Prompts Are Programs Too! Understanding How Developers Build Software Containing Prompts

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The introduction of generative pre-trained models, like GPT-4, has introduced a phenomenon known as prompt engineering, whereby model users repeatedly write and revise prompts while trying to achieve a task. Using these AI models for intelligent features in software applications require using APIs that are controlled through developer-written prompts. These prompts have powered AI experiences in popular software products, potentially reaching millions of users. Despite the growing impact of prompt-powered software, little is known about its development process and its relationship to programming. In this work, we argue that some forms of prompts are programs, and that the development of prompts is a distinct phenomenon in programming. We refer to this phenomenon as *prompt programming*. To this end, we develop an understanding of prompt programming using Straussian grounded theory through interviews with 20 developers engaged in prompt development across a variety of contexts, models, domains, and prompt complexities.

Through this study, we contribute 14 observations about prompt programming. For example, rather than building mental models of code, prompt programmers develop mental models of the FM's behavior on the prompt and its unique qualities by interacting with the model. While prior research has shown that experts have well-formed mental models, we find that prompt programmers who have developed dozens of prompts, each with many iterations, still struggle to develop reliable mental models. This contributes to a rapid and unsystematic development process. Taken together, our observations indicate that prompt programming is significantly different from traditional software development, motivating the creation of tools to support prompt programming. Our findings have implications for software engineering practitioners, educators, and researchers.

CCS Concepts: • Software and its engineering \rightarrow Software development methods; • Human-centered computing \rightarrow Empirical studies in HCI; • Computing methodologies \rightarrow Artificial intelligence.

Additional Key Words and Phrases: Prompt engineering, Straussian grounded theory methodology

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1 Introduction

"I suspect that machines to be programmed in our native tongues—be it Dutch, English, American, French, German, or Swahili—are as damned difficult to make as they would be to use."
—Edsger Dijkstra, 1979

The introduction of generative pre-trained models (e.g., GPT-4 [9], Dall-E [16])—also known as foundation models (FMs)—have drastically changed how software is built by developers. AI programming assistants that generate code (e.g., GitHub Copilot [21]) have aided developers across a variety of tasks such as writing significant portions of code, learning new APIs and programming languages, writing tests [47], and information seeking behaviors [33] thereby improving the productivity of programmers [61, 83, 84]. Recently, instruction-tuned [57] large language models (LLMs), such as ChatGPT [2], have assisted developers with a broader range of software development-related tasks via writing natural language prompts. This includes resolving code issues, developing new features, refactoring, and writing configuration files [19].

The rising prominence of prompts has ushered in a new phenomenon known as prompt engineering, whereby model users repeatedly write and revise natural language prompts to achieve a task. These prompts enable more intelligent features when integrated in popular code-based software applications [58], such as Google Search [4] and Microsoft Office [3], reaching potentially millions of users [1]. As of January 2024, engineered prompts have also underpinned the creation of over 3 million custom versions of ChatGPT for a specific task, known as GPTs [5].

Despite the budding impact of prompt-powered software, little is known about the prompt engineering process and its relationship to programming. To the best of our knowledge, two such studies in software engineering currently exist. One is Dolata et al. [27]'s study of 52 freelance developers on the challenges of developing solutions based on generative AI. Their interview focuses on the positive and negative experiences with generative AI, project uncertainties, and views on freelancing. The other is Parnin et al. [58]'s study of 12 professional software developers integrating generative AI into products. Their interview topics include the participant's motivation for using AI in the product, major tasks for building the generative AI application, prompt engineering, testing, tooling, challenges, learning related skills, and concerns with AI. While these studies offer interesting preliminary insights on prompt development, they are constrained to solely freelance and professional software development, limiting the generalizability of the results to other types of programming. Further, these studies do not place targeted focus on the process of developing prompts in relation to programming activities. We address the gaps in this literature by following a more systematic and rigorous qualitative methodology—known as Straussian grounded theory [23] and performing maximum variation sampling [69] to recruit a diverse sample of programmers with varying programming contexts, models, roles, application domains, and prompt complexities to understand the process of using prompts as part of creating software applications.

In this work, we argue that some forms of prompts are programs. We view the development of such prompts and other natural language-powered software as a distinct phenomenon in programming. We refer to it as *prompt programming*, following prior work [36]. We note that the concept of programming using natural language is not novel; in 1979, Edsger Dijkstra discussed a phenomenon where one could "instruct [a machine] in our native tongues" [25]. This vision has only recently been realized, with the advent of FMs providing the means for technical feasibility and widespread use of such programs.

We argue that prompt programming is a phenomenon that warrants its own study. Programming as a discipline is broad but highly nuanced—the sociotechnical circumstance of the programming task drastically influences the nature of the programming. For example, the programming process of end-users who write software for personal use (i.e., end-user programming [43]) is fundamentally

different from the programming process of data scientists who write software to explore different possibilities in code (i.e., exploratory programming [41, 66]). The programming task varies the developer's tools (e.g., visual programming languages vs. Jupyter notebooks), focus in process (e.g., accomplishing a goal vs. exploring ideas), and key challenges (e.g., finding the right abstractions vs. managing code versions) [41, 43]. This creates disparate development experiences and necessitates the development of support tools unique to each context. Therefore, better understanding the nature of prompt programs could better inform the development of tools and environments to support the developers engaged in this type of programming activity.

We develop an understanding of prompt programming with FMs by employing the Straussian grounded theory methodology [23]. This is a qualitative research methodology aimed at developing a novel exploratory explanation of a domain, referred to in such literature as a "theory". We interview a diverse set of 20 developers who are engaged in developing prompt-powered software.

Our investigation is guided by the question: *How do programmers develop programs that incorporate natural language prompts?* To answer this, we need to consider the definitions of a *prompt* and *program*. We define a *prompt* as the following:

A natural language query to a foundation model.

For the definition of a program, we consider Ko et al. [43]'s definition of a *program*, which is "a collection of specifications that may take variable inputs, and that can be executed (or interpreted) by a device with computational capabilities." We extend this definition to derive the following definition of a *prompt program*:

A prompt that accepts variable inputs and could be interpreted by a foundation model (FM) to perform specified actions and/or generate output. This prompt is executed within a software application or code by a FM.

This definition includes developing prompts for a range of applications like GPTs and chatbots. It also includes language agents, which are an emerging paradigm where LLMs have access to tools that they can use to complete complex tasks. This includes tools for mathematical reasoning [65] and code interpreters to execute generated code [29]. However, we note that our definition of prompt programming excludes cases where a developer converses with an FM once to achieve a task (e.g., working with ChatGPT to debug the current error message in the console), as these prompts do not accept variable inputs and are not executed within a software application or code.

Through our investigation, we contribute 14 main observations (see Figure 1). While some of our results corroborate the results from Dolata et al. [27]'s and Parnin et al. [58]'s studies (e.g., fault localization not being certain (#11)), our results differ in notable ways. First, we find prompt programmers develop mental models [67] of the FM's behavior on the prompt (#1) and its unique qualities (#4) by interacting with the model. While literature suggests that experts have well-formed mental models compared to novices [67], prompt programmers struggle to develop reliable mental models (#2) even after writing dozens of prompts, each with many iterations. This creates a rapid and unsystematic development process (#10). Additionally, we find that prompts can be composed and decomposed (#9) and that prompt programs' testing occurs at different scopes (#14). While these observations exhibit some similarities to software development, the stochastic nature of FMs significantly complicates this process (see Section 5). Taken together, our 14 observations indicate that prompt programming is significantly different from traditional software development, necessitating the creation of new tools and processes to support prompt programming. These findings have implications on software practitioners, academics, tool creators, and educators interested in the role of generative AI in software engineering.

Study Findings

- 1. Programmers develop a mental model about the FM's behavior on the prompt.
- 2. Programmers' mental models are not reliable.
- 3. Programmers use external knowledge sources and prior experience to develop their mental model.
- 4. Each FM has its own set of qualities and capabilities.
- 5. Minute details in the prompt matter.
- 6. Prompts are finicky and fragile.
- 7. Assumptions of the requirements must be explicitly stated.
- 8. Requirements can evolve as the capabilities of the FM are discovered.
- 9. Prompt programs can be composed and decomposed.
- 10. Prompt programming is rapid and unsystematic.
- 11. Fault localization is not certain.
- 12. Programmers need to find representative data for the task.
- 13. Evaluating prompt programs requires assessing qualitative constructs.
- 14. Testing occurs at different scopes.

Fig. 1. An overview of the study findings. See Section 4 and Section 5 for the full details.

2 Related Work

We discuss related work on prompt engineering (see Section 2.1 and human aspects of software engineering for AI (see Section 2.2). Due to the quickly evolving landscape of prompt development and FMs, our work is up-to-date as of September 2024.

2.1 Prompt Engineering

Prior work has conducted empirical studies of prompt engineering. Some works have focused on chatbot development with end users through prompts [80–82]. In a user study of 10 people who used a tool to create chatbots through prompts, Zamfirescu-Pereira et al. [82] identified several challenges of prompt development, including opportunistic prompt design approaches, a lack of systematic testing, and writing prompts that did not generalize. Jiang et al. [36] evaluated a prompt development tool on 11 users from diverse roles, including designers, content strategist, and front-end developers. Problems participants faced included the prompt easily breaking and fixating on examples as well as having difficulty evaluating large amounts of text.

Other work has investigated creating tools to facilitate prompting across a variety of contexts. This includes the creation of a prompt pattern catalogue to solve common problems encountered when conversing with a language model (LLM) [74], such as question refinement. A separate catalogue was created for software engineering tasks [75], such as specification disambiguation. Other tools include interfaces for prompting, such as PromptAid [54], PromptMaker [36], and PromptIDE [68]. These tools included separate views to view the dataset, iterate the prompt, track prompt performance, and search for prompts.

Perhaps most related to our study are studies that investigate prompt engineering in the context of software engineering. Dolata et al. [27] conducted a study with 52 freelance developers on their experience with developing prompt-powered software. The participants enumerated a number of challenges, including having difficulty identifying the source of incorrect responses, budget constraints, and unrealistic client expectations. Meanwhile, Parnin et al. [58] ran an interview study with 12 professional programmers who developed product copilots. They found that participants

followed a general process of exploration, implementation, evaluation, and productization. Noted challenges included the trial and error nature of prompt development and creating benchmarks.

This body of literature provides an initial understanding of the unique aspects of prompt programming. However, they are constrained to specific types of developers (i.e., end-users, professional programmers, and freelancers), limiting the generalizability of the results. Additionally, these studies do not specifically study the process of writing prompt programs with respect to software development activities. Our study builds upon these works by employing a more systematic and rigorous qualitative methodology, Straussian grounded theory [23], to study the process of writing prompt programs by intentionally sampling a broad range of prompt programmers along various axes, such as prompt complexity, programming context, and role.

2.2 Human Aspects of Software Engineering for Al

Numerous works have studied the human aspects of building ML-enabled systems. This domain offers some preliminary insights on the challenges of developing prompt programs with FMs. This form of software development also involves working with and wrangling non-deterministic, opaque neural models [31]. This is similar to prompt programming, as developers must also contend with nontransparent, stochastic FMs. Prior work describes the development of models as highly experimental [31, 55, 56, 71, 76]. Literature also stresses the importance of collecting high-quality data for the domain [12, 27, 31, 55, 56, 62] as well as the use of quantitative metrics, like accuracy, precision, and recall, to measure model performance [56, 71].

However, developing ML components introduces unique challenges for developers. Models can be difficult to debug due to its non-determinism [31]. Multiple sources have identified the issue of *training-serving skew*, when training data does not generalize to production data [55, 56, 71]. To reduce this gap, models are re-trained with new data over time [55]. Additionally, expertise across a variety domains, such as software engineering and data science, are distributed across roles [31, 56, 71]. In an interview study with 45 practitioners, Nahar et al. [56] found this could introduce collaboration challenges between different roles, such as unclear model requirements, handling evolving data, and inadequate datasets. Finally, several works note the lack of AI literacy can make requirements elicitation, communication, and collaboration with clients challenging [26, 56, 76].

This body of literature serves as a foundation for understanding prompt programming. We extend this body of work by comparing building ML-enabled systems to prompt programming and understanding what aspects of this prior literature applies to prompt programming.

3 Methodology

Since there is limited literature on how developers create prompt programs, we use a qualitative approach to develop our understanding by exploring the *process* of developing prompt-powered software. In particular, we use the grounded theory methodology, which allows qualitative researchers to develop a novel exploratory explanation (called a "theory") for a particular domain. There are three popular approaches in grounded theory: Glaserian/classical [32], Straussian [23], and constructivist [18] methodologies, which vary in their procedures and epistemology [22]. We present our results in Section 4 and Section 5.

Our approach is based on Straussian rounded theory [23], which involves defining a research question, developing theoretical sensitivity towards the phenomenon via a broad literature review, generating a theory through simultaneous data collection and analysis, and performing a focused literature review to contextualize the results [22, 23]. In this section, we first discuss our grounded theory process (Section 3.1). We then describe our participants (Section 3.2) and interview protocol (Section 3.3), and close with a discussion of the limitations to our method (Section 3.4).

3.1 Grounded Theory Process

Below, we describe our grounded theory process for the study. It contains five main stages: defining a research question, developing theoretical sensitivity, generating the grounded theory, triangulating with literature, and validating the theory. We describe this process in further detail below.

Defining a research question. Our grounded theory process began with defining a research question. We study the phenomenon where developers write a program using natural language, rather than pure code: How do programmers develop programs that are natural language prompts? Prompts can be used in a variety of contexts, such as interacting with ChatGPT in conversation [19], but are not programs. Thus, we apply the definition of a prompt program described in Section 1.

Developing theoretical sensitivity. Before the study, the researchers should develop an intuition of what is occurring in the data towards the phenomenon being studied, known as *theoretical* sensitivity [22]. This can be done through professional experience and literature reviews so the researcher can extract insights from the data; however, the researcher should not be constrained by prior knowledge while developing the theory [23].

We entered the study with some theoretical sensitivity since two authors are software engineering and AI researchers and have developed multiple prompt programs themselves. Thus, following prior work [53], we consider our background and adapt our literature review strategy to be a broad but lightweight review of prompting. The first author reviewed foundational prompting papers in machine learning venues [17, 73] and a notable survey paper on prompting techniques in natural language processing (NLP) [51]; in addition, that researcher reviewed two empirical studies on how people develop prompts [27, 82] from human-computer interaction (HCI) and software engineering venues. We used this literature review in combination with the authors' existing domain expertise to develop questions for the interview protocol (see Section 3.3).

Generating the grounded theory. We conducted 60-minute interviews with a diverse set of 20 developers who had developed prompt programs (see Table 1) over Zoom. Interviews were audio recorded and transcribed; recordings were deleted afterwards. Two authors were present for the first 6 interviews to become familiar with the data; the first author conducted the remaining interviews.

To develop the initial theory, three authors first independently performed line-by-line coding on the first two interviews in separate codebooks to become further sensitized to the data. Each code contained a description of the code as well as observations from the interviews. They then reconvened to merge the individual codebooks by identifying codes with similar concepts and merging them into a shared codebook. The remaining codes were then discussed and added or removed to the codebook based on unanimous vote. The first author then coded the next interview; two authors reviewed the codes for agreement. We identified five instances of disagreement. These disagreements were then discussed and resolved. Next, the three authors performed axial coding, grouping the emerging codes into preliminary categories upon unanimous vote.

For the remaining interviews, the authors individually open coded the interview transcripts, making note of any new codes that emerged in the shared codebook. Following the open coding, a memo for each interview was created to record notable parts of the interview to further refine the emerging theory. The authors met regularly to discuss the new codes and observations. New codes and observations were added to the shared codebook upon unanimous vote and the categories were further refined as more data was collected.

As the theory developed, we performed maximum variation sampling [69] to obtain a diverse set of participants that could challenge or extend the theory. We recruited participants through snowball sampling within the authors' social networks and in online open-source communities who met the definition of creating a prompt program (see Section 1). Participants were recruited based on

Table 1. An overview of the participants in the study. We report the participant's development context, number of years of programming experience, number of prompts written previously, prompt complexity, model type, application domain, and task. Model types can be open source (os) or closed source (cs) and can be a language model (LM) or a vision-language model (VLM).

ID	Context	Exp.	# Prompts	Complexity	Model	App Domain	Task
P1	Academia	16 yrs	30	Single prompt	OS LM	Security	Classification
P2	Personal project	10 yrs	40	Single prompt	CS LM	Productivity	Text summarization (chatbot)
P3	Academia	8 yrs	30	Single prompt	CS LM	Research analysis	Classification
P4	Big tech (R&D)	8 yrs	10	Single prompt	OS LM	Software testing	Code generation
P5	Academia	14 yrs	35	Single prompt	CS LM	Education	Generation
P6	Academia	10 yrs	3	Multi-prompt	CS LM	Software testing	Code generation
P7	Big tech (Eng)	10 yrs	4	Single prompt	CS LM	Education	Generation
P8	Academia	10 yrs	20	Agent	CS LM	Software testing	Code generation
P9	Academia	14 yrs	20	Multi-prompt	OS VLM	Visual Q&A	Retrieval, Q&A
P10	Big tech (Eng)	7 yrs	10	Multi-prompt	CS LM	Education	Text editing
P11	Big tech (R&D)	8 yrs	5	Agent	CS LM	Productivity	Data generation
P12	Big tech (Eng)	14 yrs	100+	Multi-prompt	CS LM	Productivity	Code summarization
P13	Big tech (Eng)	20 yrs	6	Multi-prompt	CS LM	Productivity	Code generation
P14	Big tech (Eng)	5 yrs	3	Single prompt	CS LM	Productivity	Code generation
P15	Big tech (Eng)	5 yrs	3	Single prompt	CS LM	Career	Q&A (chatbot)
P16	OSS	8 yrs	_	Agent	CS LM	Software dev.	End-to-end workflow
P17	Startup (R&D)	6 yrs	5	Single prompt	CS LM	Robotics	Code generation
P18	Startup (Eng), OSS	3.5 yrs	15	Agent	CS LM	Software testing	Test generation
P19	Startup (Eng)	3 yrs	5	Agent	CS LM	Research analysis	End-to-end workflow
P20	Freelance	9 yrs	1	Single prompt	CS LM	Literature	Q&A (chatbot)

the types of model used (e.g., open-source models vs. closed-source models, vision language models vs. language models), application domain (e.g., robotics, education, productivity), organization size (e.g., large technology company vs. startup), programming context (e.g., academia, industry, freelance, open-source software), role, and/or prompt complexities (e.g., a language agent that is able to use tools vs. single prompt vs. multi-prompt). We initially achieved theoretical saturation after interviewing 14 participants. We continued to recruit participants to ensure our observations held across a variety of situations, including in open-source software and startups. We stopped data collection after reaching 20 participants.

Triangulating with literature. While developing the theory on prompt programming, we triangulated our findings with prior literature. Since the relevant literature was not identifiable via keyword search, we follow prior work [56] in performing a focused literature review by forward and/or backward snowballing the set of 5 papers from the initial literature review. Relevant literature spanned several communities, including NLP, HCI, programming languages, software engineering, and machine learning. Of the 502 papers considered, we identified 33 as relevant. See the supplemental materials for this set of papers [13]. The first author applied codes from the emerging theory to the papers, making updates to the codes as necessary to further refine the theory.

Validating the grounded theory. To validate the theory, we assess the fit of the theory. Straussian rounded theory suggests validating the theory with professionals and study participants to see if they resonate with the findings [23]. To this end, we e-mailed the participants and an external

Interview Questions

- Did you experience any difficulties while using existing tools to develop a prompt?
- Did you refer to external information sources to develop the prompt? If so, which ones?
- Did you ever refer to a previous version of the prompt as you were developing a new version?
- Did you use any metrics or heuristics to determine when the prompt was successful?
- How did you identify what caused an incorrect output? Were you confident in your answer?
- Did your prompt change after deployment?

Fig. 2. A subset of the interview questions. Refer to the supplemental materials [13] for the full protocol.

researcher who studies prompt programming a summary of the theory as well as a draft of Section 4 and Table 1. We asked them to evaluate the correctness of the theory as well as any feedback for the theory based on their personal experiences. In total, 8 people responded to this inquiry. All respondents indicated general agreement with the findings, some with a few wording clarifications.

Additionally, to assess the coding reliability between authors, the first author randomly selected and open coded two interviews at the category level. The labels were then removed with the original highlighted text spans remaining intact. One author was assigned to each interview and applied the code categories to each highlighted text span. Based on this procedure, our inter-rater reliability was 0.89 and 0.81 based on Cohen's κ —both almost perfect agreements [45].

3.2 Participants

A summary of our participants is in Table 1. The inclusion criterion was developers who had created at least one prompt program before, according to the definition presented in Section 1. Our participants were men (N=17) and women (N=3) from a broad range of roles in technology, including Machine Learning Engineer, Senior Software Engineer, Ph.D. Student, and Principal Data and Applied Scientist. All participants had prior programming experience (median 8.5 years) and had written a prompt program before (median 10 programs). Participants also regularly used foundation models: 10 participants reported using them more than once daily, 5 participants reported using them once daily, and 5 participants reported using them weekly.

3.3 Interview Protocol

The interviews were 60 minutes long and were conducted over Zoom. The procedure was approved by our Institution's Review Board. Participants were compensated with a \$20 Amazon gift certificate.

To begin, the participant completed a demographic and background survey with questions such as gender, number of years of programming experience, and number of prompt programs developed. We follow best practices in reporting gender in HCI [64]. Then, the interviewer presented the participant with the definition of a prompt program and asked the participant to recall the most recent time they wrote a prompt program. If the participant had access to the prompt, they retrieved the prompt and any associated history with the prompt. The participant then provided a brief overview of the prompt. To re-familiarize the participant with their prompt and their process, the participant discussed the prompt's design choices (i.e., a decision made in how to implement the prompt). Next, they discussed the challenges they faced while developing the prompt. Finally, the participant discussed the overall process they used to develop the prompt.

To develop the interview protocol, we identified several themes to explore: data, requirements, design, implementation, evaluation, debugging, and deployment based on the broad literature review and the authors' prior experience developing prompt programs (see Section 3.1). We then

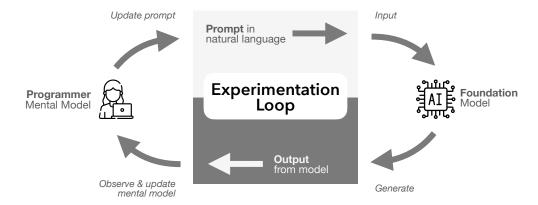


Fig. 3. A programmer uses their prior experience with the foundation model (FM) to construct a mental model of how the FM may perform on the task; they use this mental model to write the prompt. After observing how the model responds, the developer uses this new information to update their mental model, which influences the next iteration of the prompt.

generated questions focused on each theme in the interview protocol. The challenges were discussed before the process so it was not biased by the discussion about the prompting process. A sample of the interview questions are included in Figure 2; the full interview protocol and the demographic and background survey are included in the supplemental materials [13].

Following best practices in software engineering research [44], we piloted the interview protocol with three individuals who had developed prompt programs to clarify the wording of the survey and interview as well as validate our definition of prompt program.

3.4 Threats to Validity

Below, we discuss the threats to validity of this study.

Internal validity. Participants could have memory biases that could introduce errors in their recounting of their prompt design choices and development experience. To reduce this threat, we asked participants to recount their most recent prompt that met the definition of a prompt program. When possible, we asked participants to review their prompt to ground their answers. Further, the authors' own previous experiences with prompt development could also introduce confirmation biases of the developed theory. Overall, we reduced the limitations of this study by performing triangulation with prior literature and validating the theory with study participants and a professional who have engaged in prompt programming.

External validity. Using snowball sampling and recruiting within the authors' social networks may introduce sampling bias, so our sample may not be representative of all developers creating prompt programs. Additionally, self-selection bias could influence the results. Interviews were conducted in English and could cause less representation from non-native English speakers. Also, some participants were unable to disclose all details of their process due to company policy. Thus, the results from this study may not fully generalize beyond our sample of participants.

4 Properties of Prompt Programming

We find that prompt programming is the interaction between three entities: the developer, the foundation model, and the prompt. To write a prompt, a programmer uses their prior experience with the FM to construct a mental model of how the FM might perform on the task. This mental

model informs how the prompt is written. After the prompt is run, the developer observes the generated output to create a hypothesis or new belief about the model's behavior, which then is used to update the developer's mental model. The updated mental model is then used to influence the next prompt version.

Thus, prompt programs are both very *flexible* in terms of accepting a range of inputs, but also very *overfit* as it is the product of the specific FM being used, task at hand, and observations of the developer. We first discuss the aforementioned properties of prompt programming in further detail (see Section 4.1) and end with a discussion of its implications (see Section 4.2).

4.1 Results

4.1.1 *Programmer.* During prompt programming, the programmer spends significant effort developing a mental model of how the FM might behave on the task.

Programmers develop a mental model about the FM's behavior on the prompt to predict how it may behave. Technology users form mental representations of their interactions with devices, which can be developed through hands-on experience with the technology [67]. Understanding the ML model's abilities is important but challenging for developing ML-enabled systems [12, 26, 31, 76], including with FMs [10, 34, 36, 77]. Just as developers form mental models of code by exploring the codebase or talking to colleagues [46], participants described developing a mental model of the FM's behavior on the prompt by running the prompt. All participants developed their mental model by observing the FM's performance, either by examining individual examples (P6, P7, P8, P9, P10, P12, P14, P15, P16, P17, P18, P19, P20) or looking at metrics (P4, P5, P7, P8, P9, P11, P14, P15, P16, P18, P19). Based on these observations, the participant formed a hypothesis or belief about the model's behavior and updated the prompt accordingly. This often included creating a new explicit instruction, "guideline" (P8), "rule" (P14), or "mandate" (P20) in the prompt to address the observation (see Section 5.1.3), as noted by Zamfirescu-Pereira et al. [81].

The programmer's mental model was the accumulated beliefs about the FM's behavior. These beliefs could differ or even contradict between individuals. For instance, while some participants (P1, P4, P5, P6, P9, P15, P16, P18, P20) included examples in the prompt for few-shot learning [17] to achieve better results, others (P7, P13, P19) believed the inclusion of examples caused the prompt to overfit to those examples: "[we did not] use few-shot prompting because...it over-indexes on the examples. After a while, you start seeing very repetitive and monotonous output" (P7). This overfitting of examples has been found in NLP literature [51] and has also been noted in practice [36].

Programmers' mental models are not reliable. Mental models are known to be incomplete and inaccurate [67]. Due to the lack of transparency of neural models [12] like FMs in prompt engineering [54], participants mentioned they were not always confident about their developed mental models (P2, P4, P5, P6, P8, P9, P10, P15, P17, P18, P19): "It's a black box model. Nobody knows what's going on inside. It's a science of faith" (P17). Additionally, the stochastic nature of FMs [15] made it difficult for participants to predict the model's behavior, as found in prior work [36]: "I have never been confident [in predicting an FM's behavior]...and I don't think I ever will" (P10).

Some participants (P1, P3, P9, P13, P19) had the FM generate explanations to understand its behavior. Whereas in NLP literature, these explanations are not *faithful* to the FM (i.e., accurately reflecting the model's actual reasoning process) [35], participants felt that it helped them understand the model's behavior: "You can reason about [the LLM] if you can see [its] thought process" (P19).

Programmers use external knowledge sources and prior experience with FMs to develop their mental model. Prior to prompt programming, participants (P1, P2, P4, P11, P12, P15, P16, P18) developed their mental model of the FM through "prompt intuition" (P15) (i.e., prior experience

of interacting with FMs): "I knew what works generally just being in the field" (P8). Literature also points to external knowledge sources as helpful for prompt programming [36, 58]. Participants used official resources, such as guides from the organization or AI companies like OpenAI (P6, P10, P14, P15), online courses (P7), research papers (P1, P2, P5); informal resources, like blogs, articles (P5, P10, P16, P20), and Reddit or Twitter posts (P5, P16, P20) written by "everyday users" (P20); expert colleagues (P1, P14, P15); and other example prompts (P16, P18).

While these resources were helpful, participants (P2, P10, P14, P15, P16, P20) expressed doubt as to whether they improved the prompt: "I don't know if the best practices are the best. I know they are there for a reason, but sometimes they just don't actually make that much of a change. There's a reason the [expert] is saying that... I just take it they know better than me" (P14). Even company-specific resources did not help: "Even with following these best practices...put out internally by the company, some of them just straight up didn't work" (P10). As a result, some participants felt like there were no such thing as best practices: "There are no standards for what's a good prompt or what's a bad prompt. It all seems like a haphazard science of just adding a word and maybe it will look better" (P17).

4.1.2 Foundation Model. The FM on which the prompt is run influences how the prompt is written.

Each FM has its own set of qualities and capabilities. Participants ran their prompts on models that varied in capabilities (see Table 1). Some qualities were explicit or obvious; this included the types of input the model accepted (e.g., images and text (P9)), output generated (e.g., "GPT-3.5 model's JSON output [mode]" (P7)), context window size (P2, P3, P8, P19), prompt formatting requirements (P6), generation speed (P4, P11, P15, P19), and the privacy of the model (P4).

Some capabilities were latent and were discovered by interacting with the model, as noted in prior work [10, 36]. Literature suggests FMs as having latent capabilities, as GPT's performance has improved on some tasks and regressed on others over time [20, 52]. Participants found some differences between FMs to be qualitative: "[One] model was capturing some instructions in the prompt in a much more focused manner, whereas the [other] was a little more lax" (P15). In our sample, participants (P1, P4) noted a quality difference in open-source models (e.g., Llama [70]) compared to closed-source models (e.g., GPT-4 [9]): "Getting [the prompt] to work on a smaller model was very frustrating when with a zero-shot prompt, GPT-4 would almost achieve a hundred percent performance" (P4). Participants (P1, P9) also noted some FMs were unable to complete the task: "[The model was] generating garbage, and [after 30 iterations] I concluded the model is trash" (P1).

4.1.3 *Prompt.* Prompts are sensitive to small details. Additionally, since prompts are a product of the programmer's observations about model behavior as well as the qualities and capabilities of the model, we observe that prompts can be fragile.

Minute details in the prompt matter. Participants reported developing several techniques to influence the FM into generating the desired output. In addition to using known, high-level techniques from literature (e.g., assigning personas, clearly describing the task, selecting a prompting strategy, and providing data context) [7, 49], participants described a range of subtle strategies they employed to obtain the desired output. This included specific phrasing for clarity or generality (P5, P13, P14, P16, P20); repeating phrases for emphasis (P4, P6, P10, P20); avoiding negations (P2, P12); or adding specific characters, like emojis, to encourage their appearance (P6, P10). Other participants noted strategies to visually format the prompt for organization purposes. This included using numbered or bulleted lists (P8, P9, P10, P16) as well as new lines and spacing (P1, P3, P5, P11, P12, P18). Other participants used techniques to emphasize specific parts of the prompt, including bolding (P10, P18) and capitalization (P7, P10, P12, P20).

Participants (P10, P12) also converged on creative details to include in the prompt for better performance. For instance, to prevent the FM from leaking prompts, one participant "bullied GPT"

(P10): "We have a very light threat in there saying, 'If you share any of this information we've given it, you will get in a lot of trouble, I will get in a lot of trouble and it will cause great career harm.' That worked for the most part" (P10). Another participant summarizing code told the FM to explain the code "'so a sixth grader who doesn't understand programming can understand it'. The explanations…were verbose, so I told it the description should be short…It was still super verbose. Then I added, 'sixth graders don't really like reading' and for some reason, that got it to be shorter" (P12).

Finally, participants noted the input and output data format impacted the performance of the prompt. Consistent with prior studies [50, 58], participants selected data formats that were structured and standardized, such as JSON (P3, P7, P9, P10, P11, P18), Markdown (P2, P7, P12), and XML tags (P1, P3, P7, P10, P20). Participants also noted instances where they would change the data representation to achieve better performance (P4, P13, P20): "[What worked better for us is] describing the APIs as though they are Python functions and having the documentation in a similar format to publicly available Python functions" (P13).

Prompts are finicky and fragile. As noted in NLP literature [38, 79] and empirical studies on prompting [51, 81], a prompt's performance varies based on its wording. In practice, participants found prompts to be "finicky" (P4), "fragile" (P20), "sensitive" (P1, P13), and "temperamental" (P15), since prompts would suddenly worsen in performance during prompt development, as corroborated in prior studies on prompt engineering [34, 36, 58, 77, 80, 81]. This could be due to a model's ability to follow instructions, which can change over time [20]. For instance, participants noted performance regressions in the prompt (P2, P8, P10, P12, P15, P16, P19, P20), most often by adding in "a bunch of new requirements" (P2) that would cause previous instructions to suddenly "deactivate" (P20) or be "disregarded" (P8) in the new version: "if I provide multiple guidelines, [the FM] would follow some and disregard others, especially when they're conflicting or overlapping in nature" (P8).

While prior NLP studies point to prompts being transferrable between FMs [51], participants found prompts to be "finicky between models" (P4), causing the prompt to break on the new FM and requiring additional development effort (P4, P10, P15, P18): "At one point, we had to do…a minor model version change… That broke almost everything. We had to rewrite so many prompts" (P10). This is because a change in the model could result in "a different output…or format. So that affects my whole flow. I have a regex converting [the output]…and the whole thing gets broken" (P18). This has also been found in prior prompt engineering work [27].

Finally, chaining prompts was challenging due to the finicky nature of prompts, which has been observed in other studies [27, 77]: "Two changes that do really well separately could merge and become a terrible experience for unexplainable reasons" (P13). Participants (P8, P12, P13, P19) found that integration often resulted in breakage and required significant updates to the prompts so they could work with each other. When working individually, P19 focused on performing regular integration testing of multiple prompts: "[Integration testing is] highly correlated with how it's going to perform in a production environment. In the end, we are going to integrate everything" (P19). However, collaboration could pose additional challenges in such scenarios, since programmers may be unable to perform tests with other concurrent in-progress prompts during development. P13 reported changing how she would "split up the work" (P13) with colleagues and feel an increased "rush to get my PR in before the other one does" (P13) to avoid being stuck with prompt integration.

4.2 Implications

Are the "best practices" best practices? In our study, participants' mental models on FMs conflicted, such as whether few-shot learning [17] was beneficial to prompt performance. While including examples is listed within the official prompting guide made by OpenAI [7], some of our participants (P7, P13, P19) were skeptical of this practice after observing the FM. This underscores the importance

Table 2. A comparison between traditional software development and prompt programming in terms of software engineering activities.

	Traditional software development	Prompt programming
Requirements	Expressed outside of code	Expressed in a prompt, which is also the implementation Dependent on the performance of the FM on the task
Design	Base component: Class/function	Base component: Single prompt Chained prompts are tightly coupled
Implementation	Write a program that implements a specification in code	Write a prompt that is a natural language specification that when ran on a foundation model, implements the specification Focus on rapid experimentation
Debugging	Fault can be isolated to a single line of code Can use debugging tools for more systematic debugging	Fault localization is not certain No debugging tools; reliance on shotgun debugging
Testing	Focus on code coverage metrics Testing at varying scopes (e.g., unit testing vs. integration testing)	Focus on data curation & representativeness Testing at varying scopes (e.g., testing single prompt vs. testing chained prompts)

of the observations of developers in prompt programming, especially in the face of evolving model behaviors [20, 52]. However, such knowledge and observations are rarely shared, are siloed in informal social media posts [58], and are not systematically collected and centralized. However, these observations provide valuable information about FM behavior, which at scale, could reveal the capabilities of FMs overall. Future tools could collect these observations and reasons for prompt updates. This could provide rich information for prompt provenance and version control for the individual programmer, as well as produce generalizable knowledge about the FM's behavior at scale that could be used for automatic prompt program repair.

Rethinking prompt reuse. Due to the fragility of prompts and the unique qualities of each FM, reusing prompts without modification is difficult. Prompt reuse at higher levels of abstraction, such as template-based approaches [74, 75], could be an effective way for prompt reuse. Community-based solutions for prompt sharing, like ShareGPT [8], LangSmith Hub [6], and Wordflow [72], could be a promising avenue for prompt reuse. These tools should facilitate effective search and retrieval of prompt programs, which to the best of our knowledge has not been studied. Future work could examine how prompt programmers query for previous prompts or outputs for reuse.

5 Prompt Programming Process

We found that the prompt programming process exhibited significant differences across each of the software development activities (see Figure 2). We identified six types of activities in prompt programming: requirements, design, implementation, debugging, data curation, and evaluation. We first present these results (see Section 5.1) and conclude with its implications (see Section 5.2).

5.1 Results

5.1.1 Requirements. Requirements underpin the construction of prompt programs. Similar to prior work [28, 58], participants noted the existence of functional and non-functional requirements, such as usability (P13, P15), reliability (P7, P19), latency (P4, P11, P15, P19), safety (P7, P10, P13, P19),

privacy (P4, P13, P14), availability (P4), and cost (P5, P8, P10, P11, P14, P16, P19, P20). We observed that companies found safety and privacy especially important, as noted in the literature [34, 59].

Assumptions of the requirements must be explicitly stated. At times, the FM did not perform the correct action not because of an FM error, but due to an under-specified or conflicting requirement in the prompt (P3, P4, P5, P6, P8, P12, P19). Thus, prompt programming required explicitly stating assumptions: "When you're interacting with a person, you make all these assumptions, but everybody can read between the lines... The more you design prompts, the more you realize that it's not the same as communicating with another person. The model needs more specific instructions" (P3). However, predicting which assumptions to elaborate on was challenging since "it's hard to tell when the model could go wrong" (P3): "I think observation is like 80% [of the requirements]. I knew what I wanted 20% of the time" (P8). As a result, "capturing all the rules...is very difficult in the start, and just generalizing over all the use cases there can be very difficult" (P19).

Requirements can evolve as the capabilities of the FM are discovered. Similar to building ML-enabled systems [71], requirements of the prompt could change as the capability of the FM on the task was discovered. Changed requirements included making new trade-offs between nonfunctional requirements, such as safety versus quality [28] (P7): "Our requirements did change as to how the product was perceived [by users]... So, striving for that balance between the response quality and the latency induced quite a few iterations just to see how much room do we have to play with" (P15). Additionally, participants noted defining new features based on observing how the FM performed on the task (P2, P4, P13, P18, P20): "I do add in requirements as I iterate. 'Oh, I didn't know that you would be able to do this. Let's see how much I could push this functionality" (P2).

5.1.2 Design. Complex or lengthier prompts can be decomposed into into multiple components.

Prompt programs can be composed and decomposed. Participants decomposed prompt programs into smaller components based on the complexity of the prompt program. For a single prompt, participants described decomposing the prompt into sub-components, such as into subsections (P1, P2, P5, P6, P7, P8, P13, P20). One participant noted "it is important to structure the prompt in a way that makes sense to you. Otherwise, you're not able to maintain it going forward" (P13).

Prompts can be composed or "chained" together for greater capabilities [10, 51, 77, 78]. Participants chained multiple prompts that depended on each other (see Table 1) for complex tasks: "We know what the complex task looks like, and then our job is to break that down...Evaluating each step independently of the others can help for complex tasks" (P9). Each prompt had its own responsibility: "if you are creating a robot, the motion of the hand in any scenario could be a responsibility to one agent. The movement of the legs could be given as a responsibility to another agent... Sometimes, they have to communicate with each other to perform a synchronous action" (P19). Similar to pure code systems, prompts acted as a single module with its own concern [24] which could be composed into a more complex system. Yet, composing multiple prompt programs posed challenges (see Section 4.1.3), causing coupling as the prompts were modified to work together. This is similar to engineering ML-enabled systems, whose components have tight coupling [71]. Participants tried to address this challenge by allowing APIs, such as LangChain (P4, P9, P10) or LangGraph (P19) to handle orchestration, as noted in prior work [27, 77].

5.1.3 Implementation. Prompt programming involves constant "experimentation [compared to] traditional software development" (P15) (see Figure 3) and was described as a "trial and error" (P3, P7, P10, P15) process by participants.

Prompt programming is rapid and unsystematic. Many participants (P1, P4, P6, P7, P8, P12, P13, P14, P15, P19, P20) described a process of starting with a basic prompt for the task to test

its feasibility. This prompt included a description of the task and a description of how a human would intuitively perform the task. Each update could result in unwanted behavior and necessitate prompt updates, thus going around the update-test loop again. The prompt grew in complexity as the programmer updated the prompt and observed the model's output; this was done in tandem with building a mental model of the FM (see Section 4.1.1). This process was "unscientific" (P4): "I would try a lot of different things on a prompt and it's not a very well thought-out procedure" (P6). It also occurred when participants extended existing prompt programs (P14). Prior work has characterized prompt engineering with FMs as highly iterative [10, 27, 49, 50, 58, 80–82], similar to the experimental nature of engineering ML-enabled systems [31, 55, 56, 71, 76].

During this experimentation process, "the speed and the velocity of making changes [was] high" (P19). Literature indicates that exploring the input space for an optimal prompt is challenging [10, 54] and the rapid experimentation with FMs produces many outputs, which are difficult to make sense of [30, 36, 37, 50]. Participants created many versions of the prompt to test new prompting approaches (P1, P5, P19), add new functionalities (P2, P6, P13, P16), try to fix bugs (all participants), experiment with new models or hyperparameters (P4), or incorporate feedback after a code review (P1, P14, P16). Prompt versions often branched off from each other (P4, P6, P12, P13, P15, P17, P19, P20), but could be reverted (P4, P5, P8, P10, P15, P16, P20).

As noted by earlier studies [81], changes were less drastic as the prompt stabilized and as the modifications had less of an effect on the prompt, leading "prompt engineering [to feel] like a waste of time" (P5): "If we graphed the number of...changes over the number of iterations, the gradient would be pretty high during the first iterations. Then it flattens quite a bit...because the prompt has matured enough...such that we don't need to make those big changes anymore" (P15). Thus, one participant avoided testing small prompt changes, and instead preferred to batch them together to reduce costs: "For small changes, we will wait and merge this evaluation into the next time we conduct it" (P16).

Consistent with prior work in prompt engineering [36, 58] and building ML-enabled systems [12, 31, 55, 56], the AI's nondeterminism makes it "hard to measure overall progress" (P6) on the prompt: "You can think you have something that's really good, and then try it out on a completely different set of inputs and it's just terrible. A lot of this is feeling of making progress and then backtracking" (P10). Participants developed strategies to address this challenge, like making small changes (P2, P4, P8, P15) or viewing evaluation metrics computed across a large number of examples (P4, P18): "I feel like I wasn't that confident, other than the fact that our intrinsic numbers went up" (P4).

Participants used a variety of tools to implement their prompt. GUI-based tools (P2, P4, P5, P6, P8) (e.g., GPT playground) and notebooks (P1, P3, P5, P18, P19) enabled rapid prototyping; text editors and IDEs (P1, P11, P14, P17, P20) revealed formatting, like newline characters; and FMs helped inspire or generate parts of the prompt (P2, P18). Prompts were then transferred between environments, usually through copy-pasting (P1, P2, P3, P4, P5, P8). This manual transfer at times introduced issues, such as formatting errors (P1, P5) and inconsistent performance between the model on the external environment compared to the code environment (P5).

Due to the rapid experimentation, participants (P3, P18, P19) struggled to recall previous versions and their outputs. Some tried to address this issue by tracking versions of the prompt as found in Parnin et al. [58]'s study. This included existing tools such as Git (P5, P6, P7, P10, P16, P17, P18). Other participants set up their own systems to save prompt versions and their performance. This varied in sophistication, from a text document tracking all prompts and outputs (P1, P2, P5, P12) and arbitrary file-naming systems (P9, P12, P19), to spreadsheet tables (P1, P4, P5) and custom-built tools (P8). However, participants still found it difficult to retrieve previous prompt versions (P4, P12) and confused versions due to subtle differences between prompt versions (P9, P12).

5.1.4 Debugging. Prompts can have defects or undesired outputs, which requires debugging from the programmer. Our participants observed a range of defects, such as hallucinations (P9, P14, P15, P17, P19) or not following directions (P2, P3, P4, P6, P8, P9, P10, P12, P18, P19, P20).

Fault localization is not certain. To fix errors, participants engaged in debugging behaviors. However, debugging prompts is challenging [27, 36]. The stochastic and black-box nature of FMs made it impossible to ascertain the defect's source: "Coming from a software engineering background, you...want to set breakpoints and debug, looking at the results step by step. There's no such mechanism for prompts" (P13). Thus, one challenge was knowing how to change the prompt to address the defect [54]: "I don't even know what to change in my prompt to get there" (P5). Thus, participants engaged in shotgun debugging by trying random changes to the prompt to fix the defect (P2, P7, P8, P10, P15, P18): "In most cases, it is like hit and trial. So maybe I will try a different prompt. I will try it with a different example" (P18). Prior experience and intuition were thus helpful in debugging (P2, P4, P15, P16). Participants also described strategies to gain more confidence in understanding what could fix the error. This included having the FM generate reasoning (P1, P3, P9, P13, P19); testing small, incremental changes (P12); and restricting instructions to specific parts of the prompt (P14, P20). However, participants reported that fixes did not always fix the error (P3, P4, P5, P6, P15, P16, P18, P20), as it could introduce new errors (P3, P4, P7) as documented in prior work [58].

5.1.5 Data curation. To develop prompt programs, programmers must develop new, high-quality datasets, a process referred to as "data curation" [62]. This became a central activity.

Programmers need to find representative data for the task. The shift to FM-based components put greater emphasis on finding high-quality data, consistent with prior work [12, 26, 31, 34, 55, 56, 71]. To evaluate the prompt (see Section 5.1.6) and provide examples for few-shot learning [17], data curation became important. Since many of the participants' tasks were custom or specific, using existing benchmarks was not sufficient except in general and common tasks such as jailbreaking (P19). Participants created their own datasets by mining data from the internet or from the participant's organization, as well as annotating data (P1, P3, P4, P5, P6, P7, P8, P11, P13, P14, P15, P17, P18, P20). The challenge was finding representative data for the task that worked in practice, as prompt programmers needed "to do [their] best to predict how people are going to use [the application]" (P20). Datasets did not necessarily work in practice due to training-serving skew (i.e., when training data does not generalize to production data) [55, 56, 71]: "You can test with your own dataset, but at the end of the day, you're still not completely sure how good the output is" (P7).

Participants took care in capturing the full diversity of the input distribution by dividing the inputs into categories and finding examples for each category (P1, P8, P9, P15, P19, P20). Prior work indicates the non-determinism of ML models could pose difficulties in evaluation [34, 71]—participants addressed this by paraphrasing the inputs (P16, P18, P19, P20). Despite their best efforts, the datasets participants created did not capture the full distribution of inputs. Participants relied on several methods to obtain more data, such as by using an FM to generate examples (P12, P18, P19); having colleagues stress test, "data bash" (P13), or red team [28] the prompt (P7, P10, P13, P17, P19); and deploying the prompt for user feedback (P7, P10, P13, P15, P17, P19).

Participants struggled with creating representative datasets, as found in prior studies [12]. Despite the emphasis on safety and fairness in literature [12, 31], the prompt program work less well on culturally diverse audiences upon deployment (P7, P10, P13). This reflects prior research in NLP, which found that FMs and datasets align with certain demographics (i.e., Western, college-educated, and younger populations) more than others [39, 60, 63]. Additionally, participants found aspects of manual data annotation challenging. Some participants (P3, P13) described challenges on determining labels for the dataset. Participants noted instances of low-quality data annotations:

"We found that the [annotations from non-developer colleagues] would be incorrect... It is possible that the worldview of the person doing the annotation is not scoped...so they have some limitations on how much they know [so] they don't know what the expected outcome is" (P13). Additionally, it the correct label for data was sometimes was unclear: "When do you classify as [Label A]? When do you classify as [Label B]? It was fuzzy on how you would interpret [the labels]" (P3). This reflects documented challenges of handling annotator disagreement and subjectivity [11] in NLP research, where for many tasks, the ground truth can be unclear.

5.1.6 Evaluation. Prompt programmers engage in frequent evaluation of the prompt program.

Evaluating prompt programs requires assessing qualitative constructs. Many participants' tasks often involved custom tasks that did not have a clear, quantified notion of correctness; as such, evaluating the prompt was a challenging task [27, 58]. In developing ML-enabled systems, many of the evaluation metrics focus on quantitative measures [31, 56, 71], while prompt engineering includes manual inspection [30, 54]. Participants performed manual testing of the prompt's outputs simply by qualitatively assessing the outputs (P2, P4, P6, P7, P8, P12, P13, P14, P16, P17, P18, P19, P20), since it was difficult to "quantify the concept of good" (P10) for outputs. For example, one participant who created a voice memo summarization tool did the following to test his tool: "I would just sit in the chair and talk to my phone for like 10 minutes just to fine-tune and see, 'Okay, does it ask me the right question? Does the summary make sense?"" (P2).

Manual testing was difficult to scale and quantify progress (P6, P15): "It is extremely hard to realize the impact of the [changes] without it going through some manual intervention, where there is a person who is very finely checking out the differences" (P15), especially in the face of regressions (see Section 4.1.3). Thus, several participants supplemented this assessment with quantitative metrics via programmatic testing of the prompt for a scaled evaluation (P1, P5, P8, P9, P11, P13, P14, P16, P18): "When I update or change something, I run it manually on 3 to 4 examples... In cases where I have a proper evaluation setup, I run on 50 to 100 cases. Those 50 cases make me more confident" (P18). This often involved using other FMs to generate scores for qualitative constructs (P4, P7, P9, P10, P15, P19), such as safety [28]: "I have a scoring mechanism with...an evaluation agent [where the] score is from 0 to 100 [for groundedness]... Whenever [the agent] is failing, I can shortlist those examples and then manually go through them" (P19). However, FM-based evaluations could also introduce errors: "[The evaluation agent] itself is an LLM, right? It's only 90% reliable. So 10% of the time, if the test case is failing, it's because the evaluation agent wasn't able to score it correctly" (P19).

Testing occurs at different scopes. Participants noted testing the prompts at varying scopes. For applications that involved multiple prompts, participants tested individual components of the prompt program (P8, P16, P19, P20), akin to unit testing: "Usually, each test case that we had written was aimed at testing one specific part of the prompt" (P20). Participants also described performing integration testing (P2, P8, P9, P11, P12, P13, P14, P16, P18, P19): "We evaluated each of [the prompts] separately, and now we are evaluating that as a collection" (P11). However, this type of testing was difficult, as combining prompts could yield unexpected interactions (see Section 4.1.3).

5.2 Implications

Prompt programmers are both ML practitioners and software developers. Developing ML-enabled systems requires a variety of expertise like software engineering, data science, and math [31, 71]. Yet, the expertise is captured across multiple team members, which can introduce collaboration challenges [56]. Even though prompt programming does involve both ML and programming knowledge, this expertise is now centralized in a single individual. This could reduce friction between different roles. However, in addition to traditional software engineering expertise, like

debugging, testing, or knowledge in specific programming languages [14, 48], prompt programmers must develop new skills as they engage in novel activities like building datasets and debugging model errors with data [62]. We notice that by becoming ML practitioners, prompt programmers encounter many of the long-standing challenges contended by the ML and NLP communities, like model drift [20], language [39] and cultural biases [60, 63] in datasets and models, and annotator subjectivity [11]. Close collaboration between the software engineering and ML communities is paramount to learn techniques to address these challenges in prompt programming.

Prompt programmers are inundated with information. The rapid iteration involved in prompt programming means that prompt programmers must make sense of a deluge of information. Each iteration, the participant must track the prompt, the change being made, the FM's output, and associated metrics. However, participants reported having trouble making sense of all of this information (P3, P6, P18, P19). Therefore, future work should investigate better ways for prompt programmers to version and navigate through prompt iterations and their associated artifacts, such as datasets and model outputs. Exploratory programming tools (e.g., Variolite [40]) could provide inspiration, as exploratory programming is also highly iterative and unsystematic in nature [41].

6 Discussion & Conclusion

Generative pre-trained models (e.g., GPT-4 [9]), also known as foundation models (FMs), have allowed programmers to write natural language prompts that power intelligent AI experiences [58] in software products. We study this phenomenon, *prompt programming*, by interviewing 20 developers engaged in prompt development across a variety of contexts. We use Straussian grounded theory to develop a better understanding of the prompt programming process. We identify 14 observations on prompt programming (see Section 1), which indicate prompt programming is significantly different compared to traditional software development. This produces several implications for software engineering educators, practitioners, researchers, and tool makers.

For educators. The lack of standardized best practices and unreliable mental models of prompt programmers pose significant challenges in teaching prompt programming. Participants said having prior experience with FMs and "prompt intuition" (P15) made it easier to develop and debug prompt programs. Since this knowledge is tacit, software educators could teach students with assignments that give students experience with prompt programming to develop their prompt intuition. Additionally, software engineering educators could consider teaching data science skills, such as dataset curation, data cleaning, data shaping, and debugging model errors with data [42, 62].

For practitioners. Practitioners should consider identifying potential fairness issues at the start of prompt development, rather than after deployment. This could be done by developing data collection pipelines from culturally diverse participants, following Santy and Liang et al. [63]. Additionally, practitioners should focus on developing benchmarks to catch performance regressions. These benchmarks should account for paraphrasings of the same query and be evolving to address training-serving skew [56]. Finally, practitioners should make collaboration a top concern due to the tight coupling of chained prompts. Consider regular check-ins with colleagues and frequent integration testing of chained prompts during development.

For researchers and tool makers. "[Prompt programming] will require any traditional software developer to adjust their mindset... It is much more scientific and experimental than traditional software development, and the results are not instant" (P15). Participants struggled at each step while developing prompt programs, from requirements to evaluation, as existing developer tools were not designed to handle the challenges of prompt programming. We follow Hassan et al. [34] and Parnin et al. [58] in underscoring the importance of developer tools for prompt programming. Such

explorations have begun in earnest [e.g., 10, 36, 54, 77]. Future tool ecosystems should support the full range of activities in prompt programming, from interfaces for rapid prototyping, dataset curation, and data sensemaking, to regression testing, prompt chaining, collaboration, and more.

Data Availability

To facilitate replication of the study, we provide our supplemental materials [13], which is available on FigShare at https://figshare.com/s/de7da35d6351ce374995. This includes our survey instrument, interview protocol, codebook, and the list of papers reviewed during the focused literature review. We will make these materials publicly available upon acceptance.

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