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## An overview of artificial intelligence and its application in marketing with focus on large language models

Reza Amini <sup>1,\*</sup> and Ali Amini <sup>2</sup>

<sup>1</sup> Raj Soin College of Business, Wright State University, Dayton, Ohio, USA.

<sup>2</sup> Department of Mathematics and Computer Science, Amirkabir University of Technology, Tehran, Iran.

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### Abstract

Emerging technologies like the Internet of Things, big data analytics, blockchain, and artificial intelligence (AI) have significantly transformed business operations. Among these, AI stands out as the most recent and impactful, revolutionizing marketing practices. Professionals globally are actively seeking AI solutions tailored to their marketing needs. A systematic review of existing literature can highlight AI's significance in marketing and reveal future research pathways. Integrating big data sources and AI tools into marketing practices represents a departure from traditional methods, ushering in a new era of marketing education. This paper explores recent advancements in AI within the marketing sector, highlighting how these developments enable practitioners to effectively navigate and utilize extensive and complex datasets for predictive analytics. By integrating big data and AI, marketing strategies can now be directly aligned with execution, enhancing both strategic planning and the forecasting of marketing outcomes. However, the adoption of these technologies necessitates a shift towards adaptive learning approaches, moving beyond traditional assessment methods to better accommodate the dynamic nature of today's marketing environment. The transition to big data and AI-driven approaches equips experts for the evolving demands of the modern marketing landscape. This shift transcends traditional analytics by leveraging cutting-edge AI technologies, such as Large Language Models, and enhances the utilization of big data through innovative learning experiences, such as role-playing simulations. This integration not only broadens the analytical capabilities of marketers but also fosters a more immersive and experiential understanding of data-driven decision-making.

**Keywords:** Artificial Intelligence; Big Data Analysis; Large Language Models; Marketing; Generative AI; Prompt Engineering

### 1. Introduction

Technological advancements like artificial intelligence (AI), the Internet of Things (IoT), and big data analytics (BDA) provide digital solutions to attract and retain customers by enhancing products and services [1]. In a highly competitive and technologically disruptive business landscape, organizations globally are adopting a customer-centric approach to drive growth, addressing customer needs. AI, in particular, enables organizations to track real-time data, analyze it, and respond promptly to customer demands, offering valuable insights into consumer behavior crucial for reshaping the customer experience [2]. AI tools are essential in understanding customer expectations and guiding future strategies [3].

Despite AI's significant potential for transforming various business functions, many managers still lack a thorough understanding of its capabilities and limitations. Common misconceptions about AI's capabilities can lead marketing and business managers to underestimate its risks and limitations, potentially causing ineffective resource allocation. AI has found diverse applications across sectors like healthcare, e-commerce, education, law, and manufacturing, with both

\* Corresponding author: Reza Amini

practitioners and academics viewing it as a cornerstone of future society. Technological progress has spurred investments in AI for big data analytics, generating valuable market insights. As we transition towards Industry 4.0, AI and other emerging technologies are evolving together. However, widespread AI implementation faces constraints, though scientists are working on systems embodying cognitive reasoning and self-awareness, pushing the boundaries of AI [3].

The discipline and practice of marketing are undergoing a rapid transformation, particularly with the adoption of big data-driven approaches. Since the advent of smartphones, traditional marketing strategies driven by human instincts have been supplanted by the management and analysis of vast amounts of customer and operational data by marketing analysts and data scientists. The application of analytical technologies and techniques to marketing data is refining and centralizing marketing activities across organizations, regardless of their size, industry, or online presence [4].

By 2025, the total data on the planet is projected to reach 175 zettabytes [5], with downloading this data at an average speed of 12 Megabits per second taking 1.8 billion years. This data surge includes user-generated content and data from trillions of sensors, accelerated by the COVID-19 pandemic, which may push data volume to over 180 zettabytes by 2025. One zettabyte is equivalent to 36,000 years of high-definition video. Marketing big data differs from traditional data due to its unstructured nature and the need for new analytical techniques. Marketers must leverage data science to convert raw data into actionable insights, focusing on discovery and hypothesis analysis rather than conventional deterministic methods. This shift emphasizes trending or correlation analysis over extensive datasets, highlighting that correlation-based predictions do not always imply causation [4].

The vast volume and variety of data are revolutionizing marketing, products, and services, driving innovations such as "pay as you go" car insurance, real-time pet vital signals, and satellite imagery. Operational big data sources include social media, smartphones, customer support records, and RFID tags [4]. Generative AI (GenAI) and large language models (LLMs) like ChatGPT are transforming business and society, potentially adding trillions to the global economy. Key areas of impact include customer operations, marketing, software engineering, and R&D, with significant applications in personalization, insight generation, and content creation [6].

Large Language Models (LLMs) show great promise in marketing research for tasks like data summarization, automated reporting, data cleaning, and creative writing. This study explores how LLMs can be leveraged for both qualitative and quantitative marketing research, particularly in respondent recruitment, data collection, and analysis [7]. Synthetic respondents generated by LLMs were assessed against human respondents, and findings suggest that LLM-generated responses align well with economic theory and key principles such as risk aversion. However, LLMs also have shortcomings that necessitate systematic evaluation and guideline development [6]. A structured prompt system and an architecture using the GPT-4 API were developed to generate qualitative and quantitative data. A study demonstrated LLMs' effectiveness in generating insightful qualitative data, with superior depth and niche participant identification compared to human-driven methods. Enhancements in response quality were achieved through moderated instructions to LLMs on interview depth and detail [6].

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## **2. Artificial Intelligence and Deep Learning**

### **2.1. Defining Artificial Intelligence**

When consulting experts from diverse fields such as psychology, sociology, biology, neuroscience, and philosophy, it becomes evident that the term "intelligence" can encompass over 70 different definitions [8]. Consequently, it is understandable that the term "artificial intelligence" (AI), despite its widespread usage, lacks a clear and universally accepted definition, remaining a vague concept. Instead of advocating for a singular definition, we propose three definitions that vary in their inclusiveness [9].

### **2.2. The Most Encompassing Definition**

A commonly accepted definition of AI is "intelligence demonstrated by machines," though Brooks (1991) described it as making computers perform tasks that, when done by humans, indicate intelligence. This definition shifts ambiguity to the notion of intelligence, which lacks a universal consensus and can include learning, planning, problem-solving, understanding, self-awareness, emotional knowledge, reasoning, creativity, logic, and critical thinking [9]. Opinions on AI's current state vary; some see true AI as decades away, while others consider basic regression analysis as AI. This broad definition has led to "AI washing," where companies claim AI capabilities for simple technologies. The loose definition of AI can cause confusion, misunderstandings, and potential abuses.

### 2.3. The Most Restrictive Definition

Some researchers suggest reserving the term "artificial intelligence" (AI) for "artificial general intelligence" (AGI), which refers to machines capable of understanding or learning any intellectual task that a human can [10]. Currently, machines excel at specific, limited tasks like playing chess or facial recognition, known as "weak AI" or "narrow AI." The concept of "strong AI" or AGI involves machines that can "learn to learn," but most scientists believe AGI is still decades away [11]. Some humorously define AI as "everything we cannot do yet," as techniques like optical character recognition (OCR) or rule-based expert systems from the past are now commonplace and no longer considered AI. As AI techniques become well-understood and widely adopted, they often transition out of the AI category, suggesting that recent advancements might only be incremental steps toward AGI and may not warrant the AI label [12].

### 2.4. AI and Higher-Order Learning

On one side, AI might be defined very broadly, so much so that nearly all statistical methods could fall under its umbrella. Conversely, on the opposite end, AI could be defined so strictly that nothing currently fits the definition [13].

### 2.5. Safe and Realistic Learning Environment

Our struggle to define and quantify firm objectives is not the only obstacle to adopting reinforcement learning in marketing. An AI agent learns the function  $f(S, A) \rightarrow R$  through trials, balancing exploration and exploitation, but the critical question is: "In what environment can this learning occur?" [9]. In rule-based environments like Chess or Go, perfect simulations allow AI to improve by self-play, as seen with AlphaGo's 1.3 million games. However, marketing environments lack such clear rules; customer behaviors and competition aren't governed by physical laws. Reinforcement learning with random strategies in real-world marketing would be costly, slow, and risky. Therefore, creating realistic computer simulations of customer behaviors is essential. For example, one author's reinforcement learning experiment in direct marketing led to unrealistic daily solicitations, revealing flaws in the simulated environment. Similarly, another study suggested reinforcement learning could boost charity fundraising by over 50%, but this likely wouldn't hold in real-life due to existing donor fatigue [14]. Realistic simulations must model factors like customer fatigue and solicitation-dropout relationships. Marketing managers often find campaign strategies fail unpredictably due to unmeasured factors, highlighting the need for accurate understanding. AI can approximate causal relationships with large datasets, but comprehending data-generation mechanisms and developing tools for causal inferences remains crucial. AI applications, especially in reinforcement learning, may increase the need for consumer behavior theory and precise data manipulation tools [9].

### 2.6. Biased Artificial Intelligence

Bias can occur in marketing, where AI algorithms may lead to discriminatory practices, such as charging higher prices for women or targeting specific demographics. These biases, often stemming from endogeneity, can create self-fulfilling prophecies and harm long-term profits. Endogeneity, influenced by past targeting decisions, enhances a model's apparent predictive accuracy while masking real issues [15]. It is rarely discussed in computer science literature, that AI makes causal inference obsolete. However, endogeneity can create a vicious cycle in predictive tasks like customer churn prediction, where predictions influence outcomes. Deep-learning models exacerbate this issue by detecting hidden patterns, including biases, and their complexity makes them "black boxes," leading to unquestioned acceptance of their predictions [9].

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## 3. Literature review

Artificial intelligence (AI) refers to the intelligence exhibited by machines, enabling intelligent systems to perceive their environment and achieve specific goals. Russel and Norvig (2016) describe AI as machines simulating human cognitive and affective functions in their book [16]. Over recent decades, significant advancements in AI have led to innovations like big data analytics and machine learning across various sectors. While AI often evokes images of robots, it applies to any machine emulating human-like thinking, allowing for continuous learning and problem-solving, and handling repetitive tasks without fatigue [3]. Data ingestion is crucial in AI, with systems processing and analyzing vast amounts of data, a task unmanageable for humans at the scale of organizations like Google and Amazon. AI systems can observe and react to their surroundings, using historical data to predict future scenarios, such as anticipating machine breakdowns and providing preemptive alerts [3].

### 3.1. Advantage of machine learning over other technologies

While many technologies can perform repetitive tasks, they lack the ability to think independently beyond their programmed code. In contrast, machine learning, a subset of AI, aims to empower machines with the capability to learn

tasks without predefined code. In this process, machines are exposed to various problems and examples, enabling them to learn and adapt their strategies independently to execute activities. For instance, an image-recognition machine can analyze millions of pictures, eventually developing the ability to recognize patterns, shapes, faces, and more after processing endless permutations [17].

Currently, machines primarily learn specific tasks, but efforts are subject to broaden their learning capabilities beyond singular tasks. AI experts are striving to enable machines to apply the knowledge gained from tasks like image analysis to analyze diverse datasets. Data scientists and programmers are developing general-purpose learning algorithms to facilitate machine learning across various tasks, not limited to a single domain [3].

### **3.2. Fundamental principle of artificial intelligence**

Artificial intelligence involves transferring human intelligence to machines to perform tasks ranging from simple to complex. It aims to facilitate learning, reasoning, and task execution. As technology progresses, previous definitions of artificial intelligence become outdated. There are three fundamental concepts underlying artificial intelligence: machine learning, deep learning, and neural networks. These concepts drive advancements in data mining, natural language processing, and software development. While artificial intelligence and machine learning are often used interchangeably, artificial intelligence is typically considered the broader term, with machine learning and the other two concepts being subsets of it [3].

Deep learning relies on artificial neural networks, which mimic biological neurons to process information. These networks use principles from mathematics and computer science to simulate brain functions, facilitating advanced learning and decision-making capabilities. Structurally, they comprise layers of nodes including input, hidden, and output layers [18]. Artificial intelligence simulates human thought processes through neural networks, allowing it to interpret the environment and respond accordingly, thus demonstrating the uniqueness of AI.

### **3.3. Use of artificial intelligence in enhancing customer experiences**

AI-driven chatbots with NLP improve customer interactions and AI/ML algorithms enhance data processing for better decision-making. AI also analyzes customer behaviors and preferences, transforming traditional retail into smart stores [19, 20, 21, 22].

### **3.4. Use of artificial intelligence in strategy and planning**

AI supports segmentation, targeting, and positioning (STP) by identifying profitable customer segments using text mining and machine learning, aiding strategic orientation across sectors like banking and tourism [3].

### **3.5. Use of artificial intelligence in product management**

AI-based tools assess product alignment with customer needs, enhance service innovation, and provide personalized recommendations, helping marketers understand and optimize product strategies [3].

### **3.6. Use of artificial intelligence in pricing management**

AI algorithms dynamically adjust prices in real-time based on demand and competitor strategies, utilizing techniques like multi-armed bandit algorithms and Bayesian inference for optimized pricing [23, 24, 3].

### **3.7. Use of artificial intelligence in place management**

AI enhances distribution efficiency through cobots, drones, and IoT for logistics, while service robots with emotional AI improve customer engagement. Human elements remain necessary for optimal service delivery [3].

### **3.8. Use of artificial intelligence in promotion management**

AI personalizes and customizes promotional messages, optimizes content effectiveness, and tracks customer preferences and sentiments in real-time, supporting strategies aligned with customer preferences through netnography [3].

### **3.9. Online Advertisements with LLMs**

Advertisements play a crucial role in the online search engine market, subsidizing free access to information and driving economic growth through a symbiotic relationship with content creation. The dominance of advertisements continues to grow, as seen with Netflix's ad-supported plan [25]. Large language models (LLMs) like ChatGPT are increasingly

used for various functions, sometimes replacing traditional search engines, prompting providers to explore revenue generation through advertising. This paper examines how online advertising models can be applied to LLMs and evaluates different frameworks for LLM advertising [25].

### 3.10. Marketing Workflow, Discoveries in Data and Data Science

Educational initiatives can empower learners to utilize large-scale data in marketing by augmenting internal datasets with external sources like social media and web-crawled data, addressing gaps in customer information [4]. Analyzing outlier behaviors on social media can help marketers identify key supporters and influencers for targeted engagement. This analysis extends to internal points, such as customer service interactions, to uncover unique customer preferences for personalized strategies. Transitioning to social CRM platforms integrates social media data with traditional CRM, enhancing communication and decision-making. Additionally, combining novel data sources, like seismic activity and retail data, offers insights into consumer behavior in unique contexts, demonstrating the potential of innovative methodologies to inform marketing strategies [4].

### 3.11. Marketing Discoveries in Data

Integrating big data with existing marketing datasets is crucial for extracting meaningful insights through a 17-step discovery process. This process involves exploring, analyzing, and visualizing data across various types, such as social media and traffic data, to uncover valuable insights [4]. Marketers can use this approach to validate shopper segments like brand loyal customers and impulse buyers, enriching customer data with social media behavior to discover hidden segments. The process combines hypothesis-driven methods with strategic questions to determine where, how, and when to compete [4].

**Table 1** Marketing Discoveries in Data Process (Steps 1-17)

Step	Description
1	Select data sources for marketing discovery
2	Evaluate data sources, including ownership and provenance
3	Securely record any personal identifier information (PII) in the data
4	Determine the type and size of the raw data set for discovery
5	Use data in situ and online without transferring to another system
6	If the data set includes unstructured data and the intention exists to analyze the entire dataset rather than sampling, use cloud infrastructure for data acquisition and analysis
7	Select a processing framework to suit the data set
8	Prepare data (cleansing, missing data, and anonymization excluding PII)
9	Marketing analyst conducts data exploration
10	Explore the entire dataset with exploratory visualization, noting any visual representations helpful in “telling the story”.
11	Marketing analyst codes additional knowledge using different colors for different or similar behavioral groups of known origins
12	Exploratory visualization technique using complex systems representation, e.g., node and link with color coding of knowledge
13	Communicate knowledge gained from visualization patterns to the marketing team or use it to assist decisions about the development of a hypothesis
14	Ad hoc exploration of raw data slicing and dicing
15	Analyst commences with data science extracting value trapped in the entire big data set commencing with correlations and cycling through various algorithms based on machine learning, mathematics, and statistical techniques.
16	Communicate the story of the value extracted from the data
17	Setup relevant reporting to monitor interpretation and value delivered

By following the outlined steps, marketers can uncover valuable data patterns and convey findings to their teams using open-source tools like Python Scikit-learn and Jupyter notebooks, which reduce the need for extensive data science expertise [4]. Machine learning techniques help identify intricate correlations across diverse data sources, including social media. As marketing workflows evolve, adopting a predictive mindset allows marketers to navigate big data effectively, expediting decision-making and gaining insights into consumer behavior deviations. This process emphasizes causal analysis over mere correlations to identify the next best actions [4].

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## 4. The Transformation of the Marketing

### 4.1. Mindset To Predictive Marketing

Marketing academia often focuses on understanding consumer behavior, but there's a lack of research on marketers' cognition and decision-making processes. The transition from "gut feel marketing" to data-driven approaches is propelled by big data, with machine learning algorithms generating predictive models. However, a shortage of marketing data scientists hampers the development of such models. Recommender systems and predictive analytics, used by market leaders like Amazon, Netflix, and Google, showcase the potential of data-driven insights. Yet, reliance solely on past data correlations, without considering causality, can lead to inaccuracies [4].

Despite technological advancements making predictive models more accessible, the judgment and intuition of marketers remain valuable. Combining human intuition with computer-generated predictions yields the best results in uncertain contexts. Understanding how marketers adapt to predictive tools is crucial for proactive customer engagement. Exploring new predictive marketing activities and evolving organizational structures are essential for leveraging marketing data effectively. Additionally, considering the role of strategy in shaping marketing activities in a predictive world is vital for future marketing practices [4].

### 4.2. Emergence of Large Language Model

#### 4.2.1. Artificial Intelligence

The quote "Software is eating the world" by Andreessen in 2011 has evolved into "AI is going to eat software," exemplified by Large Language Models (LLMs) like GPT-3 [26, 27]. These models, trained on extensive text and image datasets, excel at tasks like reading, summarizing, translating, and generating text, though their outputs may not always be factually accurate. Developed with significant computational resources, LLMs like GPT-3 are primarily accessible through major organizations like Microsoft [4, 28].

The natural language processing market, projected to reach \$68.1 billion by 2028, is driven by LLMs [29]. Models like OpenAI's GPT-3 and open-source LLaMA [30] are key contributors. LLMs, integrated into enterprise workflows, allow marketers to use plain English prompts to generate text, code, and ideas, facilitating tasks such as video narration or podcast transcripts [4].

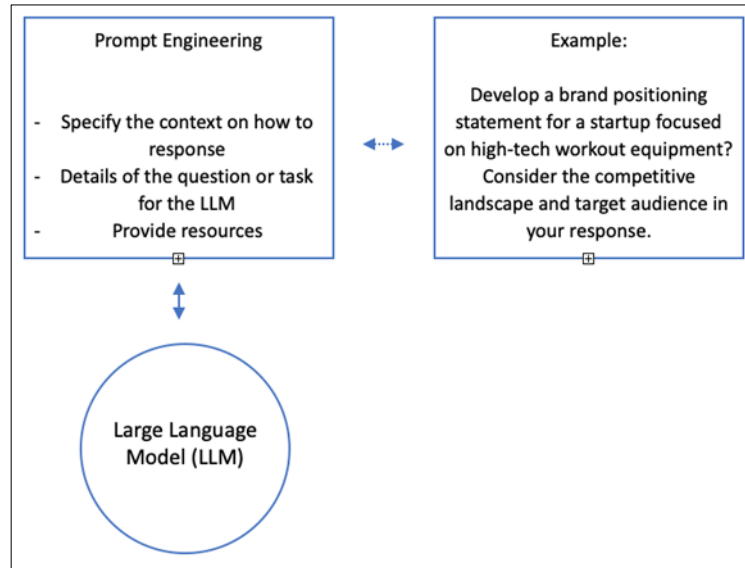
#### 4.2.2. The Importance of Prompt Engineering and Marketing

To harness the potential of AI and Large Language Models (LLMs) like ChatGPT, it's essential to understand prompt engineering. Effective prompts lead to better results, and while AI may replace prompt engineering by 2025, currently, it remains crucial, Figure 1. Various LLMs, such as those by OpenAI, serve diverse functions like code generation and text-to-video, with pricing based on token usage. Open-source models on platforms like Hugging Face Hub [31] offer settings to control output randomness, length, and novelty [4].

### 4.3. LLM-Driven Strategy, Marketing Planning and Execution Curriculum

Big data aids marketers with business intelligence in downstream marketing, and Large Language Models (LLMs) are transformative for upstream marketing planning, often lacking in practice and academia. Significant impediments to effective planning include challenges in implementing recommendations from marketing analyses, limited budgets, customer data privacy concerns, and intense competition. While strategic recommendations are well-conceived, the execution often falters. Enhancing the marketing planning process is a strategic investment that can significantly improve ROI and managerial decision-making quality. LLMs can integrate into marketing planning by analyzing internal and competitor data, conducting market analyses, and generating automated SWOT analyses. They assist in upstream planning and downstream tasks like campaign copy generation, optimizing the marketing mix by predicting and fine-tuning narrative copy and channel placements. As we approach 2025, LLMs may serve as universal marketing engines, connecting AI-driven strategy to real-time campaign execution, underscoring the need for marketers to embrace AI and

engage deeply with LLMs to augment human decision-making in marketing practice [4]. In figure 2, we show the general pipeline of where AI stands in the process of data analysis and insight extraction.



**Figure 1** Prompting in the marketing domain

#### 4.4. LLMs and Research in Marketing

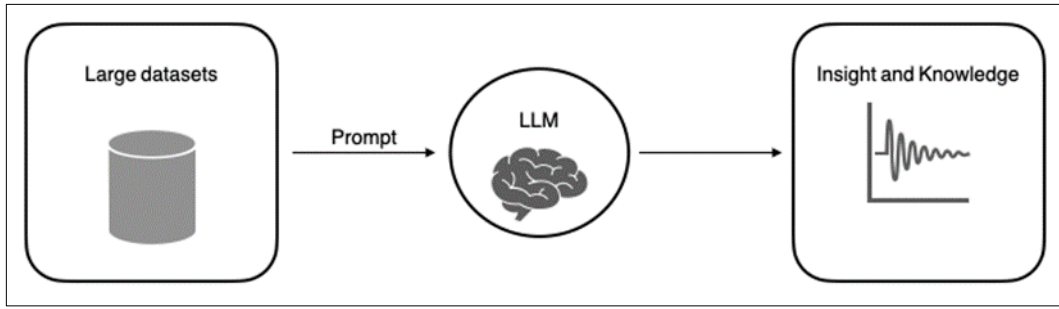
Current research on utilizing Large Language Models (LLMs) for marketing research is limited but promising. Studies show that LLMs can produce reasonable answers aligning with economic theory, displaying characteristics such as state dependence and downward-sloping demand curves [32, 33]. Some experts believe that LLMs can replicate perceptual maps from human surveys, while other experts and scientists find that LLMs mimic human decision-making in experiments. However, LLMs may not always represent diverse perspectives and can exhibit biases. Further research is necessary to evaluate their performance and develop ethical guidelines [6].

Our research highlights several unique aspects: exploring both qualitative and quantitative dimensions of marketing research, examining LLMs as AI-human hybrids in research workflows, and conducting benchmarking exercises comparing LLM-generated data with real research studies. This approach aims to provide a deeper understanding of LLMs' capabilities and limitations in marketing research, filling gaps in the current literature [6].

#### 4.5. Adaptive Learning Experiences for AI Marketing

The use of Large Language Models (LLMs), like ChatGPT, in academia has sparked debate, leading institutions such as Australia's Group Of Eight (Go8) to revise academic integrity policies to address AI-generated content. This approach may conflict with fostering innovative marketing skills, prompting a shift in assessment methods towards oral presentations and personal reflections to bypass LLM use in evaluations. While predictive analytics in big data marketing courses highlight innovation, the risks of LLMs, such as cultural biases, toxicity, and misinformation, necessitate dedicated hands-on exercises to explore these issues [4].

Educators must carefully integrate AI and LLMs into teaching practices, adapting methods to ensure effective learner engagement. Interactive platforms like Jupyter and Google Colab notebooks blur the lines between tutorials and lectures, facilitating a seamless blend of theory and practice. Combining these tools with flipped classroom models creates adaptive learning experiences that emphasize understanding major concepts and the risks of LLMs. Encouraging LLM use in class, documenting reflections, and fostering group projects can lead to authentic outputs, with instructors providing constructive feedback and promoting proper attribution and citation of ideas from recent research [4].

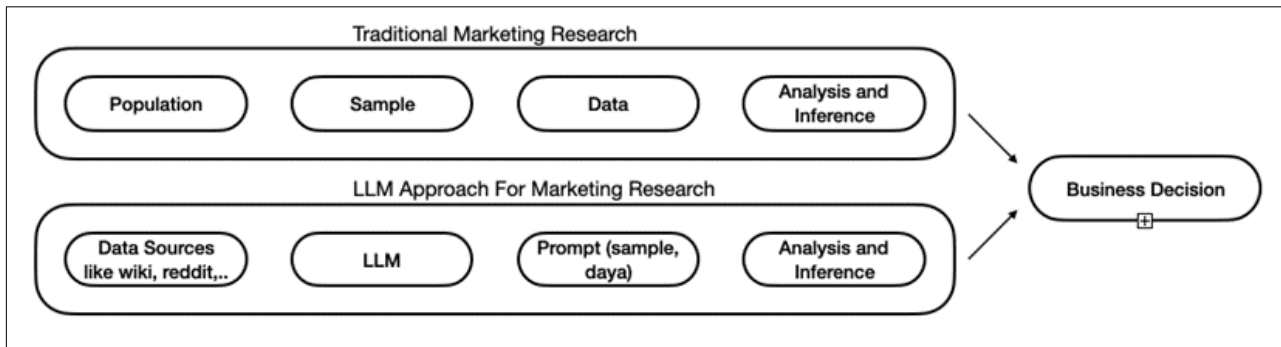


**Figure 2** Knowledge and insight extraction from massive data sets

#### 4.6. Human versus Synthetic Data

The challenge of generating synthetic data aligned with human-generated data poses significant hurdles for adopting Large Language Models (LLMs) in marketing research [34]. Traditional marketing research relies on data from representative samples to address specific business questions, ensuring data quality through criteria like representativeness and sample bias, Figure 3. In contrast, LLMs generate synthetic data based on a vast corpus of existing data, presenting challenges in reliability and validity for marketing research [6].

To reconcile these approaches, our paper focuses on evaluating the effectiveness of LLMs in inference and business decision-making. Repeated validations across diverse contexts are essential for integrating LLMs as collaborators in the marketing research process. While LLMs offer convenience and cost benefits, they require human supervision and interpretation to ensure comprehensive and accurate insights. This hybrid approach, combining LLMs with human expertise, promises more robust and reliable marketing insights and decision-making.



**Figure 3** Survey Data: Actual versus synthetic data

#### 4.7. Prompt Engineering

##### 4.7.1. The Critical Role of a Prompt in LLMs

A significant challenge in supervised learning is the need for annotated data to train a model  $P(y|x;\theta)$ , which is often impractical to acquire in large amounts. Prompt-based learning offers a solution by training a language model to estimate the probability  $P(x;\theta)$  of the text itself and using this probability to predict  $(y)$ , reducing the reliance on extensive labeled datasets. Prompts act as instructions to customize LLM outputs and interactions, establishing the context and desired output [35]. Effective prompt engineering is crucial for optimizing LLM performance, allowing for new interaction paradigms like flipped interactions where the LLM asks questions. Some approaches leverage prompt engineering to optimize input text sequences for a transformer, using core components like multi-head self-attention mechanisms and positional encodings. When a prompt is inputted, it transforms into embeddings with positional encodings to maintain sequence structure. As this encoded information passes through transformer layers, attention mechanisms determine the relevance of input segments, and well-designed prompts can direct this attention. The choice and structure of the prompt directly impact the output sequence, which we outline in a formal structure [6].

##### 4.7.2. System, User, and Assistant roles

When writing prompts for an LLM, we can use an API, such as the OpenAI API for GPT models, which provides three roles: system, user, and assistant. The system role sets the context or desired behavior of the LLM, acting as a guidepost



for interactions and defining demographic, psychographic, and professional specifications. For instance, a prompt might guide the LLM by stating, "Provide a comprehensive persona for a 28-year-old male software developer from New York who has a keen interest in fitness, deeply values sustainability, and harbors a fear of bees." The user role specifies the exact questions asked of the LLM and the desired answer format, such as bullet points or a CSV file. In marketing research, a user might ask about attitudes towards refrigerated pet food, with responses formatted on a Likert scale. The assistant role is the LLM's replies, adhering to the guidelines set by the system and user roles, providing answers in the specified formats [6]

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## 5. Conclusions

This literature review highlights the importance of facilitating tacit knowledge transfer between AI systems and marketing stakeholders, emphasizing the need for a two-way flow of observation, imitation, and practice. This bidirectional transfer recognizes that humans often possess knowledge that cannot be easily articulated. Service robots, for example, should learn from frontline employees, not just organizational knowledge bases, to avoid suboptimal performance. Equipping employees with AI, rather than replacing them, acknowledges this need.

Research should focus on two key areas: how humans can effectively transfer tacit knowledge to AI systems and how AI-generated knowledge can be transferred back to humans. This could reduce the reliance on large datasets and help infer causal relationships, building trust and enhancing control within organizations. Failing to bridge this gap risks another "AI winter," with decreased R&D investment and inactivity in the field.

LLMs can enhance marketing research by assisting in tasks such as determining interviewee profiles, developing discussion guides, generating synthetic respondents, and moderating interviews. They can suggest respondents with unique characteristics, adding diversity and inclusivity to research findings. Integrating synthetic profiles alongside human data can enrich qualitative research outcomes, offering insights from perspectives that traditional methods may overlook.

A hybrid approach that combines the strengths of human researchers with the capabilities of LLMs offers a promising path for marketing researchers. LLMs can serve as collaborators or assistants in qualitative research, providing cost-effective solutions and reaching hard-to-engage respondents, such as doctors or senior managers. Synthetic respondents generated by LLMs can offer extensive responses without fatigue, enhancing the depth of insights.

In the business-to-business (B2B) arena, where accessing end-users and buyers is challenging, LLMs can effectively supplement human-gathered information. LLMs have the potential to revolutionize information generation for various business questions at minimal cost. For instance, in survey contexts, synthetic data generated and analyzed by LLMs before fielding surveys to human respondents can provide valuable insights and guide business decisions. This approach streamlines survey processes by identifying key questions that yield meaningful insights and reducing redundancy in data collection efforts.

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## Compliance with ethical standards

### *Disclosure of conflict of interest*

The authors declare no conflict of interest.

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