [...] different groups that are working on this thing. This is where we share our progress and what we are going to look at next." These smaller communities subvert some issues around information overload, as these smaller groups are often focused on a particular topic or goal, leading participants to filter the information they share in these spaces.

Additionally, people help others learn by teaching and sharing relevant information, fostering a culture of collaboration and continuous improvement in skills related to generative AI. In terms of resources, survey participants reported more sharing than requesting help, especially within their team (see Figure 6). When sharing with their team, they reported sharing prompts the most often and sharing models the least often. For example, P1 said: "So basically we developed the prompt like a string and then we share the string OK because we are using the Jupyter notebook to make the development, we are not sharing the [tool UI]." P2 also talked about discussing prompts and parameters at meetings when team members are having trouble: "So anytime someone struggling with something like, you know you mentioned a prompt or tuning parameters, that sort of thing, you know, we'll usually discuss it either in our scrum or on slack." P7 talked about sharing artifacts like data and evaluation benchmarks, and along with P8, articles. P4 talked about teaching others as a way of improving their own learning: "teaching is the best way to learn. That's really the way that I've been able to kind of quickly acquire a lot of information and be able to talk about it confidently. You know, teaching your coworkers that you're really close with that"-P4.

Some interviewees also talked about challenges in supporting others in smaller communities. P1 talked about the need to share not just a prompt but also the parameters: "when you're using a a specific Generative AI model, maybe you have a given set of parameters. OK. And then the other guy is using your this your same prompt, your same model but a different set of parameters, but you haven't shared that information between you and so then you have different results and so the guys say like, what, to me [it] is not working." The newness of GenAI and the specificity of techniques for different use cases may have also impacted experts' ability to give advice. "So I discussed it with a few experts. [...] So I got feedback and sometimes the feedback were opposite. So some people told me, some experts told me to do long prompts to very to constrain the model and some some experts told me to do very short form, so I tried both"-P8.

4.2.3 Individual learning. Participants also sought information from external and internal content. This includes learning from sources like formal education, online courses, videos, blogs, and research papers. This individual learning is an important piece, as it is needed to enable sharing the information found within smaller and larger communities. For example, P8 said: "there's a lot of good resources on the Internet to understand LLM. I mean, I'm not up to date because I do not have to train people at this level, but there was some, I think there was the original transformer code. [...] There's a lot of visualization tools online to understand how LLM works. [...] I think some there are some very good YouTube videos on it which go at length explaining how it works and why it works [...] and then I think it's just coding trying and things like that."

Participants talked about ways of filtering the information to reduce information overload, like subscribing to particular sources of information, but that the speed of change can still lead to challenges in keeping up with all of the new information. The most commonly mentioned challenge in learning generative AI was the speed of change. P5 said that "They are constantly evolving underneath me." and P8 said that "it's hard to keep up to date because there's a lot of new things every week." P7 said that "the result that you have today may not hold till tomorrow" and that he is "barely catching up."

While these individual learning resources can be helpful, interviewees, such as P8, talked about needing to do this in combination with getting support: "I read a research article directly or and they I think they use. There's a lot of good videos on the subjects. [...] However, the hardest part was to understand how to make good prompts, which is very important for my work, for instance knowing how to do automate good prompts. For that I consulted with experts on the field, so I asked people to teach me."

An important component of individual learning is also trying out and experimenting with new technology. P6 said: "everything is experimenting, you know, in other words, like curiosity. So, you know, first start off with like chatGPT access some, you know silly questions and stuff like that. And then once you start going through, you know, the various generation and whatnot, regardless of just answering a question or even generating code." P9 also talked about a "prompt engineering boot camp" that helped them learn prompting techniques.

Overall, participants seemed to participate the most in smaller communities like their teams in order to focus on the aspects of GenAI most relevant to their work. Due to the speed of change and amount of information, they also leverage broader communities and external information to try to keep up, despite difficulties in finding the most relevant information.

4.3 How has EGP supported generative AI work and learning practices and what challenges remain?

The EGP platform was helpful in learning and experimenting with different models and prompts without needing to set up a lot of infrastructure. This improved the speed of their learning and experimentation process. The open access to the tool across the company also enabled team members across roles to experiment and learn, while also reducing the need to worry about resource constraints. Yet, participants also discussed limitations and challenges when using EGP.

4.3.1 Experimentation. Many interviewees talked about the importance of EGP for experimentation. This ranged from experimentation being "a lot easier" (P3) to not being able to prototype "at all" (P10). P10 described their use of EGP as: "we work with EGP to see what's possible" -P10. EGP was also "critical to get prototype up and running quickly to be able to showcase it to the rest of my team to talk about, to go over the architecture, to show the code, to show it all working correctly, and just to try to be able to" -P4. This ability to experiment and prototype in the EGP tool reduced risk and restriction: "Kind of get hands on GenAI world, you know, without risking any of our stuff like you know, otherwise what other our options would have been to do? ChatGPT or any of that which was not ideal" -P9. It was also very important for those new to prompting who may need to try many things to get what they need: "initially in order to get a good prompt, we were lot of us were testing on EGP UI" - P9. An important part of this experimentation was the ability to try out a variety of models. P3 said: "EGP has been really good at showing how we do compared to the competitors" and P4 said that EGP was valuable because it enabled "trying out different ones [models], seeing if a question works or is more accurate with a different model and being able the ability to quickly switch them out." This ability to switch between models improved speed: "It's also very easy to switch from one model to another, which will be way harder if I had to do it myself every time" -P8. Further, EGP supported internal test models, enabling research teams to get feedback and product teams to try out state of the art models that were soon to be available more publicly (P7).

4.3.2 Access. A level of access and lack of restriction was critical to support experimentation in EGP. There were several ways this access manifested: a lack of need to focus on the amount of tokens, ability to use the tool with real data, and universal access across job roles. Compared to PGP or other external tools, EGP had fewer resource restrictions. P6 said: "EGP, definitely I use more because like I mentioned earlier, I will surpass my my month subscription if I was using the ... PGP." This lack of restriction enabled users to test "rather than invest" (P9). Since GenAI is so new and non-deterministic, this ability to test and try out models was critical: "the development lifecycle, like what we kind of did in the last 8-9 months, it would have been more than that because the [...] other developers on the team, everyone had access to EGP, everyone was, you know, testing either using the API or the UI [...] It [PGP] was more difficult and it's restricted " -P9. Due to risks of using external tools, EGP was also important in enabling users to "test the model and with real data and see how it works" -P1.

4.3.3 Tool limitations and needs. Yet, EGP did have some limitations and did not address all challenges with generative AI tooling. For example, EGP reduced users' control over the environment, in terms of which models were available and how they could interact with those models. P8 said: "the model are not always the one [I] like to use for my for my comparison" and P6 said "with PGP is you have better control of how do you want to just say fine tune like your your model." We found several other challenges in tooling for generative AI, such as tool disconnection and tool abundance. For example, as an exploratory tool, EGP did not necessarily connect with the other generative AI tools, making it difficult to test models in more complex systems. P8 said: "sometimes I feel Generative AI tools are disconnected between each other." P4 specified: "some integration with LangChain or like another framework to be able to kind of accomplish a use case would have been really helpful." Due to the speed of change in generative AI, there are many tools and methods appearing that it would be helpful to test or try to integrate, but that is particularly difficult if they don't connect well together. P3 noted that "new tools come out all the time," while P4 found that tool deprecation or large code changes can be challenging: "I think since February since we started the project, I think like two or three of the tools that we've looked into or worked with have either been depreciated or upgraded and the code bases have changed." Thus, while EGP supported experimentation and access, the experimental nature of it potentially made it most useful for learning and initial testing than extensive building or experimentation.

5 Discussion

Work in organizations includes solitary aspects and collaborative aspects, as well as experimental aspects that may span those two categories. Here, we review what we learned in each aspect of LLM-informed work.

5.1 Identity, Diversity, Roles

As reviewed in Related Work (Section 2.2.1), research on collaborative work has emphasized diverse identities [81, 109] and identity construction [44], while members navigate changing collaborative relationships [109] and communities of practice [11, 45]. In Section 4.1, we reviewed many diverse job-roles in Figure 2. Beyond job-roles, our sample was diverse due to:

- **Roles and backgrounds** - Participants came from a wide range of roles such as ML/AI engineers, researchers, subject matter experts, architects, consultants, sales, finance, design, and project management.
- **Geographical Diversity** - Americas, Europe, Middle East, Africa, and Asia-Pacific.
- **Levels of expertise with generative AI** - Participants had different lengths of experience with generative AI, ranging from less than a year to over two years. People involved in generative AI development in the Research Division usually shared more information than the others.

- **Responsibilities in the organization** - In some cases participants with roles not connected to coding/development, like managers, were more consumers of information rather than sharers - i.e., managerial lurkers (see Section 5.4 for a discussion of lurkers and lurking).

We also found diverse types of collaboration, as shown in Figure 3, similar to previous findings [41, 71, 75, 81, 90, 99, 108, 109]. Aside from team-oriented structured collaboration, much of what we observed was improvised using collaboration tools that were not designed for generative AI, or for any type of AI, as content domain (see Section 2.3, [95]). As described in Section 2.1, scaffolded learning was primarily social in nature, rather than technological. We anticipate that tooling for generative AI will develop swiftly into more activity-centric and artifact-centric "soft structures" based on content, context, and clients' needs (soft structures may be thought of as initial ways of organizing work that are malleable by end-users to meet their specific needs).

5.1.1 Design Recommendations. Because individuals and teams are still learning about the diverse types of expertise that may be needed, we propose that it may be useful to indicate each person's role, or role-history, if those attributes can be extracted from structured discussions, for example, in github or scrums. We also highlight that participants created new, informal roles as they learned about generative AI. As noted in Section 2.1, *bridging* between team-and-team, team-and-community, community-and-community, became an important and under-recognized role (for comparison, see studies of invisible work [92] and relation work [8]).

Because of the dynamic nature of generative AI work and teams, we propose that these roles, relationships, and collaborations should be studied again in one to two years.

5.2 Supporting Experimentation

5.2.1 Generative AI needs. Perhaps because of the lack of maturity in generative AI tools and practices, experimentation played a larger role than in machine learning [41, 71, 75, 81, 90, 99, 108, 109]. Participants described challenges to learning what LLMs can do, and how to invoke those capabilities in a reliable, re-usable way. There were limited means to see what others had done in EGP, or in associated communication applications such as github or Slack.

The major exception to the preceding statements were hackathons. Hackathons were used for active learning, including experimentation as a necessary aspect of hackathons [32, 67], as means for the social construction of prompts (see Section 2.2.2, [53, 84]). As described in Section 4.3, some hackathons were conducted in specified parts of the organization, and some hackathons were company-wide. Hackathons provided exposure to new technologies and engaged the larger company community in exploring ways to solve problems using generative AI. It helped to identify the possible use cases they can work on for future products. Participants noted that hackathons were an accelerator of skill-building, helping participants learn through hands-on experience and experimentation. EGP played a critical role in enabling those hackathons.

EGP provided access to both internal test models not publicly available and open source models hosted internally for approved and safe use, allowing research teams to get feedback and product teams to try state-of-the-art models early. Teams shared experiences, prompts, parameters, data, evaluation benchmarks, and code repositories during meetings and via Slack channels to collaboratively refine their approaches. Participants used EGP for hands-on experimentation with different models and prompts without needing extensive infrastructure setup. Once participants had gone through the learning curve, EGP enabled quick prototyping, testing various models, and iterating on prompts, which was especially important for those new to generative AI prompting. The platform's open access across roles allowed team members to experiment freely, reducing resource constraints and risks associated with external tools.

5.2.2 Design Recommendations. We propose that future support systems for teams or communities should have the following features or attributes:

- **Low barrier to entry**, with clear documentation that is written for novices and newcomers. There may be an opportunity for AI-based adaptive user interfaces that can adjust to each user's skill level.
- **Easily updated resources and documentation to those resources**, to accommodate rapid changes and iterations in infrastructure and tools. Models are frequently updated in EGP for technical reasons, and models may be added or removed from organizational access for commercial reasons.
- **Strong integration with diverse collaboration tools**, including well-structured agile/scrums/kanbans for teams, and less-structured larger-scale discussion spaces (e.g., Slack) for broader communities.

5.3 Supporting Use-Case Focused Needs

5.3.1 Generative AI needs. Within the organization, numerous Slack channels have been established to discuss GenAI, a field that has been rapidly evolving and expanding, specifically in the early days in 2022. Due to its broad applicability, there are countless ways to utilize GenAI, making it challenging to keep up with the updates and developments. Participants have expressed concerns about information overload and the difficulty of identifying relevant topics in such a fast-paced environment. For a related discussion, see Section 5.4, below, on "scatter and flood."

Company-wide Slack channels can often feel overwhelming because of the sheer volume of information and the multitude of channels to monitor. These large spaces may lack the focus needed to effectively support the specific needs of particular projects, use-cases. In contrast, smaller teams have been found to be more focused and manageable, enabling them to filter relevant information and foster collaboration effectively.

However, it is important to note that small teams may miss out on insights from individuals with greater expertise usually present in large communities. Additionally, they risk duplicating efforts, as different groups may end up re-discovering or re-learning the same information independently. Therefore, striking a balance between these information resources is essential, depending on the type of learning individuals seek.

5.3.2 Design Recommendations. Participants taught us about their diverse needs and diverse usages of EGP and PGP. We suggest that systems to support teams and communities should provide both robust structuring features *and* the ability to change those structures (i.e., structures as templates, rather than as requirements). We have learned from usage of EGP and PGP that there may be diverse roles in both teams and communities. Perhaps those roles should be included in the templates.

As the organization moves toward client-centered work with PGP, there may be needs to limit access (even read-only access) to protect client-confidential information in the resources for certain teams. We have written "for certain teams," but we realize that there may be confidentiality requirements for communities as well, that we have not imagined. It seems likely that our expectations will be incorrect, which suggests a further requirement for flexibility in how teams and communities can adopt and adapt templates or other structures to organize, publicize, and protect generative AI work-spaces in PGP.

5.4 Supporting Collaborative Work Practices

Participants reported that it was moderately easy for them to find people to help them. As detailed in Section 4.2.1, sometimes participants posted explicit questions. In other cases, participants read from shared resources (github, slack, scrum, reading groups) without posting - i.e., a form of non-public participation which is known to have indirect benefits to teams and communities [30, 48, 62, 66, 96].

Section 4.2.1 helped us to identify another set of weaknesses of contemporary collaborative generative AI tools. One weakness was that it was difficult to scope the request for assistance. EGP did not have well-defined information boundaries to manage searches, inquiries, or their results. It was possible to receive a flood of potential messages and experiments, with little assistance in sorting through that flood. A second weakness occurred because relevant information was scattered across multiple repositories and multiple *types* of repositories (github, slack), with medium-specific search protocols and usages. This problem tended to be exacerbated when searching many smaller communities (Section 4.2.2). Scott et al. [89] discussed problems of scatter and flood that preceded generative AI.

5.4.1 Design Recommendations. As generative AI moves from research into product, we propose that the problems of scatter and flood [89] be addressed from a work-oriented perspective. Study of individuals' and teams' actual work should be used to guide tool development to resolve scatter and flood.

Looking forward to client-oriented generative development, we ironically anticipate a need for *greater* scatter, because some clients' work will require security to prevent the leakage of confidential information from one client's project to another. PGP has already begun to reinforce project boundaries. Because of these limitations, a community-centric approach to generative AI would benefit from having clearly-differentiated channels and repositories by client (as above), but also by type of communication. With good tooling, a developer should be able to discuss, for example, insights for prompt engineering in a shared channel while isolating the content of the prompts inside a client-specific channel.

5.5 Limitations

The organization in which we worked supports employees in multiple countries (Section 5.1). We hope that our work and recommandations reflect participants' identities and cultures. Nonetheless, our work was contained within a single global company. Experiences with other organizational cultures may be different.

We also highlight the dynamic nature of generative AI in general, the powerful competitions that are taking place among model-builders, and the resulting sociotechnical interplay between researchers, developers, and end-users (e.g, [6, 43, 69, 86]) - including cases in which those role-boundaries prove porous. It seems likely that our participants would be different next year, and their reports of experiences may be different in a year's time, too.

6 Conclusion

In this paper, we investigated the dynamic and collaborative nature of generative AI work within a large multinational technology company in which employees used a collection of collaboration tools and an experimental environment for generative AI, Experimental GenAI Platform (EGP). We identified that collaboration is most intense during project definition, prompt engineering, and manual evaluation phases. Learning usually occurs at multiple levels: individual self-study, small team communities, and broader organizational communities, often mediated by tools like Slack and hackathons.

Challenges include information overload, rapid technological change, tool fragmentation, and difficulty finding relevant expertise or resources. EGP was a critical tool for enabling experimentation, prototyping, and reducing resource constraints during a time requiring rapid learning and enablement of a workforce to stay competitive in an emerging

GenAI market. At the same time, it had limitations such as restricted model control and lack of integration with other tools.

Our paper offers design recommendations emphasizing flexible, role-aware collaborative tools, improved documentation, adaptive interfaces, and better information scatter and flood management. It highlights the evolving nature of generative AI work, the importance of diverse roles and identities, and the need for ongoing research as these practices mature.

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A Survey Questions

Table 1. Survey questions, question types, and options

Question	**Question type**	**Options**
How have you used generative AI? (select all that apply)	Multiple choice	At [anonymized]: I have been involved in an [anonymized] Research project using generative AI At [anonymized]: I have been involved in a client-facing project/product using generative AI At [anonymized] : I have been involved in an internal [anonymized] project/product using generative AI At [anonymized] : Just experimenting or to make my own work more productive (i.e. generating text to use in an email) –> did not advance through survey Outside of [anonymized] : Just experimenting or for my personal life –> did not advance through survey
What is your primary job category?	Single choice	Architect, Communications, Consultant, Data Science, Design, Enterprise Operations, Finance, General Management, Hardware Development & Support, Human Resources, Information Technology & Services, Legal, Manufacturing, Marketing & Communications Offering Management, Other, Product Services, Project Executive, Project Management, Research, Sales, Services Solutions Management, Site Reliability Engineer, Software Development & Support, Supply Chain, Technical Services, Technical Specialist, Other
What group do you report into?	Single choice	[anonymized]
What geography are you located in?	Single choice	Americas, APAC (Asia Pacific), EMEA (Europe, the Middle East, and Africa), Japan

Approximately how long have you been working with generative AI?	Single choice	Less than 6 months, 6 months - 1 year, 1 year - 2 years, More than 2 years
Which roles do you fulfill in your machine learning/AI work? Select up to three roles.	Multiple choice (drag to Primary or Secondary)	Data Scientist, Data Engineer, ML/AI engineer/architect, App developer, Subject Matter Expert, Researcher Designer, Project Manager, Product Manager, Program Manager, Business User/ End-user, Risk/Security Officer, Compliance Manger, Quality/Evaluation Engineer, Other
Choose the AI development life cycle activities you have been involved with in your generative AI work. (select all that apply)	Multiple choice	Project Definition, Data Acquisition, Data Processing, Pre-Training, Fine-Tuning, Prompt Engineering, Manual Evaluation, Quantitative Evaluation, Evaluation using an LLM, Deployment, Monitoring, Governance& Risk Management, Other
What risk dimensions do you assess or mitigate in your AI workflow? (select all that apply)	Multiple choice	Fairness (Data bias, Output bias, Decision Bias), Robustness (Data poisoning, extraction attack, prompt attack), Value alignment (hallucination, toxic output, unspecified advice), Data laws (data transfer, usage, acquisition), Privacy (PI data, data privacy rights, informed consent), Intellectual property(Data usage rights, confidential information), Transparency (provenance), Misuse (disinformation, non-consensual use, dangerous use), Harmful code generation, Explainability (unexplainable output, unreliable source, untraceable), Societal risks (job loss, human exploitation, impact on cultural diversity and environment, plagiarism), Other, None of the above
Which tools have you used in the last three months to support your generative AI work? (Drag to the groups and order by most used first)	Drag to Often, Sometimes, Once in a while, or Tested/Evaluated	EGP, PGP, [anonymized internal tools], External Tools, Other
Please describe one generative AI project you have worked on. What was the goal of the project? For example, "the goal was to enable users to ask code questions and receive suggested code."	Open ended	Open ended

Please select the types of generative AI tasks required in the project you described. (select all that apply)	Multiple choice	Question answering, Text Generation, Code Generation, Summarization, Classification, Extraction, Transformation, Other
Did the generative AI project you described involve.... (select all that apply)	Multiple choice	Chaining LLM calls, Calling tools, functions or APIs, An LLM deciding on a plan or set of steps to execute (agentic), Multiple Agents, Other complex generative AI patterns, None of these
Please select the domain of the project you described above.	Multiple choice	[anonymized]
How many collaborators are generally on your team for generative AI work?	Single choice	None, 1-3, 4-8, More than 8
How much do you collaborate with others in the following phases of generative AI work? (select all that apply) [Project Definition, Data Acquisition, Data Processing, Pre-training, Fine-tuning, Prompt Engineering, Manual evaluation, Quantitative Evaluation, Evaluation using an LLM, Deployment, Monitoring, Governance & Risk Management]	Matrix Table	I receive some support from others, I provide some support to others, I work extensively with others
Which generative AI resources do you share with or request from your team, the broader [anonymized] generative AI community, or external sources? (select all that apply) [Prompts, Code, Data, Documentation, Models, Research Papers, Other]	Matrix table	I share with my team, I have requested help with from my team, I share with the broader [anonymized] community, I have requested help with from the broader [anonymized] community, I seek from internal webpages, tools, or courses, I seek from external webpages, tools, or courses
Over the last few months, how much have you... [Read the EGP slack channel, Posted in the EGP slack channel, read other [anonymized] generative AI slack channels, posted in other [anonymized]	Matrix table	generative AI slack channels] Never, Once in a while, A few times a month, a few times a week, everyday

Overall, within the [anonymized] community, how well are you able to find experts or like-minded people to collaborate with or learn from about generative AI?	Single choice	N/A, Not well at all, Slightly well, Moderately well, Very well, Extremely well
Overall, within the [anonymized] community, how well are you able to access and find information needed for your generative AI projects or to learn necessary concepts to work with generative AI?	Single choice	N/A, Not well at all, Slightly well, Moderately well, Very well, Extremely well

B Code Book

Table 2. Themes, sub-themes, codes, prompt codes, and descriptions

Theme	Sub-theme	Code	Prompt Code	Description
Practices	Generative AI	Changes from traditional AI	Generative AI practices related to changes from traditional AI	Work practices have changed for generative AI from previous practices with traditional AI
Practices	Generative AI	Everyday work	Generative AI practices related to everyday work	Participants describe their job roles, tasks to be done, and projects
Challenges	Generative AI	Challenges with Generative AI models	Generative AI challenges related to generative AI models	Includes challenges like hallucinations, risks, security, evaluating AI models.
Challenges	Challenges with tools	Model accessibility	Challenges with tools related to model accessibility	There is a need for access to new models quickly and many different models. Some systems are limited in the models that are available.

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Theme	**Sub-theme**	**Code**	**Prompt Code**	**Description**
Challenges	Challenges with tools	Missing infrastructure	Challenges with tools related to missing infrastructure	Necessary or useful infrastructure for generative AI tasks is often missing.
Challenges	Challenges with tools	Tool Disconnection	Challenges with tools related to tool disconnection	There is a need to integrate or connect multiple tools, which is not always available.
Challenges	Challenges with tools	Tool Abundance	Challenges with tools related to tool abundance	There are many different tools being released often, leading to issues like lack of standardization and questions of tool longevity.
Challenges	Challenges with tools	Restrictions	Challenges with tools related to availability of tools	Not all tools and resources are available across team and organization boundaries.
Challenges	Challenges with tools	Other	Challenges with tools in general	Challenges with tools that are not one of the other challenges with tool types.
PGP	PGP as a tool	PGP supports speed	PGP as a tool supporting speed of development	Using PGP enables speed by reducing barriers.
PGP	PGP as a tool	PGP supports experimentation	PGP as a tool supporting experimentation	Using PGP enables experimentation due to lack of restrictions.
PGP	PGP as a tool	PGP supports models	PGP as a tool supporting model use and testing	PGP enables use and testing of a variety of models, including large models and internal models that aren't necessarily available otherwise.
PGP	PGP as a tool	PGP limitations	PGP as a tool related to usage limitations and challenges	Challenges or drawbacks to using PGP for generative AI development work
PGP	PGP as a tool	Other	PGP as a tool in general	Discussion of PGP as a tool that is not covered in one of the other PGP as a tool categories

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Theme	Sub-theme	Code	Prompt Code	Description
Practices	Tool practices	Slack for models	Tool practices related slack for model discussions	Slack can be helpful for discussion of particular models
Practices	Tool practices	Build own tools	Tool practices related to building your own tools	Need for people to build their own tools to fill in the gaps where needed tooling is missing.
Practices	Tool practices	Choosing tools	Tool practices related to choosing tools	People have a variety of reasons for selecting particular tools to work with, such as security, partnerships, community, or availability.
Practices	Tool practices	Other	Tool practices in general	Discussion of tool practices that are not covered by one of the other tool practice categories.
Challenges	Challenges in learning	Need to upskill	Challenges in learning related to the need to upskill	In order to work with generative AI, people need to learn new skills beyond just generative AI fundamentals.
Challenges	Challenges in learning	Speed of change	Challenges in learning related to the speed of change	Generative AI is changing so fast that it is hard to keep up with all of the new information.
Challenges	Challenges in learning	Information overload	Challenges in learning related to information overload	The amount of information and content around generative AI is large, making it hard to find relevant and important information.
Challenges	Challenges in learning	Documentation needed	Challenge in learning related to missing or incomplete information	Missing or incomplete documentation makes it difficult for early adopters. Also includes a need for more examples.
Challenges	Challenges in learning	Reasons for not participating	Challenges in learning related to reasons for not participating	People have a variety of reasons for not participating in broader learning communities, like a risk that their reputation will be impacted if they ask questions or lack of time.

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Table 2 – continued from previous page

Theme	Sub-theme	Code	Prompt Code	Description
Challenges	Challenges in learning	Other	Challenges in learning in general	Challenges in learning about generative AI that are not covered by the other categories of challenges in learning.
PGP	PGP for learning	Expands accessibility	PGP for learning related to expanded accessibility	PGP helps people experiment without them needing to do a lot of infrastructure setup.
PGP	PGP for learning	Documentation helpful	PGP for learning related to helpful documentation	PGP's documentation was helpful in getting started and using PGP.
PGP	PGP for learning	Other	PGP for learning in general	Discussion of using PGP for learning that does not fit into one of the other PGP for learning categories.
Practices	Learning practices	Individual learning	Learning practices related to individual learning	People use a lot of individual learning strategies, such as coding, reading internal and external content, or formal education.
Practices	Learning practices	Learning in small communities	Learning practices related to learning in small communities	People use small groups like their team, reading groups, or expert connections to learn about generative AI.
Practices	Learning practices	Sharing to help in learning	Learning practices related to sharing to help in learning	People help others learn generative AI through methods like teaching and sharing relevant information.
Practices	Learning practices	Learning from the broader community	Learning practices related to learning from the broader community	People use the broader community for learning, such as hackathons, company-wide slack channels, and Github projects.
Practices	Learning practices	Other	Learning practices in general	Discussion of learning practices that do not fit into one of the other learning practices categories.

C Prompt for AI-Assisted Coding

```
<|begin_of_text|><|start_header_id|>user<|end_header_id|>
You are an experienced user researcher and you are very familiar with analyzing interview data.
```

```
Your task is to assign THEMES from the list of 32 THEMES below to the interview STATEMENT following my INSTRUCTIONS below.
Each THEME has a name and a decription that you need to use to determine if it is a good topical match.

## THEMES
{codes from book including descriptions}

## STATEMENT
{chunk}


## INSTRUCTIONS
- Please look at the STATEMENT and select between 0 and 3 THEMES that are a good topical match and can be used
to categorize the statement.
- When matching, consider the name of the THEME as well as the description and be strict with the topical alignment.
- DO not assign the same theme twice to the statement.
- Use the exact same Code names from each theme when creating your response.
- Do not include any introductory text or explanations - output only the list of codes of the assigned theme as
described under Output Format and an empty list if no match is found.

## Output Format
Return a valid Python list containing the names of the assigned themes, e.g.:
["Code1", "Code2", "Code3"]

If no match is found, return:
[]

RESPONSE:
<|eot_id|><|start_header_id|>assistant<|end_header_id|>
"""
```