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Hey ChatGPT: an examination of ChatGPT prompts in marketing

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Abstract

Marketing is one of the areas where large language models (LLMs) such as ChatGPT have found practical applications. This study examines marketing prompts—text inputs created by marketers to guide LLMs in generating desired outputs. By combining insights from the marketing literature and the latest research on LLMs, the study develops a conceptual framework around three key features of marketing prompts: prompt domain (the specific marketing actions that the prompts target), prompt appeal (the intended output of the prompts being informative or emotional), and prompt format (the intended output of the prompts being generic or contextual). The study collected hundreds of marketing prompt templates shared on X (formerly Twitter) and analyzed them using a combination of natural language processing techniques and descriptive statistics. The findings indicate that the prompt templates target a wide range of marketing domains—about 16 altogether. Likewise, the findings indicate that most of the marketing prompts are designed to generate informative output (as opposed to emotionally engaging output). Further, the findings indicate that the marketing prompts are designed to generate a balanced mix of generic and contextual output. The study further finds that the use of prompt appeal and prompt format differs by prompt domain.

Keywords Large language models · Business · Prompt engineering · Artificial intelligence · AI

Introduction

Large language models (LLMs), such as ChatGPT and Bard, are advanced AI systems designed to understand, respond to, and generate human-like text. These models are trained on massive amounts of text data and use deep learning algorithms to develop a general understanding of their training data (Zhang et al. 2023a). LLMs have achieved state-of-the-art performances on a range of natural language processing (NLP) tasks including text classification, language translation, question answering, sentiment analysis, text generation, and arithmetic and logical reasoning (Liu et al. 2023a; Zhou et al. 2023). Due to their impressive NLP capabilities, LLMs have found practical use cases in various fields including medicine, education, software engineering, law, and business, among others (Koubaa et al. 2023; Ray 2023).

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Prompt engineering is the process of crafting effective instructions, called prompts, to guide LLMs in generating desired outputs (Liu et al. 2023b; Logan et al. 2021). Prompts are text inputs written in natural language to which LMMs respond by creating custom outputs. Prompts thus define how users interact with LLMs (Bach et al. 2023). Moreover, the way prompts are designed by users plays a crucial role in the quality and accuracy of the resulting output (White et al. 2023), making the task of crafting effective prompts a critical endeavor for anyone interacting with LLMs (Sorensen et al. 2022).

Considering the importance of prompts, this study seeks to examine marketing prompts to understand how marketers are interacting with LLMs. This emphasis on marketing prompts affords a unique perspective into how marketers are leveraging LLMs in their work. The study specifically uses ChatGPT as its empirical context as it is one of the earliest and most widely used LLMs to date. Literature reviews and commentaries on the use of AI in marketing suggest that AI has the potential to impact multiple aspects of the marketing function including market research, marketing strategy, and execution of the marketing mix elements (Davenport et al. 2020; Huang and Rust 2021; Kumar et al. 2021). However, as many of the existing reviews and commentaries predate

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recent advances in LLMs (Schiessl et al. 2022), there is a paucity of studies examining the application of LLMs in marketing including how marketers are leveraging LLMs through prompt engineering.

To help guide and organize the empirical work, the study combines insights from the marketing literature and the latest research on LLMs to develop a conceptual framework based on three key features of marketing prompts: prompt domain, prompt appeal, and prompt format. Prompt domain maps the marketing prompts to specific marketing actions that they target, such as social media marketing, content marketing, email marketing, search engine optimization, and so on. This feature thus captures the various areas of marketing where LLMs are being actively applied. Prompt appeal denotes the intended output of the prompts in terms of being informative or emotional. This feature is associated with the informative and emotional appeal of marketing stimuli, which is central to how marketers connect to customers by supporting their decision-making process or enhancing their consumption experience (Puto and Wells 1984; Taylor 1999). Finally, prompt format consists of zero-shot and few-shot prompts and reflects the intended output of the prompts being generic or contextual. Zero-shot prompts represent plain questions or descriptions of tasks that LLMs can respond to without the need for unique contexts, relevant examples, or background information from the user (Reynolds and McDonell 2021). In contrast, few-shot prompts incorporate unique contexts, relevant examples, or background information from the user that LLMs take into account when generating their responses (Brown et al. 2020). Consequently, the output from zero-shot prompts tends to be generic, while the output from few-shot prompts tends to be contextual (Kojima et al. 2022). Together, the three prompt features address the what of marketing prompts (what marketing tasks the prompts target) and the how of marketing prompts (how the prompts are designed and the nature of their intended outputs). The empirical part is based on marketing prompt templates collected from X, which were analyzed using a combination of NLP and descriptive statistics.

The findings contribute both to theory and practice. Theoretically, the findings are one of the first to provide a systematic and data-driven insight into marketing prompts. By combining insights from the marketing literature and the latest research on LLMs, the study analyzes marketing prompts with respect to their domain (social media marketing, content marketing, email marketing, etc.), their appeal (informative or emotional), and their format (zero-shot or few-shot). The findings thus shed light on the what of marketing prompts (what marketing actions the prompts target) and the how of marketing prompts (how marketing prompts are designed and the nature of their intended outputs in terms of being emotional or informative; and generic or contextual). Managerially, the findings provide practical guidance for marketers to design relevant and insightful prompts for various marketing tasks. Marketers can use the findings to identify appropriate areas of marketing for LLM intervention and to design various forms of marketing prompts that are suitable for different circumstances such as emotional prompts, informative prompts, zero-shot prompts, and few-shot prompts.

Theoretical background

Marketing and AI

Marketing has increasingly become “data driven, automated, and intelligent” (Chintalapati and Pandey 2022, p. 38). AI, defined as “a system’s ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Kaplan and Haenlein 2019, p. 15), is at the forefront of ongoing transformation of marketing (Kumar et al. 2021). When applied in the context of marketing, AI can help businesses achieve automation of marketing processes, personalization of market offers, and meaningful engagement with customers and employees (Davenport et al. 2020; Kumar et al. 2021).

Marketing firms are investing heavily in AI (Mustak et al. 2021). Global spending on marketing AI is expected to reach $107 billion by 2028 (Statista 2023). Academic research on the application of AI highlights a broad-based impact on the marketing function. After performing a systematic review of the literature on AI in marketing, Mustak et al. (2021) suggested that AI is being applied to understand customer sentiment, analyze customer satisfaction, measure customer loyalty, manage brands, and improve customer satisfaction. Similarly, Chintalapati and Pandey (2022) identified several areas of AI application in marketing including digital marketing (e.g., search, recommender systems, programmatic advertising), content marketing (e.g., content generation, content personalization), market research (e.g., customer segmentation, customer behavior), experiential marketing (e.g., voice, virtual reality, image), and marketing operations (e.g., marketing automation, forecasting, predictive analytics). Kumar et al. (2021) highlighted personalization of the marketing mix, more precise prediction of future trends, disintermediation and direct engagement with consumers, and productivity enhancement as key benefits of AI adoption in marketing. However, these reviews and commentaries lack a framework to link AI with strategic marketing actions systematically and comprehensively.

Huang and Rust (2021) provided a framework for applying AI for strategic marketing planning. First, they introduce the notion of multiple AI intelligences, similar to human intelligence, that are used for different tasks including mechanical, thinking, and feeling AI. Mechanical AI is designed for task automation and relies on traditional machine learning algorithms such as classification. Thinking AI is designed to identify patterns and regularities in data. Text mining, speech recognition, and facial recognition are examples of thinking AI. Feeling AI is designed for two-way interactions involving humans and is good at analyzing feelings and emotions. NLP, sentiment analysis, text-to-speech, and chatbots are examples of feeling AI. The framework introduces a marketing research-marketing strategy-marketing action cycle that views marketing strategic planning as a circular process connected by a feedback loop. Marketing research is conducted to understand the market, competitors, and customers. This insight is then used to develop a segmentation, targeting, and positioning strategy, which in turn informs the marketing actions needed for execution (i.e., the 4Ps). The framework then maps the three AI types and their various applications to the three elements of strategic marketing planning. Market research is believed to benefit from mechanical AI (for data collection), thinking AI (for market analysis), and feeling AI (for customer understanding). Marketing strategy is believed to benefit from mechanical AI (for segmentation), thinking AI (for targeting), and feeling AI (for positioning). Marketing action is believed to benefit from mechanical AI (for standardization), thinking AI (for personalization), and feeling AI (for relationalization).

It is worth noting that extant reviews and commentaries in the literature predate the recent advances in LLMs and are based on AI models built on rule-based or supervised machine learning paradigms (Schiessl et al. 2022). Although the insights and frameworks can serve as a starting point, they are limited in addressing the emergent capabilities of LLMs such as prompt engineering. With this in mind, an overview of LLMs and prompt engineering is provided in the subsequent sections.

Large language models

Large language models (LLMs), such as ChatGPT and Bard, are advanced AI systems designed to learn the underlying structure and pattern of their training data (Hariri 2023; Teubner et al. 2023). LLMs learn by creating a probability distribution over a given word being valid in a sequence of words (Nvidia 2023). LLMs employ an unsupervised learning technique, which circumvents the need for labeled data, enabling them to learn from a massive amount of unlabeled and unstructured text data including books, the internet, social media, and so on (Zhang et al. 2023b). As Lui et al. (2021) noted, "because the raw textual data necessary to train LMs is available in abundance, these LMs can be trained on large datasets, in the process learning robust general-purpose features of the language it is modeling." (p. 21).

LLMs are pre-trained in a task-agonistic manner, with the primary goal of learning the underlying pattern of their training data without any specific task in mind (Hassani and Silva 2023; Tamkin et al. 2021). Due to this generic learning orientation, LLMs acquire a comprehensive representation of the language that they are modeling, enabling them to excel at a variety of NLP tasks such as text generation, text summarization, text classification, text translation, sentiment analysis, topic modeling, and so on (Liu et al. 2023a). Additionally, LLMs are capable of logical reasoning and arithmetic operations (Ray 2023). They can also understand context and nuances, which makes them excellent conversational agents for human interaction (Shahriar and Hayawi 2023).

LLMs rely on the transformer, a neural network architecture that possesses a self-attention mechanism for computing the relative importance of input tokens (Zhang et al. 2023b). This allows LLMs to pay attention to relevant parts of the input sequence and better handle long-term dependencies, thereby improving model performance in a wide range of NLP tasks (Zhou et al. 2021). Conversational LLMs such as ChatGPT and Bard are also fine-tuned using what is known as reinforcement learning from human feedback (RLHF), which involves modifying their output based on human feedback (Kacon et al. 2023; Koubaa et al. 2023). RLHF helps LLMs to better align their output to human preferences, making them more helpful, accurate, and aware of human values and intentions when interacting with users (Shahriar and Hayawi 2023).

Prompt engineering

Prompt engineering is the process of crafting effective instructions using natural language to guide LLMs in generating desired responses (Liu et al. 2023b; Logan et al. 2021). Bach et al. (2022) defined prompt engineering as "the practice of representing a task as a natural language utterance in order to query a language model for a response" (p. 1). It involves constructing text inputs, called prompts, that can elicit accurate and relevant outputs from LLMs by guiding and constraining their behavior (Wu et al. 2022; Zamfirescu-Pereira et al. 2023).

Prompts shape the behavior of LLMs by communicating the nature of the desired task, how the task should be executed and how the output should be formatted (White et al. 2023). As LLMs are large probability models, their outputs on generative tasks cannot be fully predicted by users beforehand, potentially causing a gap between user-desired output and model-generated output (Liu and Chilton 2022). This gap can be overcome by constraining LLMs through tailored instructions and providing relevant contexts (Reynolds and McDonell 2021).

Prompts can be designed in a variety of ways depending on the task at hand and the nature of the desired output. For complex reasoning and arithmetic tasks, chain-of-thought prompting has been shown highly effective. Chain-of-thought prompting primes LLMs to break down tasks into smaller, logical components and solve each task component step-by-step, using the output from a previous step as an input to the next step (Wei et al. 2023). Adding phrases such as “let us solve this problem step by step” to a prompt activates chain-of-thought reasoning among LLMs (Wei et al. 2023).

For image generation, incorporating certain modifiers into prompts has been shown to be effective. These modifiers are akin to keywords in online searches and might include subject terms, style modifiers (e.g., impressionistic), quality boosters (e.g., eclectic, epic, etc.), and so on (see Oppenlaender 2022). When examples of input–output pairs are available, supplying these pairs as examples to LLMs can enhance their accuracy as the models can learn from the examples (Brown et al. 2020). This prompting strategy can be used when the desired output needs to be modeled after existing examples (Logan et al. 2021). Incorporating precise task signifiers has also been suggested as an effective prompt design template, especially for zero-shot prompts (Reynolds and McDonell 2021). A task signifier cues the desired task to LMMs (e.g., translate, categorize, rephrase, etc.), thereby priming the models to access relevant insight about the core task. LLMs can also be prompted by assigning them specific roles (e.g., pretend that you are a marketing manager, or act like a data scientist). This prompting strategy enables LLMs to adopt the role of the designated expert or persona and approach the task accordingly.

Conceptual framework

To guide the empirical work, a conceptual framework was developed by combining insights from the marketing literature and the latest research on LLMs. The conceptual framework is built around three key features of marketing prompts: prompt domain, prompt appeal, and prompt format. The importance of these features and the rationale for incorporating them in the conceptual framework are discussed below.

Prompt domain denotes the specific marketing actions targeted by the prompts, which might include creating social media posts, analyzing customer segments, performing keyword research for search engine optimization, conducting competitor analysis, planning marketing campaigns, and so on. Prompt domain helps to map each marketing prompt to a specific marketing action, thereby addressing the what of marketing prompts—that is, which specific marketing tasks the prompts target.

Prompt appeal and prompt format deal with the how of marketing prompts—that is, how the prompts are designed to generate desired outputs. Prompt appeal denotes the intended output of the prompts being informative or emotional. The marketing literature has long recognized that informative and emotional appeals are integral to how marketers interact with customers. Customers purchase and consume products for rational and hedonic reasons (Batra and Ahtola 1991; Hirschman and Holbrook 1982), and they seek informative and emotional marketing stimuli to support their decision-making process and enhance their consumption experience (Taylor 1999). Informative and emotional appeals thus underlie marketers’ interaction with customers (Tafesse and Wien 2018). Prompt appeal provides insight into the type of output marketers seek from LLMs and how they intend to employ it in their interaction with customers.

Prompt format deals with the intended output of marketing prompts being generic or contextual and consists of two types: zero-shot and few-shot (Brown et al. 2020). Zero-shot prompts are plain questions or descriptions of tasks (Kojima et al. 2022). They provide no examples or unique contexts from the user that LLMs can take into account when generating responses. Consequently, the output from zero-shot prompts tends to be generic, such as an explanation of a specific concept, standard content templates, or a list of items (Bach et al. 2022). In contrast, few-shot prompts incorporate relevant examples, contexts, or background information from the user that LLMs need to take into account when generating responses (Kojima et al. 2022). Consequently, the output from few-shot prompts tends to be more contextual and unique to the prompt in question.

Methodology

Dataset

A sample of marketing prompt templates was collected from X for analysis. The marketing and AI community have begun to share prompt templates on X as a means of engaging their followers. These publicly shared prompt templates reflect the intuition of the community about the capabilities of LLMs for marketing tasks. Because the prompt templates come from multiple sources, they provide a good representation of marketing prompts that are currently being explored and discussed in the community, which would eventually influence actual practice through a diffusion process.

X was manually searched using the following combination of keywords: “ChatGPT + marketing + prompts,” “AI + prompts + marketing,” and “prompt + templates + marketing,” which returned hundreds of marketing prompt templates. Manual searching was used since X has abruptly ended the ability to search and download tweets through its API in an automated fashion. The data collection was conducted in May 2023. To ensure data quality, only those prompt templates shared by credible accounts were considered. These include marketing professionals, digital marketing service providers, and AI experts. The details of the accounts from which the marketing prompts were obtained are summarized in Table 1.

Once appropriate prompt templates were found, which were typically shared as a thread, each prompt in the thread was copied into an Excel file sheet. This process resulted in 357 marketing prompt templates. Although an effort was made to gather additional prompt templates by extending the data collection period, the newly shared prompt templates tend to be replicas of previously shared ones and show little originality.

Operationalization of prompt features

Our analysis centers prompt domain, prompt appeal, and prompt format. Given ChatGPT's well-documented NLP capabilities including text classification (Wei et al. 2022; Zhao et al. 2021), it was employed in the current study to operationalize these three prompt features. As a means of validation, ChatGPT's classification was formally compared with the results of an independently performed classification by a human using inter-rater reliability scores.

To operationalize prompt domain, ChatGPT was first asked to create a comprehensive list of digital marketing approaches along with a concise definition of each. ChatGPT returned 19 state-of-the-art digital marketing approaches consisting of search engine optimization (SEO), pay-per-click advertising, social media marketing, content marketing, email marketing, influencer marketing, affiliate marketing, video marketing, mobile marketing, display advertising, native advertising, remarketing/retargeting, chatbot marketing, voice search optimization, augmented reality, virtual reality marketing, marketing analytics, social media listening, and user-generated content. Rather than using externally supplied definitions, using internally generated definitions can be handy for a classification task as LLMs tend to rely on their internal knowledge for downstream tasks (White et al. 2023). The definitions generated by ChatGPT are consistent with existing academic (Minculete and Olar 2018) and practitioner sources (HubSpot 2022).

Subsequently, the prompt templates were coded by the first author using the 19 digital marketing approaches suggested by ChatGPT to check their applicability as a coding instrument. This initial coding revealed prompts that deal with marketing strategy and branding issues could not be categorized into one of the 19 digital marketing approaches suggested by ChatGPT. Likewise, the initial coding revealed a handful of digital marketing approaches that did not apply to the marketing prompts in the dataset (e.g., native advertising, voice search optimization, augmented reality, virtual reality, and social media listening). Therefore, marketing strategy and branding categories were added to the coding instrument, while the inapplicable digital marketing approaches were removed. At the end of this process, 16 marketing approaches were synthesized as part of the final coding instrument. Following this, ChatGPT was instructed to categorize each marketing prompt template into one of the 16 proposed marketing approaches (see Table 2 for the exact prompt used for this task).

Table 1 Summary characteristics of accounts

Account type	Professional interest	Number of followers	Number of marketing prompts shared
Individual, verified	AI marketing	937	18
Individual, verified	AI marketing	27,400	20
Individual, verified	AI marketing	2198	20
Individual, verified	AI marketing	38	8
Individual, verified	Email marketing	117,300	5
Individual, verified	Content creator	548	20
Individual, verified	AI content creator	74,900	15
Institutional, non-verified	Search engine optimization	17,100	25
Individual, verified	Digital marketing	243	20
Individual, verified	AI expert	168	20
Institutional, verified	Search engine optimization, digital marketing	29,000	20
Institutional, verified	CRM, digital marketing	826,000	25
Institutional, verified	Digital marketing	23,000	20
Institutional, verified	AI marketing	14,500	34
Institutional, verified	AI marketing	780	42
Institutional, verified	AI marketing and webhosting	8731	45

Table 2 Prompts used for categorizing marketing prompts using ChatGPT

Prompt domain	Prompt appeal	Prompt format
Given the following list of marketing approaches: Search engine optimization, Pay-Per-Click advertising, Social media marketing, Content marketing, Email marketing, Influencer marketing, Website optimization, Video marketing, Mobile marketing, Display advertising, Remarketing/Retargeting, Chatbot marketing, Marketing analytics, User-generated content, Marketing strategy (segmentation, targeting and positioning), and Branding (brand story telling, brand building, PR) Categorize the following marketing prompt into one marketing approach Marketing prompt:	Categorize the appeal of the following marketing prompt either as informative, emotional or mixed. Informative prompts are those that primarily seek to derive factual information, gain explanations, or ask for assistance on a specific task. Emotional prompts are those that primarily seek to evoke emotions and the expected outputs are motivating, aspiring, or entertaining. Mixed appeal prompts are those that seek to derive a combination of informative and emotional appeals. Please include a succinct justification for your categorization Marketing prompt:	Categorize the following marketing prompt as few-shot or zero-shot based on the following definitions:Zero-shot learning refers to the ability of a language model to perform a task or provide accurate responses on unseen or unfamiliar examples or contexts; few-shot learning refers to training a language model with a limited amount of labeled data or examples for a particular task or domain. Please include a succinct justification for your categorization Marketing prompt:

To operationalize prompt appeal, ChatGPT was first asked to develop a concise definition of informative, emotional, and mixed appeals. It was instructed to focus on the intended output of the prompt templates in its definition of prompt appeal. Because of this, the proposed definitions reflect whether the prompts seek to generate factual and informative output or evoke emotions. After checking the accuracy of ChatGPT's definitions, it was asked to categorize each prompt template into informative, emotional, or mixed. ChatGPT was also asked to provide a concise justification for its categorization to verify its reasoning.

Finally, to operationalize prompt format, as was done earlier, ChatGPT was first asked to develop a concise definition of zero-shot and few-shot prompts. The definitions are consistent with those offered in the LLM literature (Kojima et al. 2022; Liu et al. 2023b). Subsequently, ChatGPT was asked to categorize each prompt template into zero-shot and few-shot. ChatGPT was also asked to provide a concise justification for its categorization to verify its reasoning. Table 2 reports the actual prompts used to operationalize prompt domain, prompt appeal, and prompt format using ChatGPT. Table 3 reports sample prompt templates and their categorization.

Inter-rater reliability

To ensure the reliability of ChatGPT's categorization, a trained research assistant independently coded the prompt templates. The research assistant used the same definitions of the three prompt features used by ChatGPT. The results of the manual coding were subsequently compared with that of ChatGPT using Cohen's Kappa (k), which is a popular inter-rater reliability score (Banerjee et al. 1999). Cohen's Kappa is more robust than a simple inter-rater agreement percentage as it adjusts for chance agreement:

$$k = \frac{p_0 - p_e}{1 - p_e}$$

where p_o is the observed agreement among raters and p_e is the probability of chance agreement. For C categories, N observations to categorize, and n_{ci} the number of times rater i predicted category c:

$$p_e = \frac{1}{N^2} \sum_c n_{c1} n_{c2}$$

Cohen's Kappa, k, can range between -1 and $+1$, where $k < 0$ when observed disagreement between coders exceeds chance agreement, $k = 0$ when observed agreement between coders is equal to chance agreement, and $k > 0$ when observed agreement between coders exceeds chance agreement. According to McHugh (2012), $k > 0$ can be interpreted as follows: 0.01–0.20 none to slight

Table 3 Operationalization of prompt features and sample marketing prompts

Prompt feature	Categories	Concise definition of categories	Sample prompts
Prompt domain	Branding (brand story telling, brand building, PR)	The strategic process of creating, establishing, and promoting a distinctive and recognizable brand identity for a product, service, or organization	"Help me create a powerful brand story for my [product/service] using the Hero's Journey framework."
	Chatbot marketing	Utilizing AI-powered chatbots to interact with customers, provide instant support, and assist in sales or lead generation	"Discuss how businesses can use AI tools to improve customer service and reduce churn rates."
	Content marketing	Creating and distributing valuable, relevant, and consistent content to attract and retain a clearly defined audience, with the goal of driving profitable customer action	"List [number] ideas for blog posts about [topic]."
	Display advertising	Placing visual banner or image ads on websites, mobile apps, or social media platforms to increase brand visibility and drive traffic	"How would you improve the click-through rate of a travel agency's display ads?
	Email marketing	Sending targeted promotional messages or newsletters to a list of subscribers to build relationships, drive sales, and increase customer loyalty	"Craft a pitch email for selling "your product"
	Influencer marketing	Collaborating with influencers on social media platforms to promote products or services to their followers	"For my [product/service], create a guideline for my influencer marketing strategy, using the 4Cs of Influencer Marketing (Content, Credibility, Clout, Cost-effectiveness)."
	Marketing analytics	Leveraging data analytics and insights to make informed marketing decisions, personalize marketing campaigns, and enhance customer experiences	"Outline a plan for tracking and measuring the success of our marketing initiatives for <PRODUCT>, including the key performance indicators and analytics tools we should utilize to assess campaign performance."
	Marketing strategy	A comprehensive plan and set of actions devised by a business to achieve its marketing objectives. It involves making informed decisions regarding market segmentation, targeting, competitive analysis, positioning, and customer acquisition and retention	"Identifying and analyzing target audience segments requires understanding the product, market research techniques, and factors like demographics, psychographics, and buyer behavior. The model may need additional information about the product, specific target audience characteristics, and research goals to provide accurate and insightful analysis for the marketing strategy."
	Mobile marketing	Targeting mobile device users with marketing messages delivered through mobile devices	"Discuss some of the best practices when developing a mobile marketing strategy and how businesses can leverage it."
	Pay-per-click advertising	Running targeted ads on search engines or social media platforms where advertisers pay based on the number of clicks received	"Write [number] Google Ad headlines from [URL]."
	Remarketing/retargeting	Displaying targeted ads to users who have previously visited a website or shown interest in a product or service	"ChatGPT, could you draft a friendly reminder for customers who have items left in their shopping cart?""
	Search engine optimization	Optimizing website content to improve search engine rankings and increase organic (non-paid) traffic	"ChatGPT, can you write a compelling and SEO-friendly description for [product]?"
	Social media marketing	Promoting products or services through social media platforms to engage with the target audience, build brand awareness, and drive website traffic	"Create a 3-month social media campaign calendar for our product with the goal to [insert goal] and mention the channels we should focus on."
	Video marketing	Using videos to promote products or services, engage with the audience, and deliver brand messages	"Generate 5 different YouTube descriptions for our video about [topic]."
	User-generated content	Encouraging customers to create and share content related to a brand, product, or campaign, leveraging user-generated content in marketing efforts	"I will provide feedback from the users about our product. Use the feedback to create ecom ads with user-generated content that would convert into sales. Here is the list of user feedback messages:"
	Website optimization	Improving a website's performance and usability by optimizing its content and design	"I'm trying to drive [desired result] on my landing page. What are five compelling call-to-actions I can use?"
Prompt appeal	Informative	Prompts designed to derive factual information, explanations, or task assistance from ChatGPT. They focus on conveying details, generating information, or offering solutions	"What are 10 main points that are crucial to marketers trying to acquire new customers?"
	Emotional	Prompts designed to evoke emotions. Their outputs can be aspirational, motivational, or capable of generating an emotional response	"Generate a list of 10 quotes from satisfied customers for an affiliate marketing course"
	Mixed	Prompts consisting of a mix of both informative and emotional appeals	"Write a list of 10 catchy and descriptive YouTube video titles for <Topic of your choice>"

Table 3 (continued)

Prompt feature	Categories	Concise definition of categories	Sample prompts
Prompt format	Zero-shot	Zero-shot learning refers to the ability of a language model to perform a task or provide accurate responses on unseen or unfamiliar examples or contexts. It leverages the model's general understanding and knowledge to make inferences or generate outputs for new scenarios	"Tell me ways I can use framing techniques in ad copy to influence my audience's perception of my product or service"
	Few-shot	Few-shot learning involves training a language model with a limited amount of labeled data or examples for a particular task or domain. The model learns to generalize from the limited training data and can then apply that knowledge to perform the task on new, unseen examples with similar characteristics. Few-shot learning enables the model to adapt and make predictions even when only a small amount of data is available for training	"As a marketing manager at [company], you've been tasked with running a co-branded campaign on Instagram for [product]. Your partner is [influencer name], who has a large following in your target demographic. How would you plan and execute this campaign to maximize reach, engagement, and sales? What are some potential challenges you might face and how would you address them? What metrics would you use to measure the success of the campaign?"

agreement, 0.21–0.40 fair level of agreement, 0.41– 0.60 moderate agreement, 0.61–0.80 substantial agreement, and 0.81–1.00 almost perfect agreement. In our case, Cohen's Kappa, k, was 0.77 for prompt domain, 0.69 for prompt appeal, and 0.73 for prompt format. Therefore, the research assistant achieved a substantial agreement with ChatGPT. The first author resolved differences between ChatGPT and the research assistant by independently coding the disputed prompt templates. The coding results of ChatGPT and the research assistant from which Cohen's Kappa scores were computed are reported in the Appendix.

Results

Before the results of the main analyses are presented, some initial exploratory observations about the prompt templates are in order (Fig. 1). In Fig. 2, word clouds of the words used in the prompt templates are plotted—separated into verbs and nouns. The verbs indicate frequent marketing actions that ChatGPT is asked to execute, while the nouns indicate the subject area and context of the marketing actions. Before generating the most frequent words, the original prompt templates were preprocessed in the tradition of NLP by removing stop words and special characters, and converting the words into lower cases. The most frequent verbs in the prompt templates consist of "use" (appeared 30 times), "include" (appeared 23 times), "engaging" (appeared 18 times), "targeting" (appeared 16 times), and "develop" (appeared 16 times). The most frequent nouns in the prompt templates include "product" (appeared 157 times), "marketing" (appeared 84 times), "target" (appeared 65 times), "create" (appeared 59 times), and "audience" (appeared 56 times).

Next, the distribution of the word count of the prompt templates is plotted in Fig. 3. The average word count of the prompt templates is about 19 words, which is equivalent to a single full-line sentence. The brevity of the average prompt template indicates that the designers of the prompt templates envision a relatively simple interaction between marketers and ChatGPT. Although short prompts can be effective for simpler tasks, longer prompts with richer context and background information might be needed for contextually meaningful output (Reynolds and McDonell 2021; White et al. 2023).

Prompt domain

The frequency of the marketing actions targeted by the prompt templates is plotted in Fig. 4. The prompt templates targeted 16 marketing actions altogether. Except for marketing strategy and branding, all other marketing actions fall within the realm of digital marketing. The most frequent marketing action targeted by the prompt templates is social media marketing. These prompts deal with such tasks as creating content for social media, designing a social media ad, and optimizing for user engagement on social media. The second most popular marketing action targeted by the prompt templates is email marketing. These prompts focus on brainstorming email ideas, crafting email templates, and optimizing emails for greater audience engagement. Next is content marketing, where the prompt templates are designed to plan, create, or improve content such as blog posts, newsletters, infographics, and product descriptions. The fourth most frequent marketing action is marketing strategy, where the prompt templates focus on such issues as customer acquisition, customer retention, targeting, competitive analysis, and campaign planning. This is followed by search engine optimization, where the prompt templates target such actions as creating search-optimized content, generating keyword suggestions, and incorporating user-supplied keywords into content. Some other interesting marketing actions targeted by the prompt templates include marketing analytics (e.g., asking about specific metrics, identifying appropriate analytics tools, etc.) and remarketing/retargeting (e.g., designing retargeting ads, identifying product recommendations based on past purchases, etc.). Overall, the prompt templates address a wide variety of marketing actions. Given the relatively small number of prompt templates analyzed, the diversity of the marketing actions targeted by the prompt templates is quite impressive, suggesting that LLMs are beginning to influence marketing practices more broadly. Illustrative prompt templates for each marketing action are provided in the last column of Table 3.

Prompt appeal

The realization that consumers are driven by both rational and hedonic considerations during the purchase and consumption of products and services has motivated the development of informative and emotional messaging strategies to appeal to consumers' rational and hedonic motivations (Puto and Wells 1984; Taylor 1999). The informative appeal typically provides detailed and factual information to customers, while the emotional appeal typically provides aspirational, symbolic, or experiential cues to customers (Tafesse and Wien 2018). This notion is employed here to categorize

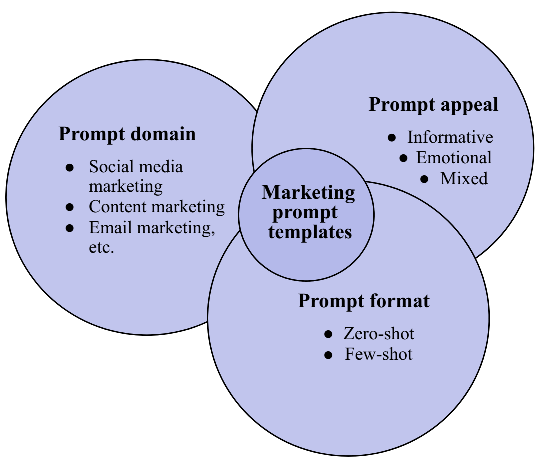

Fig. 1 Conceptual framework

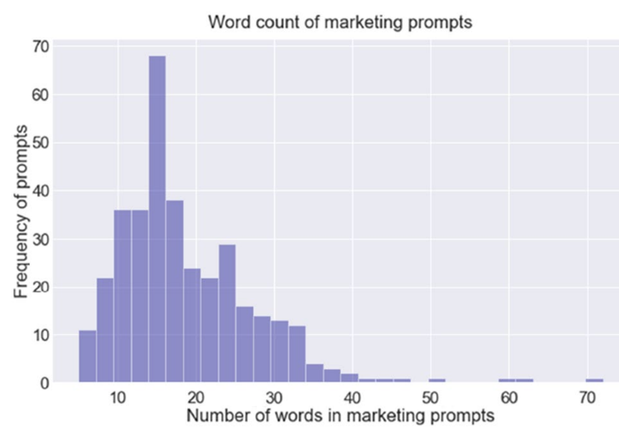

Fig. 3 Frequency distribution of the word count of marketing prompts

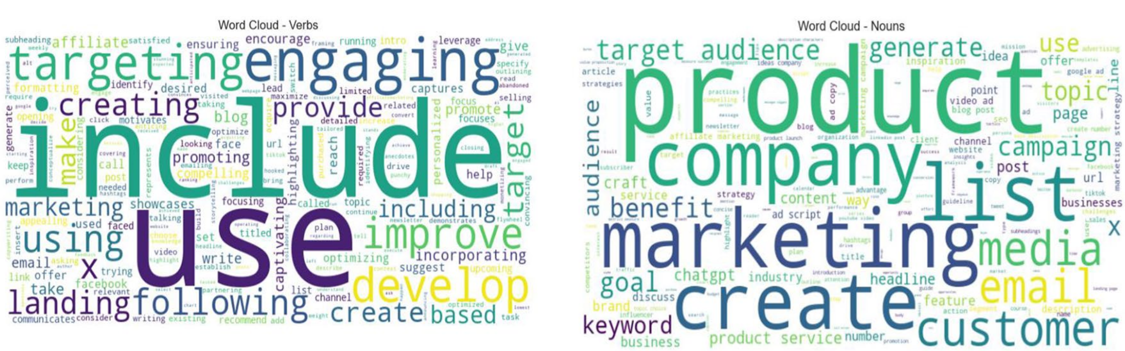

Fig. 2 Word cloud of marketing prompts

marketing prompts into informative, emotional, or mixed based on their intended output.

The results of this analysis are shown in Fig. 4, which indicate that the majority of the prompt templates are categorized as informative (65%). In contrast, those with a mixed appeal account for 29% of the prompt templates, while those with purely emotional appeal account only for 6% of the prompt templates. These findings suggest that many of the prompt templates are intended to generate informative and factual outputs, while prompt templates intended to generate emotionally engaging output are less common. This is surprising for two reasons. First, LLMs are capable of producing not only informative output but also emotionally engaging output as demonstrated in their ability to write song lyrics, stories, poems, and jokes (Cao et al. 2023). Second, the efficacy of emotional messaging in marketing has been well-documented in terms of eliciting desired customer responses (Tafesse and Wien 2018). Emotional messaging allows marketers to establish emotional bonds with customers around their core product, brand, or service offerings (Ashley and Tuten 2015). In turn, such emotional bonds drive favorable customer behavior including customer satisfaction, customer loyalty, and positive customer engagement (Harmeling et al. 2017).

Prompt format

Prompt format captures whether the prompt templates contain relevant context, examples, or background information. Zero-shot prompts consist of plain questions or task descriptions without relevant contexts, examples, or background information from the user that LLMs can take into account when generating responses. In contrast, few-shot prompts incorporate relevant contexts, examples, or background information from the user that LLMs take into account when generating responses.

The results of the analysis of prompt format are shown in Fig. 4, which indicate that few-shot prompts (55%) are slightly more frequent than zero-shot prompts (45%). A closer look at the few-shot prompts suggests that they typically incorporate specific contexts related to products, customers, customer segments, or desired marketing goals (see the last column of Table 6 for an actual example of few-shot prompts). For instance, for social media marketing-related actions, the few-shot prompts provide contexts related to product type, target audience, media format (e.g., carousel), and desired goals (e.g., create awareness, generate leads, etc.). For content creation, the few-shot prompts provide such contexts and examples as title and outline of the desired content and website URLs to read from. The zero-shot prompts typically consist of plain questions about explaining certain marketing concepts, clarifying how certain marketing approaches work, or a request for generic content template, or list of items. The findings indicate that the few-shot prompts are used when the tasks at hand require detailed context and background information from the user, such as campaign planning, competitor assessment, and customer segment analysis. In contrast, the zero-shot prompts are used when the tasks at hand are generic and require no unique context or background information from the user, such as defining marketing concepts, explaining marketing approaches, creating a list of items, and generating standard content templates.

Prompt appeal by prompt domain

This section explores whether the use of prompt appeal varies by prompt domain. To help address this issue, the frequency of prompt appeal is plotted for each marketing action in Fig. 5. As can be seen, the informative appeal is the dominant type of appeal for several marketing actions including social media marketing, content marketing, email

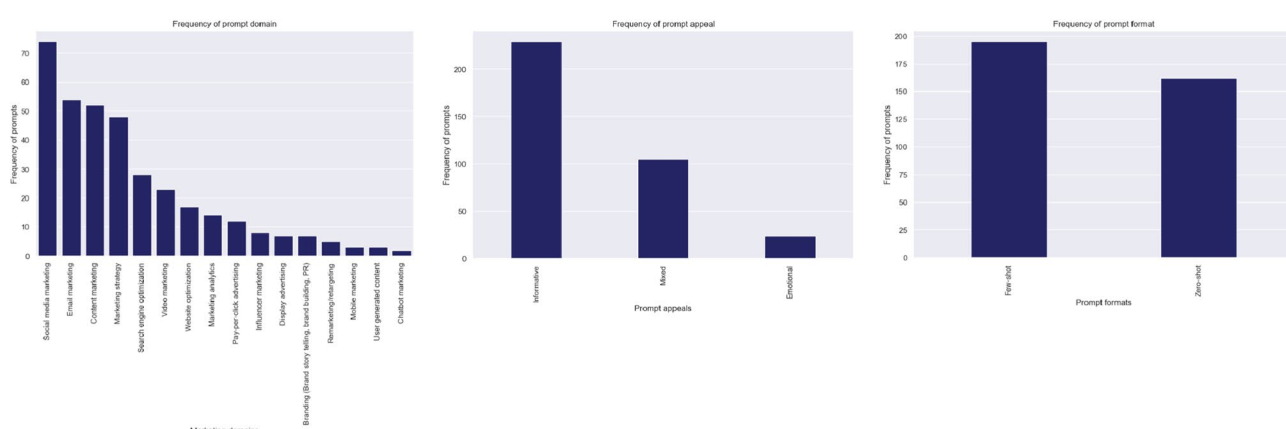

Fig. 4 Frequency distribution of prompt domain, prompt appeal, and prompt format

marketing, and search engine optimization. However, there are some marketing actions in which mixed and emotional appeals play greater roles. These include branding, video marketing, display advertising, pay-per-click advertising, and user-generated content. These latter marketing actions appear to be more amenable to emotional and experiential messaging. These findings suggest that the use of prompt appeal differs systematically by prompt domain. While some marketing actions rely primarily on informative appeal, others rely on emotional appeal.

Prompt format by prompt domain

Additionally, the study explored whether prompt format varies by prompt domain. To help address this issue, the frequencies of zero-shot and few-shot prompts are plotted for each marketing action, as shown in Fig. 5.

The results show that zero-shot prompts play a prominent role in such marketing actions as content marketing, email marketing, marketing analytics, display advertising, and remarketing/retargeting. These findings suggest that the questions and tasks associated with these marketing actions are designed to be generic—that is they are intended to gain plain explanations of concepts and approaches, generate standard content templates, or a list of items. In contrast, few-shot prompt templates play a prominent role in such marketing actions as marketing strategy, search engine optimization, website optimization, pay-per-click advertising, and video marketing. In this latter group of marketing actions, the prompts are more contextual and contain relevant details and background information from the user, thereby allowing LLMs to produce contextually relevant and localized outputs. It thus appears that, in areas where context is relevant, such as marketing strategy and search engine optimization, few-shot prompts are frequently employed; whereas in areas where context is less relevant or standard content templates are readily available, such as email and content marketing, zero-shot prompts are frequently employed.

Discussion

The present study examined marketing prompt templates shared by marketing and AI practitioners on X. To conduct a systematic and meaningful analysis of the prompt templates, a conceptual framework was developed based on three key features of marketing prompts: prompt domain, prompt appeal, and prompt format. Together, these features address the what and the how of marketing prompts. Specifically, prompt domain represents the specific marketing actions targeted by the prompt templates, while prompt appeal and prompt format represent how the marketing prompts are designed and the nature of their intended output in terms of being emotional or informative; and generic or contextual. The analysis of these three prompt features sheds light on how LLMs are being applied by marketers to support their work.

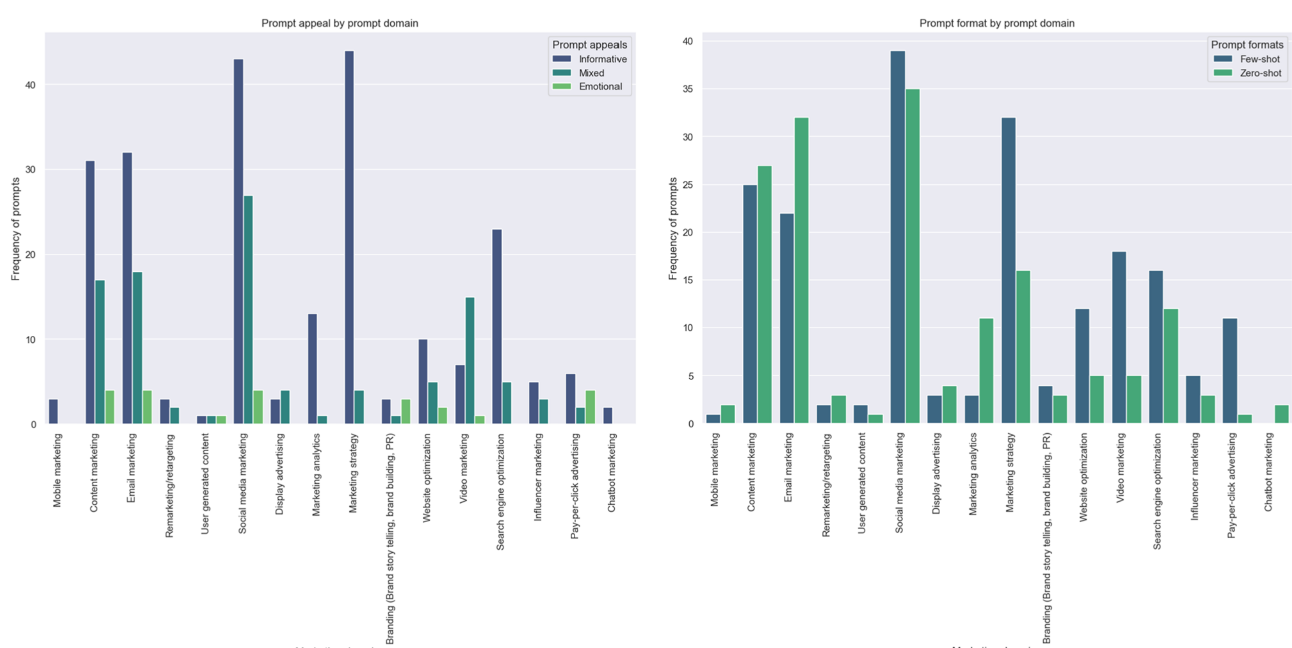

Fig. 5 Frequency distribution of marketing domain by prompt appeal and prompt format

Pertaining to marketing domain, the findings suggest that ChatGPT has already found broad applications across several areas of marketing. The study identified 16 marketing actions targeted by the prompt templates. Most of these actions fall within the realm of digital marketing including social media marketing, email marketing, content marketing, and search engine optimization. Marketing strategy, which encompasses such issues as customer acquisition, customer retention, competitive analysis, and campaign planning, is also a popular area of ChatGPT application. The breadth of the marketing domains targeted by the prompt templates highlights the deeper impact that LLMs are beginning to exert on marketing practices (Dwivedi et al. 2023). They also highlight the versatility of LLMs in identifying, evaluating, and executing a variety of marketing actions (Huang and Rust 2021). For instance, for email, social media, content, and video marketing, the data show that LLMs are used to brainstorm content ideas, create and optimize content calendars, and personalize content based on channel type and audience behavior. For marketing strategy, LLMs are used to analyze customer segments more deeply and insightfully, to probe and choose different targeting and positioning strategies, and to identify and analyze effective customer acquisition and retention strategies. For website and search engine optimization, LLMs are used to diagnose the structure and content of websites, generate and evaluate ideas for improving the user experience, and research relevant keywords for search engine optimization.

Pertaining to prompt appeal, the findings present a highly skewed picture, where the prompt templates primarily target informative output, while prompt templates designed to generate emotionally engaging output are rather infrequent. This uneven deployment of prompt appeal is surprising given the accumulated evidence in the marketing literature that emotional messaging is highly beneficial to derive greater customer engagement behavior on digital platforms (Tafesse and Wien 2018; Tellis et al. 2019). Additionally, LLMs are recognized for their capability to craft emotionally evocative content such as poems, lyrics, stories, and jokes (Cao et al. 2023). As the deployment of LLMs in marketing is still at an early stage, the prompt templates might lack sophistication and nuance due to the relative inexperience of their designers. As prompt designers gain more experience and LLMs become more widely diffused, we might begin to see more frequent use of emotional prompts. Such developments are important as one of the main responsibilities of marketing is to move customers toward establishing an emotional bond with brands. Developing and executing emotional messaging across customer touchpoints is essential to establishing emotional bonds with customers (Ashley and Tuten 2015; Tellis et al. 2019). Emotional bonds, in turn, drive favorable customer behavior including customer satisfaction, customer loyalty, and positive customer engagement (Harmeling et al. 2017). By experimenting with emotional prompting approaches, marketers can leverage LLMs to enhance their emotional messaging capability.

Concerning prompt format, the findings present a balanced picture of few-shot and zero-shot prompts. Given the nascent state of LLM use in marketing, one might be inclined to anticipate more widespread use of the structurally simpler zero-shot prompts relative to the structurally more complex few-shot prompts (Kojima et al. 2022; Logan et al. 2021). One potential explanation is that some of the prompts are designed by AI practitioners, who might possess a deeper knowledge of how LLMs work and how to effectively prompt them. It is worth noting that few-shot prompts are more elaborate as they contain examples, relevant contexts, and background information from the user that help in the generation of contextually relevant outputs. In contrast, zero-shot prompts are plain descriptions of tasks with no specific examples, relevant contexts, or background information from the user. As a result, the output from zero-shot prompts tends to be generic and lacks context and localization. When the request is generic and LLM can fulfill them without using specific examples or unique contexts, zero-shot prompts may suffice (Reynolds and McDonnel 2021). This includes asking for a list of items, defining or elaborating marketing concepts, explaining how specific marketing approaches work, or asking for generic content templates. However, zero-shot prompts might be unfit for more complex tasks where context is relevant. For instance, when marketers are planning to perform competitor analysis or customer segmentation analysis, providing sufficient context and relevant details about the competitors (e.g., industry, size, market share, etc.) and customer segments being analyzed (e.g., demographic, location, lifestyle, income, preference, etc.) is essential for LLMs to provide contextually relevant output (Kojima et al. 2022). Overall, it is vital for marketers to first evaluate how much unique context and details are needed to effectively perform the task at hand and design their prompts accordingly.

Managerial implications

The findings offer multiple implications for marketing practitioners. First, going by the diversity of the prompt domain, it can be concluded that ChatGPT is being applied across a range of marketing tasks including social media marketing, content marketing, email marketing, marketing strategy, and search engine optimization. The current scope of ChatGPT's application points to the potential for ChatGPT and other LLMs to broadly impact marketing practice. These findings highlight the need for marketers to prepare themselves and their organizations for a future in which LLMs play a growing role in their profession.

Second, the findings indicate that most of the prompt templates analyzed in the current study were designed to generate informative outputs, while prompt templates designed to generate emotionally engaging outputs were scarce. When the goal is to generate emotionally engaging output, therefore, the current prompt templates that are dominated by informative appeal are less useful. To generate emotionally engaging output, marketers need to tweak existing prompt templates. In our data, emotional prompts are typically designed by adding emotionally evocative words and expressions to the prompts such as enticing, compelling, attention-grabbing, eye-catching, and punchy. Marketers can, therefore, design emotional prompts by explicitly instructing LLMs to incorporate desired emotions in their output such as "be funny," "be aspirational," "be nostalgic," "be hyperbolic," and so on.

Third, the findings indicate that nearly half of the prompt templates analyzed are zero-shot prompts. However, these prompts may not be appropriate for generating contextually relevant solutions as they lack relevant examples, contexts, or background information that LLMs can use to create their output. If the task at hand requires context, such as analyzing a firm's customer segments or developing a custom marketing campaign, relevant details and background information about the company, the product, the customer base, and desired goals should be incorporated into the prompts. Incorporating relevant contexts and background information into marketing prompts allows LLMs to customize their output and provide custom solutions that fit the specific problem at hand. Zero-shot prompts are only appropriate for generic questions such as asking for an explanation of a specific concept or creating a standard content template. Overall, marketers should familiarize themselves with zero-shot and few-shot prompts and recognize when these prompt formats are appropriate to use.

To summarize, although the marketing prompt templates shared online, such as those analyzed in the current study, can provide marketers with a starting point for interacting with LLMs, it is important to realize that creating effective prompts is very much a trial-and-error process. It involves creating prompts, evaluating the outputs, and tweaking the original prompts through interactive dialog with LLMs until a satisfactory solution is obtained. Engaging in such a trial-and-error process not only improves the quality of the outputs from LLMs but also deepens marketers' understanding of LLMs and how they work.

Limitations and future research

The current study suffers from some limitations which are pointed out in this section along with avenues for future research. First, the manual data collection approach used in the current study constrained both the volume and scope of the marketing prompt templates that were collected and analyzed. A large volume of marketing prompts would have generated a more generalizable and comprehensive picture of the prompt engineering practices in marketing. Future research may seek to collect and analyze a large volume of marketing prompts using automated data collection methods.

Second, the fact that the prompt templates are shared online does not guarantee that they will be adopted by marketers. For instance, it is possible that the prompts shared on X are modified by marketers before they are used to query LLMs. There is, therefore, a need for future research to find ultimate prompts that are used by marketers to query LLMs. Such data help researchers to gain a more realistic picture of the prompts used in marketing.

Finally, in the current study, user engagement with the prompts has not been examined. Engagement metrics signify the popularity and potential acceptance of the prompt templates by users. However, the study could not examine user engagement as it is highly influenced by the type of accounts that shared the prompts (e.g., the number of followers of the accounts). As only 16 accounts are included in our data, the lack of variability in the data makes it inappropriate to examine user engagement. This problem can be overcome by gathering prompt templates from a large number of accounts.

Appendix

See Table 4, 5, and 6.

Table 4 Coding results for prompt domain

ChatGPT coding	Prompt domain	Human coding									
		Content marketing	Email marketing	Marketing analytics	Marketing strategy	Pay-per-click	Search engine optimization	Social media marketing	Video marketing	Website optimization	Total
	Content marketing	38	0	0	4	0	0	3	2	5	52
	Email marketing	5	47	1	1	0	0	0	0	0	54
	Marketing analytics	2	0	9	0	0	0	2	0	0	13
	Marketing strategy	2	0	1	43	0	0	0	0	0	46
	Pay-per-click	1	0	0	0	8	0	3	0	0	12
	Search engine optimization	4	0	0	0	0	16	0	0	5	25
	Social media marketing	1	0	2	0	1	0	64	3	1	72
	Video marketing	0	0	0	0	0	0	2	21	0	23
	Website optimization	2	0	0	0	0	0	0	0	15	17
	Total	55	47	13	48	9	16	74	26	26	314
	Cohen's Kappa = 0.77										

Note: For prompt domain, only those domains with more than ten code counts are presented to save space

Table 5 Coding results for prompt appeal

Chat-GPT coding	Prompt appeal	Human coding			
		Informative	Emotional	Mixed	Total
	Informative	221	2	0	228
	Emotional	0	32	5	32
	Mixed	327	18	47	97
	Total	253	52	52	357
	Cohen's Kappa = 0.69				

Table 6 Coding results for prompt format

ChatGPT coding	Prompt format	Human coding		
		Few-shot	Zero-shot	Total
	Few-shot	161	34	195
	Zero-shot	13	149	162
	Total	174	183	357
	Cohen's Kappa = 0.72			

Data availability The data used in this study is available upon request from the corresponding author.

Declarations

Conflict of interest The authors declare that they have no conflict of interest in this study.

References

Ashley, C., and T. Tuten. 2015. Creative strategies in social media marketing: An exploratory study of branded social content and consumer engagement. *Psychology & Marketing* 32 (1): 15–27.

Bach, S.H., Sanh, V., Yong, Z.X., Webson, A., Raffel, C., Nayak, N.V., Rush, A.M., et al. 2022. Promptsource: An integrated development environment and repository for natural language prompts. arXiv preprint http://arxiv.org/2202.01279.

Banerjee, M., M. Capozzoli, L. McSweeney, and D. Sinha. 1999. Beyond kappa: A review of interrater agreement measures. *Canadian Journal of Statistics* 27 (1): 3–23.

Batra, R., and O.T. Ahtola. 1991. Measuring the hedonic and utilitarian sources of consumer attitudes. *Marketing Letters* 2: 159–170.

Brown, T., B. Mann, N. Ryder, M. Subbiah, J.D. Kaplan, P. Dhariwal, D. Amodei, et al. 2020. Language models are few-shot learners. *Advances in Neural Invnformation Processing Systems* 33: 1877–1901.

Cao, Y., Li, S., Liu, Y., Yan, Z., Dai, Y., Yu, P.S., and Sun, L. (2023). A comprehensive survey of AI-generated content (AIGC): A history of generative AI from GAN to chatgpt. arXiv preprint http://arxiv.org/2303.04226.

Chintalapati, S., and S.K. Pandey. 2022. Artificial intelligence in marketing: A systematic literature review. *International Journal of Market Research* 64 (1): 38–68.

Davenport, T., A. Guha, D. Grewal, and T. Bressgott. 2020. How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science* 48: 24–42.
Dwivedi, Y.K., N. Kshetri, L. Hughes, E.L. Slade, A. Jeyaraj, A.K. Kar, R. Wright, et al. 2023. "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management* 71: 102642.
Hariri, W. 2023. Unlocking the potential of ChatGPT: a comprehensive exploration of its applications, advantages, limitations, and future directions in natural language processing. arXiv preprint http://arxiv.org/2304.02017.
Harmeling, C.M., J.W. Moffett, M.J. Arnold, and B.D. Carlson. 2017. Toward a theory of customer engagement marketing. *Journal of the Academy of Marketing Science* 45: 312–335.
Hassani, H., and E.S. Silva. 2023. The role of ChatGPT in data science: How AI-assisted conversational interfaces are revolutionizing the field. *Big Data and Cognitive Computing* 7 (2): 62.
Hirschman, E.C., and M.B. Holbrook. 1982. Hedonic consumption: Emerging concepts, methods and propositions. *Journal of Marketing* 46 (3): 92–101.
Huang, M.H., and R.T. Rust. 2021. A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science* 49: 30–50.
HubSpot. 2022. The who, what, why, & how of digital marketing. https://blog.hubspot.com/marketing/what-is-digital-marketing
Kaplan, A., and M. Haenlein. 2019. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons* 62 (1): 15–25.
Koubaa, A., W. Boulila, L. Ghouti, A. Alzahem, and S. Latif. 2023. Exploring ChatGPT capabilities and limitations: A critical review of the NLP game changer. *Preprints*. https://doi.org/10.20944/preprints202303.0438.v1.
Kocoń, J., Cichecki, I., Kaszyca, O., Kochanek, M., Szydło, D., Baran, J., Kazienko, P., et al. 2023. ChatGPT: Jack of all trades, master of none. arXiv preprint http://arxiv.org/2302.10724.
Kojima, T., S.S. Gu, M. Reid, Y. Matsuo, and Y. Iwasawa. 2022. Large language models are zero-shot reasoners. *Advances in Neural Information Processing Systems* 35: 22199–22213.
Kumar, V., D. Ramachandran, and B. Kumar. 2021. Influence of new-age technologies on marketing: A research agenda. *Journal of Business Research* 125: 864–877.
Liu, P., W. Yuan, J. Fu, Z. Jiang, H. Hayashi, and G. Neubig. 2023a. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *ACM Computing Surveys* 55 (9): 1–35.
Liu, V., and Chilton, L.B. 2022, April. Design guidelines for prompt engineering text-to-image generative models. In *Proceedings of the 2022 CHI conference on human factors in computing systems* (pp. 1–23).
Liu, Y., Han, T., Ma, S., Zhang, J., Yang, Y., Tian, J., Ge, B., et al. 2023a. Summary of chatgpt/gpt-4 research and perspective towards the future of large language models. arXiv preprint http://arxiv.org/2304.01852.
Logan IV, R.L., Balažević, I., Wallace, E., Petroni, F., Singh, S., and Riedel, S. 2021. Cutting down on prompts and parameters: Simple few-shot learning with language models. arXiv preprint http://arxiv.org/2106.13353.
McHugh, M.L. 2012. Interrater reliability: The kappa statistic. *Biochemia Medica* 22 (3): 276–282.
Minculete, G., and P. Olar. 2018. Approaches to the modern concept of digital marketing. *In International Conference Knowledge-Based Organization* 24 (2): 63–69.
Mustak, M., J. Salminen, L. Plé, and J. Wirtz. 2021. Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda. *Journal of Business Research* 124: 389–404.
Nvidia. 2023. An introduction to large language models: Prompt engineering and P-tuning. https://developer.nvidia.com/blog/an-introduction-to-large-language-models-prompt-engineering-and-p-tuning/
Oppenlaender, J. 2022. A taxonomy of prompt modifiers for text-to-image generation. arXiv preprint http://arxiv.org/2204.13988.
Puto, C.P., and W.D. Wells. 1984. Informational and transformational advertising: The differential effects of time. *Advances in Consumer Research* 11: 638–643.
Ray, P.P. 2023. ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope. *Internet of Things and Cyber- Physical Systems.* 3: 121–154.
Reynolds, L., and McDonell, K. 2021, May. Prompt programming for large language models: Beyond the few-shot paradigm. In *Extended abstracts of the 2021 CHI conference on human factors in computing systems* (pp. 1–7).
Schiessl, D., H.B.A. Dias, and J.C. Korelo. 2022. Artificial intelligence in marketing: A network analysis and future agenda. *Journal of Marketing Analytics* 10 (3): 207–218.
Shahriar, S., and Hayawi, K. 2023. Let's have a chat! A Conversation with ChatGPT: Technology, applications, and limitations. arXiv preprint http://arxiv.org/2302.13817.
Sorensen, T., Robinson, J., Rytting, C.M., Shaw, A.G., Rogers, K.J., Delorey, A.P., Wingate, D., et al. 2022. An information-theoretic approach to prompt engineering without ground truth labels. arXiv preprint http://arxiv.org/2203.11364.
Statista. 2023. Artificial intelligence (AI) use in marketing - Statistics & Facts. https://www.statista.com/topics/5017/ai-use-in-marketing/#editorsPicks
Tafesse, W., and A. Wien. 2018. Using message strategy to drive consumer behavioral engagement on social media. *Journal of Consumer Marketing* 35 (3): 241–253.
Tamkin, A., Brundage, M., Clark, J., and Ganguli, D. 2021. Understanding the capabilities, limitations, and societal impact of large language models. arXiv preprint http://arxiv.org/2102.02503.
Tellis, G.J., D.J. MacInnis, S. Tirunillai, and Y. Zhang. 2019. What drives virality (sharing) of online digital content? The critical role of information, emotion, and brand prominence. *Journal of Marketing* 83 (4): 1–20.
Teubner, T., C.M. Flath, C. Weinhardt, W. van der Aalst, and O. Hinz. 2023. Welcome to the era of chatgpt et al. the prospects of large language models. *Business & Information Systems Engineering* 1: 1–7.
Wei, J., X. Wang, D. Schuurmans, M. Bosma, F. Xia, E. Chi, D. Zhou, et al. 2022. Chain-of- thought prompting elicits reasoning in large language models. *Advances in Neural Information Processing Systems* 35: 24824–24837.
White, J., Fu, Q., Hays, S., Sandborn, M., Olea, C., Gilbert, H., Schmidt, D.C., et al. 2023. A prompt pattern catalog to enhance prompt engineering with ChatGPT. arXiv preprint http://arxiv.org/2302.11382.
Wu, T., Terry, M., and Cai, C.J. 2022, April. Ai chains: Transparent and controllable human-AI interaction by chaining large language model prompts. In *Proceedings of the 2022 CHI conference on human factors in computing systems* (pp. 1–22).
Zamfirescu-Pereira, J.D., Wong, R.Y., Hartmann, B., and Yang, Q. 2023, April. Why Johnny can't prompt: How non-AI experts try (and fail) to design LLM prompts. In *Proceedings of the 2023 CHI conference on human factors in computing systems* (pp. 1–21).
Zhao, Z., Wallace, E., Feng, S., Klein, D., and Singh, S. 2021, July. Calibrate before use: Improving few-shot performance of language models. In *International Conference on Machine Learning* (pp. 12697–12706). PMLR.
Zhang, C., Zhang, C., Li, C., Qiao, Y., Zheng, S., Dam, S.K., Hong, C.S., et al. 2023a. One small step for generative AI, one giant

leap for AGI: A complete survey on ChatGPT in AIGC era. arXiv preprint http://arxiv.org/2304.06488.

Zhang, C., Zhang, C., Zheng, S., Qiao, Y., Li, C., Zhang, M., Hong, C.S., et al. 2023b. A complete survey on generative AI (AIGC): Is ChatGPT from GPT-4 to GPT-5 All You Need? arXiv preprint http://arxiv.org/2303.11717.

Zhou, C., Li, Q., Li, C., Yu, J., Liu, Y., Wang, G., Sun, L., et al. 2023b. A comprehensive survey on pretrained foundation models: A history from BERT to CHATGPT. arXiv preprint http://arxiv.org/2302.09419.

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