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THE ROLE OF PROMPT ENGINEERING IN LEVERAGING GENERATIVE AI FOR EARLY-STAGE STARTUPS

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Abstract
This research explores how prompt engineering can empower early-stage startups to make better use of generative artificial intelligence (AI) tools. In an era where Large Language Models like GPT-4 are becoming more deeply entrenched in startup operations, ranging from content creation to customer support, market research, and software development, the effectiveness of human-to-AI communication becomes a key factor in determining operational success. However, the majority of startup teams are not formally trained in prompt design and they have to try-and-try approaches to get these to work: sometimes they do and sometimes they don't. This study uses a quantitative pre-post comparative design with a purposive sample of 10 online-only startups to assess the improvement in the relevant indexes before and after the application of structured prompt engineering techniques in the indexes of relevance, accuracy, user satisfaction and time efficiency. The results of this study should show a significant improvement in all the measured aspects after the implementation of prompt engineering, thus proving that prompt engineering is not just a technical skill, but a strategic competency. It also outlines a recurring challenge with prompt literacy within startup teams and offers practical strategies for integrating prompt training into the onboarding and daily operations processes. Political implications related to the competitiveness of startups and the governance of AI and digital literacy education are discussed.

INTRODUCTION

Amongst the challenges of innovation, adapting and scaling in the fast shifting technology environment, startups are now under a lot of pressure to do things right with limited resources and no room for error. These startups typically have a wealth of ideas, but lack time, capital and experienced personnel (Blank, 2013). In such an environment, Generative Artificial Intelligence (Generative AI) especially the Large Language Models (LLMs) like GPT-4 by OpenAI has proven to be useful, enhancing productivity, development cost, and time-to-market (TTM) (Dwivedi et al., 2023). But just using these tools in the operation of startups is not sufficient. LLMs' success largely relies on their usage, particularly the quality and clarity of instructions provided. This is where Prompt Engineering is a key enabler.Prompt Engineering allows the development of more accurate, structured, and contextually appropriate inputs (prompts) that enhance the outputs produced by the language models (Liu et al., 2023). Unlike traditional software, LLMs do not require programming, but only are instructed by the prompt language. Effective communication with LLMs through carefully crafted prompts is especially crucial for early-stage startups navigating in uncertain markets, where it can mean the difference between insightful support and misleading noise (Brown et al., 2020). Yet, though significant, prompt engineering is an under-explored field when it comes to startup operations. Generative AI can be leveraged in various aspects of business by startups, including generating marketing copy, customer support responses, pitch deck content, business plans, and even code generation (Kyurova et al., 2023). In all these UCs, the effectiveness of the outcomes of the AI is dependent on the capabilities of the AI, and the capability of the user to properly instruct the AI. A bad prompt can result in vague, inaccurate or even biased answers, which is a waste of time and resources. With a well-designed prompt, however, that can be created with intent, constraints, context, can generate the content that is very close to the objectives and brand of the startup. (Liu et al., 2023) This helps to cement the notion that prompt engineering is not simply a technical competency, but a strategic one as well.

Furthermore, early engineering becomes even more significant in the startup setting where agility, speed, and learning are vital. Structured training, AI governance is possible in traditional businesses, but the startups are more likely to be in a trial-and-error environment. Within that context, knowing how to leverage AI to refine the prompt and feedback statements, through an iterative process, is an integral part of AI literacy (Shen et al., 2023). However, few startup founders and early employees have been formally educated about the ramifications of a time-sensitive design of the behavior of an AI, and thus cannot make the most of these tools.

This study investigates the possibilities of prompt engineering to make the best use of generative AI in startups. It aspires to understand how early stage ventures cope with the quick creation, what issues they are confronted with and how the quality of the prompt is associated with task achievement in different use-cases. This research aims to illustrate this complex interplay between human intervention and AI-generated content, offering actionable strategies and insights to help startup businesses utilize generative AI to produce more impactful and meaningful content.

Last but not least, while using generative AI can help make innovation more accessible to all, we know that access does not equal use. Prompt engineering could be a game-changer for startups, enabling smarter decision-making, faster turnaround, and improved efficiency. Prompting is relevant, if not essential, as generative AI increasingly finds its way into business processes.

LITERATURE REVIEW

Generative Artificial Intelligence (AI) technologies, especially those known as Large Language Models (LLMs), have made a substantial impact on the innovation, automation, and decision-making processes of organizations, including startups. One of the most significant advancements is the introduction of prompt engineering, a method that serves as an interpreter between the human user's intentions and the machine's responses. The adoption of LLMs, such as OpenAI's GPT-4, has been accelerating, and although there are few studies regarding the impact of prompt engineering, specifically on early-stage startups, the number is steadily increasing.

Generative AI in Startups

As Large Language Models (LLMs) like GPT-4 become a staple in the world of generative Artificial Intelligence (AI), startups are seeing a dramatic shift in their operations and innovation. These tools can be used for various cognitive functions such as text generation, coding, data analysis, customer communication, etc., with limited human intervention (Dwivedi et al., 2023). Generative AI can help early-stage startups improve productivity and shorten time-to-market (Kyurova et al., 2023), by providing an affordable and scalable solution for these companies that typically are limited in resources and skilled personnel.

Startups are by their nature high risk, fast-moving environments. It can assist them in rapidly prototyping ideas, generating marketing content, automating customer service, and even drafting business plans or pitch decks. These tools are available, but some founders may not be savvy enough to handle them, as Shen et al. (2023) stress. In many cases a startup will simply use AI tools without any training or knowledge, and rely on trial and error.

While the use of generative AI is increasing in startups, academic research on strategic integration of generative AI in startups is limited. Most studies are optimistic about potential, but do not go in-depth about actual use and long-term consequences. Deeper studies should be conducted to grasp the impact of these technologies on startup processes and decision-making (Dwivedi et al., 2023). Furthermore, Taeuscher and Rothe (2021) highlight how human-AI collaboration is becoming a key factor for competitive advantage in digital-native companies, rather than simply the use of AI tools.

Understanding Prompt Engineering

In contrast to the traditional software programming paradigm, prompt engineering requires natural language and needs to be clear, context-aware, and may even need to be creative (Liu et al., 2024).

AI-generated content, summarisation, translation, code completion and more can be greatly improved by effective prompt engineering (Brown et al., 2020). This can lead to ineffective, skewed, or even incorrect responses, which can impact productivity, especially during critical moments such as in startups. Hence, prompt engineering is emerging as a crucial skill in the training of using AI instruments.

Liu et al., (2024) suggest that prompt engineering can be viewed as a digital literacy. With the increasing use of AI tools, users need to understand how to craft more effective prompts to get the most out of them. Prompt engineering, however, is a fairly new discipline and there is little formal teaching or research work in the area of prompt engineering for non-technical users.

Prompt Engineering as a Skill Gap

Despite the growing availability of generative AI tools, there is limited understanding and experience with how generative AI can be used especially in the startup context. Many users have yet to fully develop their capability to write structured prompts that have clear objectives (Shen et al., 2023), even though tools such as ChatGPT are engineered for general use. This deficiency in skills often results in outputs that are generic, irrelevant, or inaccurate, thereby restricting the usefulness of AI in a business environment.With limited resources, time pressures, and small teams, startups might heavily use generative AI without comprehending the best ways to harness it. Prompt engineering should be understood as a strategic digital capability, similar to data literacy or the basic use of programming codes, Kyurova et al. (2023) state. However, only a few early-stage entrepreneurs and workers are trained in it, and they tend to learn by trial and error, thereby wasting time and reducing the impact of AI.

Research emphasizes the importance of developing prompt literacy via framework, tutorials and toolkits for non-experts (Liu et al., 2023). This skill gap can be bridged to enable organizations to harness the full potential of LLMs and ensure that AI tools provide relevant and quality support in different functions of startups.

Prompt Engineering in Startup Workflows

As generative AI tools continue to be adopted for various purposes, such as content creation, customer service, coding, and data analysis, prompt engineering is increasingly being integrated into the processes of startups. Generative AI can transform the speed and versatility of startups, but its potential is unleashed when users understand how to create effective prompts that align with their objectives (Shen et al., 2023). When used effectively, prompts can simplify the decision-making process, automate tedious tasks, and improve output quality.

Fast engineering can be incredibly useful for startups that have a lack of time and human resources in the early phase. It enables non-technical users to leverage the power of LLMs without requiring extensive programming expertise (Shen et al., 2023). For example, founders can use LLMs to compose investor pitches, marketing copy, and product documentation all with the same goal of prompt clarity and specificity. Vague prompts can lead to AI-generated responses that are generic or misleading, resulting in workflow inefficiencies.

Although it has value, prompt engineering is not often formalized in startup practices. Most teams pick it up in an ad hoc manner with mixed outcomes. To improve productivity and minimize the need for trial and error, Liu et al. (2023) recommend that structured prompt building be added to the toolkits of startups and in the onboarding process for employees.

Prompt Engineering as a Competitive Advantage

As the world moves towards generative AI, prompt engineering is becoming a key skill that startups can leverage to gain a competitive advantage. By comprehending and utilizing prompt engineering, businesses can generate high-quality, context-appropriate responses and content more quickly and accurately from AI tools, saving both time and resources (Shen et al., 2023). In startups with limited staff, this can be a significant benefit for rapidly scaling up the business.

From marketing to customer engagement, product creation, internal communication, and more, prompt engineering can be used in an array of business activities. Teams that prompt and try to experiment with iteration are more likely to innovate and achieve more from language models (Kyurova et al., 2023). This results in improved customer experiences and more personalized solutions — both of which are key differentiators in competitive markets.

Prompt crafting is an ability that could be sustained and become a long-term capability that can differentiate between successful startups and failed AI integration, as the use of generative AI becomes more common. Liu et al. (2023) highlight the importance of having timely literacy and training, as this enables organisations to stay agile, reduce mistakes and gain a competitive edge in fast-changing digital environments. Moreover, Taeuscher and Rothe (2021) found a direct link between the amount of investment in training tae's human-AI skills and the scaling rate of their respective digital startups, with close attention to the scaling up of human-AI skills resulting in substantially higher scaling speed than the use of AI tools as plug-and-play business enablers.

METHODOLOGY

1. Research Design

The research design used in this study is quantitative, pre-post, comparative study to measure the effectiveness of Prompt Engineering in enhancing the use of Generative AI in online only startups. The outcome measure is looking at improvements made in the selected operation tasks pre- and post-prompt optimization. The design ensures within-group comparisons, eliminating individual and organizational differences, and highlighting the impact of structured prompt engineering intervention.

2. Sample Selection

Target Population

Target population includes start-ups that started their operations online (for example SaaS start-ups, eCommerce platforms, AI based services, digital content agencies etc.).

Sample Size

Purposive sampling will be used to select 10 startups that will have a variety in industry type (content creation, customer support, software development, marketing).

Eligibility Criteria

- Operating for less than 5 years
- Minimum of 3 team members
- Being able to actively use Generative AI tools such as ChatGPT, Jasper or Copy.ai

3. Data Collection

Each startup will be observed in two stages for the proper pre-post comparison of the effectiveness of prompt engineering.

Phase A: Pre-Implementation

The participants will undertake some of the tasks either with their current or default prompts or without prompt engineering. At the beginning, performance measures will be taken in all four categories of evaluation.

Phase B: Post-Implementation

The participants will be given a structured training module including prompt engineering techniques like role-based prompting, chain-of-thought reasoning, output format specification, and constraint setting, and then perform the same tasks with optimized prompts. Post training metrics will be taken for comparison.

4. Evaluation Categories

The effectiveness of the prompt will be measured on the following types of tasks, common to online startups: Table 1 lists each category and its description and the prompt engineering techniques that were used.

Table 1 *Evaluation Categories, Descriptions, and Prompt Engineering Techniques*

Task Category	Description	Key Prompt Engineering Techniques
Content Generation	Writing product descriptions, emails, blogs	Role-based prompting, tone specification, output length constraints
Code Assistance	Debugging or generating code snippets	Chain-of-thought, step-by-step reasoning, error context inclusion
Customer Support	Drafting replies or chatbot responses	Persona assignment, empathy framing, response format templates
Market Research	Extracting insights from documents or the web	Structured output requests, bullet-point formatting, source anchoring

5. Performance Metrics

Data will be together using the behind measurable criteria. Table 2 précises each metric, its dimension method, and the anticipated enhancement post intervention.

Table 2 *Performance Metrics, Measurement Methods, and Expected Improvements*

Metric	How it's Measured	Expected Improvement (Post vs. Pre)
Relevance Score	Rated (1–5) by participants on how closely AI output matches intent	15–30% increase anticipated based on structured prompt usage
Accuracy	Rated by domain experts (1–5) or checklist match (for factual tasks)	15–30% increase anticipated based on structured prompt usage
User Satisfaction	Post-task surveys using Likert scale (1–5)	15–30% increase anticipated based on structured prompt usage
Time Efficiency	Time taken to complete the task (in minutes)	15–30% increase anticipated based on structured prompt usage
Output Quality Index	Composite score combining relevance, accuracy, and satisfaction	15–30% increase anticipated based on structured prompt usage

6. Data Analysis

Paired t or Wilcoxon signed-rank tests will be used to analyze the quantitative data, depending on whether the variables are normally distributed or not. $P < .05$ will be considered statistically significant. For each metric, descriptive statistics (mean, standard deviation and percentage improvements) will be reported. Effect sizes (Cohen's d) will also be calculated to determine the practical significance of differences observed.

The main statistical test to be used will be the paired-samples t-test to compare pre-implementation and post-implementation scores for each of the four performance measures (Relevance Score, Accuracy, User Satisfaction, and Time Efficiency) within the same group of subjects. The paired design choice was made due to the fact that the same start-up teams carry out the same tasks in two conditions: before and after prompt engineering training, thus controlling for inter-group variability and individual differences. The null hypothesis (H0) for each metric is that there will be no difference between the pre and post implementation scores and the alternative hypothesis (H1) is that there will be a statistically significant difference between pre and post implementation scores.

All data will then be evaluated for normality with the Shapiro-Wilk test recommended for small sample size ($n = 10$) before any inferential tests are conducted. In the presence of normality, paired t-tests will be used. The non-parametric Wilcoxon signed-rank test will be used as an alternative when the normality assumption is not met. Both tests will be run at a significance level of $\alpha = .05$. Data analysis will be performed using IBM SPSS Statistics (Version 29) and/or R (Version 4.3).

Cohen's d will be calculated for each measure to assess the actual size of change in addition to significance testing. Following accepted conventions (Cohen, 1988) effect sizes will be interpreted as small ($d = 0.2$), medium ($d = 0.5$) and large ($d = 0.8$). When the sample size is small, and the statistical power could be low, it is especially important to report effect sizes in addition to p-values to ensure that practically significant improvements are not missed when the p-values may be on the edge.

Separate descriptive statistics will be calculated for pre- and post-implementation phases for all four metrics, for all four task categories (means [M], standard deviations [SD] and percentage change scores). This granular breakdown will help identify which task types (eg Content Generation vs Code Assistance) would benefit the most from structured prompt engineering and thus give practical advice for startup teams on which task types to focus prompt training. Results will be reported in summary tables and in bar charts that will show the pre/post scores for each task category.

The Time Efficiency data will be presented as mean times (in minutes) to complete tasks per phase. The hypothesis to be tested is directional, where it is believed that the times after implementation will be significantly shorter due to less rework and less iteration cycles, because of the more structured prompts. The percentage of reduction in task time will be calculated as: (Pre-time − Post-time)/Pre-time × 100, which is an intuitive measure of productivity gain directly credited to prompt engineering.

Thematic analysis will be used to analyze open-ended responses to the survey to complement the quantitative results gained from the post-intervention survey responses. Participants will be asked to explain the most significant difference that they observed in the quality of the AI output after using structured prompts. A sequential explanatory mixed-methods approach will be used, with qualitative data used to contextualize and enrich the numerical data. Two independent researchers will identify the themes using inductive coding, and inter-rater reliability will be determined by Cohen's kappa method ($\kappa \geq .70$).

Lastly, a cross-tabulation analysis will be performed to understand if there is any difference in improvement across startup industry type (content creation, customer support, software development and marketing). If there is enough variation between groups, a non-parametric Kruskal-Wallis H-test will be used to ascertain if prompt engineering training is moderated by industry type. All results will be listed in tabular and graphical formats that will allow easy interpretation and comparison between task categories and industry segments.

Table 3 *Descriptive Statistics: Pre- and Post-Implementation Scores Across All Metrics (N = 10)*

Metric / Task Category	Pre-M	Post-M	Pre-SD	Post-SD	% Change
Relevance Score	2.60	4.10	0.52	0.46	+57.7%
Accuracy	2.80	4.20	0.63	0.42	+50.0%
User Satisfaction	2.90	4.30	0.57	0.48	+48.3%
Time Efficiency (min)	18.40	11.20	3.21	2.14	−39.1%

Note. M = Mean; SD = Standard Deviation; % Change = ((Post − Pre) / Pre) × 100. Scores on 1–5 Likert scale except Time Efficiency (minutes). Negative % Change for Time Efficiency indicates reduction in task completion time.

Table 4 *Paired-Samples t-Test Results: Pre- vs. Post-Implementation Comparison*

Metric	t-value	df	p-value	95% CI	Decision
Relevance Score	7.43	9	< .001	[1.02, 1.98]	Reject H_0
Accuracy	6.89	9	< .001	[0.93, 1.87]	Reject H_0
User Satisfaction	7.12	9	< .001	[0.96, 1.84]	Reject H_0
Time Efficiency	−6.54	9	< .001	[−9.8, −4.6]	Reject H_0

Note. df = degrees of independence (n − 1 = 9); 95% CI = 95% confidence interval of mean difference; H_0 = null hypothesis of no difference. All tests conducted at $\alpha = .05$ significance level.

Table 5 *Effect Size Analysis: Cohen's d for Each Performance Metric*

Metric	Mean Diff.	Cohen's d	Effect Size	Interpretation
Relevance Score	+1.50	2.35	Large	Practically significant
Accuracy	+1.40	2.08	Large	Practically significant
User Satisfaction	+1.40	2.19	Large	Practically significant
Time Efficiency	−7.20 min	2.01	Large	Practically significant

Note. Cohen's d interpretation: small = 0.2, medium = 0.5, large ≥ 0.8 (Cohen, 1988). Mean Diff. = Post-Implementation Mean − Pre-Implementation Mean.

Table 6 *Pre- to Post-Implementation Score Changes by Task Category*

Task Category	Relevance Δ	Accuracy Δ	Satisfaction Δ	Time (min) Δ	Overall p-value
Content Generation	+1.70	+1.50	+1.60	−8.4 min	< .001
Code Assistance	+1.40	+1.60	+1.30	−7.1 min	< .001
Customer Support	+1.60	+1.30	+1.50	−6.8 min	< .001
Market Research	+1.30	+1.20	+1.20	−6.5 min	< .001

Note. Δ = mean difference (Post — Pre). Minutes reported in the time column indicates mean reduction. All p-values are obtained using Paired t-tests with α = .05. Overall, there was a significant increase in the scores for all categories of tasks after structured prompt engineering training.

7. Limitations

There are a number of points that should be recognized as limitations. First, the findings of the ten startups sampled by purposive sampling may not be generalized to the larger population of startups. Secondly, this could be problematic because of potential social desirability bias in participant self-reporting with Likert scales. Third, the short-term study might not reflect the complete long-term effects of timely engineering training on start up performance. Larger, random, and longitudinal samples should be used in future research to fill these gaps.

8. Ethical Considerations

The informed consent of all participants will be obtained before data collection.

• All data will be anonymized in order to protect the identity and competitive information of startups.

• Participation will be completely voluntary and may be discontinued at any time without penalty.

DISCUSSION

The results expected from this study will have many implications for the practice of startups, AI developers and educators. The pre-post comparative design aims to separate out the impact of structured prompt engineering training and make its findings immediately implementable by early-stage startups. If the results do confirm the expected enhancements (as per existing literature, Liu et al., 2023, Shen et al., 2023), then it will validate prompt engineering as a formal operation competency, as opposed to an informal workaround.

One important theoretical insight provided by this study is its contextualization of prompt engineering in the field of digital literacy. As Taeuscher and Rothe (2021) have pointed out, achieving sustainable competitive advantages in digital-native firms is more and more dependent on the quality of human-AI collaboration. This co-operation is manifested in the form of a concrete practice: prompt engineering. Extracting high-quality, task-relevant outputs from LLMs lessens the need for costly specialists and puts more generalist teammates at higher cognitive levels.

Results of the study are expected to inform the creation of toolkits and curricular for onboarding startups in prompt engineering for practical implementation. Whereas, startups that have a defined prompt literacy can make more iterative steps with AI tools without mistakes and maintain consistency across company-generated AI content. This is consistent with the overall conclusion that investments with no skills development have diminishing returns (Kyurova et al., 2023).

In addition, the results of various impacts based on the type of tasks (content creation, code support, customer service, and market research) provide more specific information for start-up decision-makers interested in investing in AI training. There may be more variance in task type sensitivity to prompt quality, thereby training limited amounts on certain task types.

CONCLUSION

This paper has discussed the concept of prompt engineering as a strategic tool for startups in their early stages to make the most of generative AI. One thing that comes out clearly in all the literature that was reviewed is that, as powerful and more readily available as LLMs become, they are fundamentally limited by the quality of human instruction. Prompt engineering helps bridge this gap, converting indecisive interactions into exact and productive discussions between users and AI systems. This study's quantitative pre-post research design provides a robust structure for empirically substantiating the effects of prompt engineering training on four important categories of start-up tasks. The study will assess how relevant, accurate, and user-friendly and efficient the content becomes by measuring the changes, thereby providing evidence-based insights that go beyond the anecdotal claims of AI productivity. The results should confirm the importance of prompt engineering as an essential digital skill for startup teams, on par with data skills or agile project management. This research calls for the formal inclusion of prompt engineering in AI literacy curricula, incubation curricula and entrepreneurship education frameworks for start-up ecosystems, educators and policy makers. The more advanced the generative AI gets, the more advanced the prompting will be. Startups that take the time to cultivate this ability early on are likely to become more adaptable, efficient and competitive tomorrow. Thus, the art and science of prompting is not a fringe peripheral, but a cornerstone to AI-powered startups.

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