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► **To cite this version:**

Moritz Joerling. Integrating GenAI interactions in marketing studies: A methodological guide. *International Journal of Research in Marketing*, 2026, 43 (1), pp.28-47. <10.1016/j.ijresmar.2025.12.003>. <hal-05489669>

HAL Id: hal-05489669

<https://hal.science/hal-05489669v1>

Submitted on 2 Feb 2026

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Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

International Journal of Research in Marketing

journal homepage: www.elsevier.com/locate/ijresmar

Integrating GenAI interactions in marketing studies: A methodological guide

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ARTICLE INFO

Keywords:

AI
generative AI
GenAI
Web applications

ABSTRACT

Reflecting the ubiquitous presence of generative AI (GenAI), marketing researchers have begun integrating it as an interaction partner in research studies; however, technical barriers and methodological gaps limit its broader adoption. This paper provides a comprehensive guide for implementing GenAI interactions in marketing studies, particularly within the Qualtrics platform. First, a literature review categorizes diverse GenAI applications—from scaling qualitative methods to creating novel experimental paradigms—distinguishing between GenAI as research method versus research object to help researchers identify untapped opportunities. Second, the paper presents a decision framework for when GenAI offers value over traditional methods and explains the principal architecture (frontend, API, backend) that enables researchers to connect any GenAI model to their studies. Crucially, it demonstrates how AI coding assistants can translate natural language instructions into functional code, eliminating programming barriers for non-technical researchers. Third, step-by-step tutorials establish emerging best practices through four implementations spanning text and image modalities: search assistants, automated interviewers, co-creation tools, and hyper-personalized messaging. These implementations serve as adaptable templates empowering researchers to create custom solutions for their unique questions. By mastering AI coding assistants rather than copying specific code, researchers gain methodological independence in a rapidly evolving landscape. This work democratizes GenAI integration and enables previously impossible experimental paradigms.

1. Introduction

The rapid development of generative AI (GenAI) has opened new opportunities in marketing research. No longer confined to traditional methods, researchers can now integrate GenAI interactions in their studies in a powerful dual capacity: as both a fascinating subject of investigation and a revolutionary methodological instrument, deploying it to conduct scalable interviews, simulate complex participant interactions, and create experimental interventions that would have been impossible before (Blanchard et al., 2025; Chopra & Haaland, 2023; Pataranutaporn et al., 2024; Salvi et al., 2025). This convergence of studying AI and studying with AI marks a paradigm shift in marketing research methodology.

Recent studies demonstrate GenAI's versatility across diverse research contexts. In experimental settings, interactions with ChatGPT have produced durable reductions in conspiracy theory beliefs (Costello et al., 2024) and enhanced creative performance in ideation tasks (Lee & Chung, 2024). As a methodological tool, GenAI has proven capable of conducting qualitative interviews—even in

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<https://doi.org/10.1016/j.ijresmar.2025.12.003>

Received 15 May 2025;

Available online 10 December 2025

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domains unrelated to AI, such as investigating stock market investment aversion (Chopra & Haaland, 2023). Researchers have also explored how firsthand experience with GenAI shapes the evaluation of AI-generated content (Celiktutan et al., 2024) and whether demographically-targeted LLM responses are more persuasive than generic messages (Hackenburg & Margetts, 2024) or whether GenAI-based personalized video ads are more effective than generic nonpersonalized video ads (Kapoor et al., 2025).

While these applications are promising, significant barriers remain. The technical implementation can be daunting for researchers without programming expertise, and a lack of standardized methodologies threatens to create inconsistent participant experiences and compromise validity. Moreover, marketing researchers whose work is not inherently AI-focused may not recognize how GenAI could support their research methods—from conducting hundreds of in-depth interviews simultaneously to creating new innovative paradigms that would be impossible without GenAI interactions.

This paper bridges these gaps by providing marketing researchers with both the basic conceptual knowledge and practical tools to harness the potential of GenAI interactions in research studies. Drawing on consultations with marketing researchers about their needs and challenges, the paper makes three key contributions.

First, the paper synthesizes and categorizes existing GenAI applications in behavioral research, revealing patterns in how these tools serve different research purposes. The analysis distinguishes between GenAI as a research method (e.g., automated interviewing on stock market investments, participant simulation on social media) versus a research object (e.g., studying AI persuasion, human-AI collaboration), helping researchers identify untapped opportunities in their own domains.

Second, the paper presents the principal architecture of GenAI integrations (frontend, GenAI service via API, backend) that enable researchers to connect virtually any GenAI model to their studies. This approach transcends specific tools or platforms, ensuring longevity despite GenAI's rapid evolution. Crucially, the paper illustrates how AI coding assistants can translate natural language instructions into functional code, democratizing GenAI implementation for researchers without programming skills. Researchers do not need to write code themselves; they need sufficient understanding to articulate their requirements and guide the implementation process—precisely the knowledge this paper provides.

Third, the paper showcases this practical approach with detailed walk-throughs for different marketing-relevant implementations (one presented in the manuscript and three in the [web appendix](#), pages 23–30): an AI-powered search assistant revealing how consumers navigate information search with GenAI; an automated qualitative interviewer for scalable, in-depth consumer insights; a multi-modal co-creation tool investigating human-AI collaboration across text and image generation; an application that allows testing the persuasion power of GenAI by creating hyper-personalized output based on participant information. Each implementation includes exact prompts for coding assistants and step-by-step instructions for a researcher's own implementation.

The power of this approach extends beyond the provided examples as the same architectural principles and implementation steps apply to any other GenAI integration. Hence, researchers can transfer this knowledge to create custom applications that are tailored to their specific questions and needs. By mastering AI coding assistants rather than following specific code, researchers gain methodological independence as well as the agility to integrate emerging models and design novel paradigms in a landscape where new models and GenAI capabilities evolve monthly. All code, and materials are publicly available at <https://github.com/QualtriGen>, enabling immediate application and community-driven development. The following section presents results from group discussions with researchers about their current understanding and perspectives on using GenAI interactions in research studies.

2. Understanding the researcher perspective

Five group discussions with sixteen marketing researchers from European and US institutions have been conducted to understand the different implementation challenges.¹ These discussions, involving researchers across all seniority levels from PhD students to full professors, revealed both enthusiasm for GenAI's potential and significant barriers to its integration in research studies (please see pages 3–9 in the [web appendix](#) for a detailed coding table with direct quotes from the discussions; the full transcripts are available: https://osf.io/53pqt/?view_only=bc7c976267274a90adc75ecd9c31bd74). The group discussions revealed the following key themes.

2.1. Current awareness and perceived opportunities

While researchers recognized GenAI's transformative potential, actual implementation remains rare. The gap between recognition and implementation emerged as a central theme across all discussions, with most participants having never implemented GenAI in their own research despite seeing its value. When asked about specific applications, many researchers struggled to envision concrete possibilities: "I have no idea how I would be able to use it [...] to come up with ideas of how to use it, I have no idea what the capabilities of AI are."

Through guided discussion, however, participants identified various potential applications, ranging from studying AI's persuasive characteristics to using it as a tool to make experiments more immersive and dynamic. They recognized immediate benefits of using GenAI as a methodological tool, including the scalability of interviews and the anonymity of a non-human interviewer that may encourage participants to be more forthcoming on sensitive topics. Participants also saw value in improved ecological validity and increased engagement through more realistic and interactive experimental settings compared to standard questionnaires. Additional use cases emerged, including using AI for participant priming and manipulation checks, facilitating idea generation in product

¹ I thank an anonymous reviewer for suggesting the integration of group discussions.

development studies, and even preventing bot participation by serving as a quality control mechanism.

2.2. Key barriers to implementation and how this guide addresses them

Technical complexity and time investment. While researchers see enormous potential and compelling applications in the GenAI integrations, most of the group discussants have never tried it themselves, mainly because of technical barriers. Many researchers feel they lack the necessary skills and are hesitant to invest the required time: “You need to study and dive into how it works and how such a tool is created. It might be possible for many of us, but it takes some time”. To overcome the technical complexity barrier, particularly the lack of coding skills that prevents implementation, this paper showcases how researchers without coding skills can translate natural language into the required code with the support of coding assistants. This approach—using AI to implement AI—transforms learning of sophisticated programming skills into minutes of describing research needs. The paper provides the essential technical knowledge and prompts researchers need to direct these assistants effectively, along with best practices that eliminate the trial-and-error process, making implementation accessible to researchers who, as one participant noted, are “very bad with technology... [and] just know how to prompt.”

Loss of experimental control. Researchers expressed deep concern about the unpredictability of AI responses. “When you’re running experiments, it’s really important to keep things controlled and AI is a little bit uncontrolled,” one participant noted. Another worried that AI might “blur the manipulations” by improvising beyond intended experimental conditions. This tension between ecological validity and experimental control emerged as a fundamental challenge. To address this concern, the step-by-step guides demonstrate how to capture complete interaction logs—every prompt and AI response—in Qualtrics’ embedded data fields for post-hoc analysis. Additionally, the paper provides a decision framework (Table 2) helping researchers identify when GenAI’s dynamic interactions enhance research value despite reduced control—such as when studying AI phenomena or improving ecological validity—versus when absolute experimental control is essential and traditional methods should be preferred. Finally, the paper and web appendix (pages 20–22) also provide detailed information on API parameters that control AI behavior, such as temperature settings that affect output randomness, along with error tracking instructions to monitor technical issues. However, perfect control remains elusive for the moment as GenAI’s outputs are probabilistic (Blanchard et al., 2025).

Ethical and institutional uncertainties. Participants described uncertainty about ethical boundaries and IRB requirements, with one noting their board requires “exact wording for all participant interactions,” making ad hoc AI responses problematic. Another attendee stated that even AI developers admit they “don’t know themselves either” why AI responds certain ways, calling it a “black box.” To navigate these uncertainties, the guide outlines differences between open and proprietary models. When using proprietary GenAI models via APIs, providers can access and potentially store participant interactions—a crucial consideration for IRBs. For research involving sensitive information or vulnerable populations, the paper recommends using open models on private infrastructure to maintain full data control. While a complete discussion of all ethical concerns is beyond this manuscript’s scope, the web appendix (pages 40–41) provides additional literature and guidance for navigating institutional review processes with these novel methodologies.

Academic legitimacy concerns. Finally, researchers worried about peer review acceptance, anticipating that early adopters would “bear a cost of reviewers who have no idea what you’re doing.” Beyond individual papers, participants identified this as requiring field-wide acceptance of new methodological standards. This paper serves as a foundational resource to establish legitimacy, providing clear documentation that researchers can cite and reviewers can reference to understand these emerging methodologies. The comprehensive literature review demonstrates growing adoption across marketing research, helping normalize these approaches.

3. Previous research studies and existing GenAI implementations

With the rise of GenAI, researchers are increasingly using these tools for direct participant interaction in their research studies. This section synthesizes these pioneering studies, summarized in Table 1, to identify their key applications and technical methodologies. As a testament to the field’s rapid evolution, many of the works are currently only available as preprints. The synthesis of the literature reveals that GenAI serves two fundamentally different purposes in behavioral research, each with distinct methodological implications. When used as a research method, GenAI transforms how researchers gather insights by leveraging AI’s unique capabilities to scale qualitative methods or create entirely new research paradigms. When studied as a research object, GenAI becomes the phenomenon under investigation, with researchers examining how AI influences human attitudes and behaviors, or how different AI characteristics shape user interaction.

3.1. GenAI as a research method

Studies employing GenAI as a research method offer unprecedented scalability and enable entirely new research paradigms. For example, a recent study deployed a large language model (LLM) to conduct 381 in-depth interviews exploring stock market investment barriers (Chopra & Haaland, 2023). With this interview tool, the researchers uncovered psychological barriers that were subsequently validated through traditional surveys (e.g., the belief that stock market participation is a demanding, high-maintenance activity requiring constant monitoring and research). In another study, researchers have created controlled social media environments using LLMs with assigned political personas, precisely manipulating partisan balance to test how being outnumbered affects user comfort and platform perceptions—an experiment impossible with real platforms due to practical constraints (Allamong et al., 2024). Another methodological innovation used personalized LLMs to generate users’ ‘future selves’ at age 60, including AI-generated backstories and

Table 1
Studies using GenAI for participant interaction in behavioral research.

Reference	Research description		Research Question	Key Findings	GenAI integration Interface	GenAI Service [Modality]	API usage	Description
	Purpose of GenAI integration	Research Topic						
Allamong et al. (2024)	Research method	Social media	How does partisan imbalance in feeds affect user comfort & platform perception?	Being outnumbered reduces comfort and worsens perceptions of the platform and its users.	Custom social media platform (https://www.polarizationlab.com/social-media-accelerator)	GPT-3.5 [text]	Probably but not explicitly mentioned	GPT-3.5-powered AI agents with assigned political views to simulate controlled partisan environments.
Argyle et al. (2025)	Research object	Persuasion	Are customized or interactive AI messages more persuasive than generic ones?	AI messages were persuasive, but customization and interactivity offered no extra benefit over a generic message.	Custom chat integrated in Qualtrics	GPT-4 [text]	Yes	GPT-4 was embedded in a survey to test real-time persuasive strategies, isolating the effects of customization vs. interaction.
Celiktutan et al. (2024)	Research object	Co-Creation	How do people perceive their contribution to a human-AI co-production?	Individuals tend to overvalue their own contributions to tasks co-produced with GenAI compared to the contributions of others.	Public ChatGPT website	ChatGPT [text]	No	Participants used the public ChatGPT website for a task; their perceptions were then measured via a survey.
Chopra and Haaland (2023)	Research method	Interview	Can an AI fully automate qualitative interviews to generate high-quality data?	An AI interviewer successfully conducted 381 in-depth interviews, maintained engagement, and uncovered deep insights.	Custom chat integrated in Qualtrics	GPT-4 [text]	Yes	A multi-agent GPT-4 system was built to act as an autonomous interviewer, handling probing, transitions, and summarization.
Costello et al. (2024)	Research object	Persuasion	Can conversational AI durably reduce conspiracy beliefs?	A single 5–10 min dialogue durably reduced conspiracy beliefs for at least 2 months.	Custom chat integrated in Qualtrics	GPT-4 [text]	Yes	GPT-4 was prompted to use the Socratic method, asking open-ended questions to encourage users to reflect reasoning.
De Freitas et al. (2025)	Research object	Support	Can interacting with an AI companion reduce consumer loneliness?	Interacting with an AI companion significantly reduces momentary loneliness, on par with human interaction.	Custom chat app	GPT-3 & GPT-4 [text]	Yes	A custom chat app (“Chatty”) provided an AI companion with a specific personality, memory, and realistic typing indicators.
Doshi & Hauser, (2024)	Research object	Co-Creation	How does GenAI access affect the individual and collective creativity of co-created content?	GenAI increased individual story creativity (novelty/usefulness) but reduced collective diversity, making stories more similar to each other.	Custom web interface	GPT-4 [text]	Yes	Writers could request 3-sentence story ideas from GPT-4 to use as inspiration for their short stories.
Flamino et al. (2025)	Research object	Persuasion	How effective are LLM agents as confederates and surrogates in a debate?	Agents were unpersuasive confederates but improved debate productivity. They are not yet realistic surrogates for human behavior.	Custom chat interface	GPT-4 & Llama 2 [text]	Yes	LLM agents with unique personas debated humans, using a mix of GPT-4 and Llama 2 to generate conversational responses.
Gaerth, Melumad, and Meyer (2025)	Research method	Modality	Do people disclose more or less personal information when speaking or writing to another agent?	Speaking feels more social, which leads to higher social desirability bias and people disclosing less negative personal information when speaking.	ChatGPT mock-up in Qualtrics	ChatGPT [text & speech]	No	Simulated ChatGPT interface

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Table 1 (continued)

Reference	Research description		Research Question	Key Findings	GenAI integration Interface	GenAI Service [Modality]	API usage	Description
	Purpose of GenAI integration	Research Topic						
Hackenburg and Margetts (2024)	Research object	Persuasion	Does LLM-based microtargeting increase persuasion compared to generic messages?	GPT-4 messages were persuasive, but microtargeting showed no significant persuasive advantage over a well-crafted generic message.	Custom chat interface	GPT-4 [text]	Yes	A web app utilized participant data to generate real-time, personalized, persuasive messages from GPT-4 for comparison.
Hosanagar & Ahn (2024)	Research object	Co-Creation	How do different human-AI collaboration designs affect creative writing quality and diversity?	Human-led designs yielded higher quality and satisfaction than AI-led designs. AI reduced content diversity, but human-led designs mitigated this.	Public ChatGPT website	GPT-3.5 [text]	No	Participants wrote stories using ChatGPT 3.5 following specific collaboration protocols (e.g., Human Confirmation, Copilot).
Hussein et al. (2026)	Research method	Manipulation	Can an AI interaction focused on “identity reflection” increase attitude extremity?	Reflecting on identity with an AI agent significantly increased attitude extremity and preference for extreme political candidates.	Custom chat integrated in Qualtrics	GPT-4 [text]	Yes	An LLM agent was invisibly prompted to guide the conversation to “convince” participants their opinion was identity-relevant.
Kapoor, Kumar, and Trulaske (2025)	Research object	Persuasion	Can personalized GenAI video ads increase engagement over other ad formats?	Personalized GenAI video ads increased ad clicks by 6–9 percentage points over personalized image and generic video ads.	WhatsApp	Proprietary [video]	Yes	A proprietary text-to-video engine created a “digital avatar” of a brand ambassador to speak personalized ad messages.
Karakaş and Jaeger (2025)	Research object	Persuasion	Can a brief LLM conversation change attitudes about meat consumption?	A short chat with GPT-4 significantly weakened participants’ stated commitment to eating meat.	Public ChatGPT website	GPT-4 [text]	No	Participants had a 5–10 min semi-structured conversation with the public ChatGPT-4; attitudes were measured pre- and post-chat.
Lee and Chung (2024)	Research object	Co-Creation	Does using ChatGPT enhance human creativity compared to Google or no tools?	Using ChatGPT increased the creativity of generated ideas compared to both unassisted ideation and using Google Search.	Public ChatGPT website	GPT-3.5 [text]	No	Participants generated ideas using either ChatGPT, Google, or no tools. Final ideas were rated for creativity by human judges.
Maier et al. (2025)	Research object	Co-Creation	How do human-led vs. model-led interaction modes affect idea quality and diversity?	“Question-mode” (human-led) improved quality while preserving diversity/ownership, whereas “Modelled” improved quality but reduced diversity.	Custom web interface	GPT-4 [text]	Yes	A custom chatbot used specific strategies (asking questions, giving suggestions, or rewriting) to support users in an ideation task.
Melumad and Yun (2025)	Research object	Search	How does using an LLM vs. a search engine affect search behavior and performance?	LLMs are more efficient for search but lead to lower-quality, less creative outputs due to overreliance on AI suggestions.	Custom chat integrated in Qualtrics	GPT-3.5 [text]	Yes	An embedded ChatGPT interface was compared against an embedded Google interface for a travel planning task.
Pataranutaporn et al. (2024)	Research method & object	Support	Can having a conversation with an AI-generated future self reduce anxiety and	A brief interaction with an AI-generated future self significantly decreased anxiety and increased future	Custom chat interface	GPT-3.5 [text] & StyleClip [image]	Yes	Personalized GPT-3.5 using survey responses about users’ goals and qualities to create a “future self” character at age

(continued on next page)

Table 1 (continued)

Reference	Research description		Research Question	Key Findings	GenAI integration Interface	GenAI Service [Modality]	API usage	Description
	Purpose of GenAI integration	Research Topic						
Potter et al. (2024)	Research object	Persuasion	increase future self-continuity? Do LLMs have political biases, and can they influence user attitudes?	self-continuity compared to control conditions. LLMs show a clear liberal bias, and brief exposure to politically slanted AI responses significantly shifts user attitudes.	Custom chat integrated in Qualtrics	GPT-4, GPT-3.5, Llama 2 [text]	Yes	60, and age-progressed photos for a chat. A web app showed users 10 political responses from an LLM prompted to be liberal or conservative to measure persuasive effects.
Sabour et al. (2025)	Research object	Persuasion	Can an LLM agent manipulate human decision-making and risk-taking?	An LLM agent successfully manipulated participants, significantly increasing their risk-taking when prompted to give risk-promoting advice.	Custom chat interface	GPT-4 [text]	Yes	Participants played a financial game while getting advice from a GPT-4 agent secretly prompted to be risk-promoting or risk-averse.
Salvi et al. (2025)	Research object	Persuasion	Is GPT-4 more persuasive than humans in a conversational debate?	GPT-4 was significantly more persuasive than human debaters (by 81.7 %), using stronger arguments and more formal language.	Custom chat interface	GPT-4 [text]	Yes	Participants debated controversial topics with either another human or a GPT-4 agent in a randomized controlled trial.
Schoenegger et al. (2025)	Research object	Persuasion	Are LLMs more persuasive than incentivized human persuaders?	GPT-4 was significantly more persuasive than financially motivated humans, causing a 23 percentage point greater belief change.	Custom chat interface	GPT-4 [text]	Yes	Participants read a persuasive message generated by either an incentivized human or a GPT-4 model prompted for max persuasion.
Spatharioti et al. (2023)	Research object	Search	Do consumers prefer LLM search for products, and how does it affect their choice?	Consumers find LLM search more useful. It leads to a narrower search process and a final choice closer to the AI's first suggestion.	Custom chat interface	Unspecified LLM [text]	Yes	A custom platform presented users with either a conversational AI or a traditional search engine to study product discovery behavior.
Xu et al. (2023)	Research object	Search	How does ChatGPT compare to Google on search efficiency?	ChatGPT is faster and more satisfying, but Google users demonstrate better information retention.	Public ChatGPT website	GPT-3.5 [text]	No	Participants used either the public ChatGPT or Google website to answer questions, then were tested on efficiency, satisfaction, and recall.

age-progressed images, enabling researchers to study interventions for psychological wellbeing (Pataranutaporn et al., 2024). Again other research utilized LLM interactions to manipulate psychological constructs at the individual level (Hussein et al., 2026). By instructing an LLM to engage participants in “identity reflection”, adaptively guiding them to see their opinions as self-defining, this research demonstrates that increased identity relevance drives preferences for extreme political candidates. Despite these demonstrations of GenAI transcending traditional methodological constraints, only a fraction of current studies leverage GenAI as a research method, suggesting vast untapped opportunities for marketing researchers.

3.2. GenAI as a research object

More frequently, researchers integrate GenAI into their research studies to investigate the phenomenon of GenAI and its direct effects on people’s attitudes and behaviors. Within this category, three dominant themes emerge. The most prominent theme in this area is *persuasion*. While often explored in political or societal contexts—such as reducing conspiracy beliefs (Costello et al., 2024) or influencing political opinions (Argyle et al., 2025; Hackenburg & Margetts, 2024; Potter et al., 2024)—these applications are directly applicable to marketing. A common technique involves personalizing the AI’s arguments by incorporating the participant’s own attributes (e.g., demographics, political opinion) into the instructions to the GenAI model. The model can then create hyper-personalized or micro-targeted output that might be potentially more convincing than non-personalized messages. While the potential of this method has been emphasized (Teeny & Matz, 2024), empirical evidence remains mixed. Initial studies found that text-based personalized messages did not perform better than standard messages in persuasion tasks (Hackenburg & Margetts, 2024). However, the same principle was used to generate hyper-personalized video ads, which showed a higher ad engagement than non-personalized video ads (Kapoor et al., 2025).

A second major research stream examines how AI transforms *online search*, with studies revealing fundamental changes in consumer behavior. Experiments comparing LLM-assisted search with traditional search engines demonstrate that while LLMs make search more efficient, they lead to shallower knowledge acquisition (Melumad & Yun, 2025). Moreover, consumers perceive LLM search as more useful than traditional search engines, but their eventual decisions may be less accurate due to overreliance when the LLM erred (Spatharioti et al., 2023; Xu et al., 2023).

A third stream explores *AI as a collaborative enhancer*. Most remarkably, controlled experiments show that AI companions can reduce loneliness—opening both opportunities and ethical questions for marketing applications, particularly in service industries where human connection has traditionally been paramount (De Freitas et al., 2025). Moreover, studies of creative tasks demonstrate that ChatGPT use increased creativity scores compared to both unassisted and Google-assisted ideation, suggesting AI’s potential as a creative partner (Lee & Chung, 2024). However, other research warns that generative AI can homogenize content, reducing the collective diversity of ideas (Doshi & Hauser, 2024). Crucially, though, this limitation is not inevitable; studies show it can be mitigated when the interaction is designed for the human to lead the creative process (Hosanagar & Ahn, 2024; Maier et al., 2025). Finally, research has uncovered that individuals systematically overvalue their own contributions in AI collaborations compared to how they evaluate others’ contributions in identical situations (Celiktutan et al., 2024).

3.3. Technical implementation approaches

Turning to the technical implementation, the review shows that a majority of studies integrated GenAI interactions into Qualtrics (e.g., Argyle et al., 2025; Chopra & Haaland, 2023; Costello et al., 2024). Exceptions typically arose when the research required specialized functionality, such as a custom mobile app for a social companion (De Freitas et al., 2025), a simulated social media interface (Allamong et al., 2024), or a field study conducted via WhatsApp (Kapoor et al., 2025). The choice of the integrated AI model is remarkably consistent, with researchers almost exclusively using Large Language Models (LLMs) from OpenAI, despite the availability of potentially cheaper or better-performing alternatives. This monopolistic pattern raises concerns that research findings may be model-specific to some extent rather than generalizable to AI broadly and that the field becomes vulnerable to changes in OpenAI’s policies or practices. Remarkably, no study to date has systematically compared different models for research applications.

The technical implementation approaches also reveal a fundamental trade-off between simplicity and control. Some studies opted for public website integration, directing participants to use ChatGPT’s public interface (Celiktutan et al., 2024; Lee & Chung, 2024). This method is technically simple but comes with disadvantages. The researcher has no control over the model’s instructions (i.e., the system prompt), cannot prevent the conversation from being potentially influenced by a participant’s prior chat history, and cannot access the interaction data for analysis. The second, more sophisticated approach is the integration of a GenAI model into a researcher-controlled user interface (e.g., Qualtrics) via an Application Programming Interface (API). This method provides the researcher with full control over the interaction and complete data access. However, it introduces technical challenges and pitfalls that create a significant barrier for those without coding expertise. Within this API approach, some studies call the model directly from the Qualtrics platform (Costello et al., 2024), while others use a back-end server as an intermediary (Hackenburg & Margetts, 2024).

While these pioneering studies demonstrate the transformative potential of GenAI interactions in behavioral research, their adoption in marketing research remains surprisingly limited. This gap between potential and practice may stem from several barriers identified in the group discussions, the first being a lack of awareness about what is possible with GenAI interactions in research studies. The literature review above addresses this by showcasing diverse applications and their potential. However, as the literature review also reveals, there are different kinds of implementations ranging from simple public website integration to sophisticated API-based systems, and many researchers mentioned the technical implementation as a main barrier to adopting GenAI interactions. Hence, the following section addresses this technical barrier by first providing an overview of when GenAI tools provide value in

contrast to traditional methods, offering a decision framework for researchers, and then diving into practical explanations and step-by-step walkthroughs for successful implementation.

4. The practical implementation of GenAI interactions into research studies

Drawing from the literature review, the technical nature of GenAI models—including their probabilistic behavior, data processing requirements, and interaction capabilities—and insights from the discussions, the following table provides an overview of when GenAI interactions provide value in research studies. This serves as a decision framework for researchers to determine when GenAI offers legitimate methodological value versus when traditional methods remain more appropriate, before diving into technical implementation details (Table 2).

When researchers believe a GenAI integration would be beneficial in their research studies, they can draw upon existing valuable resources for its implementation. One of them is the open-source template provided alongside the research on reducing conspiracy beliefs (Costello et al., 2024). This resource is excellent for researchers seeking a practical, ready-to-use starting point. With this tool, a researcher can download the provided Qualtrics template file, insert an API key, and run a text-based conversational study where a participant chats with an AI inside the survey page. Another relevant approach involves the development of user-friendly, no-code platforms, such as the LUCID solution (Garvey & Blanchard, 2025). This type of tool is very valuable for ensuring maximum accessibility. With this solution, researchers can use a simple interface to set up text-based conversational studies with the GPT-4 model, typically by entering their instructions and API key into web forms, without writing code.

While these resources excel at implementing established paradigms and might be a good point to start, the section below addresses a different challenge: enabling researchers to create entirely novel GenAI integrations tailored to their specific research questions. The approach presented here demonstrates how AI coding assistants can translate a researcher's natural language description—whether for voice-enabled interviews, GenAI online search, or image generation tasks—directly into functional code. This method combines the accessibility of no-code solutions with the flexibility traditionally reserved for programmers. A researcher can describe their exact needs (“I want participants to speak their responses to a GenAI driven interview bot in Qualtrics”) and receive working code minutes later.

The following sections outline this approach, beginning with the foundational components to provide researchers with a conceptual understanding of GenAI integrations, followed by introducing the practical method for using AI coding assistants to generate the necessary code from natural language instructions. This is demonstrated through step-by-step walkthroughs of marketing-relevant applications that showcase the breadth of possibilities this method enables.

4.1. Foundational architecture for integrating GenAI interactions in research studies

Building GenAI-driven applications fundamentally involves two core elements: a frontend and a GenAI service (please see page 3 in the [web appendix](#) for a Glossary of technical terms). The frontend is the user-facing interface, such as a Qualtrics survey, where participants input information. The GenAI service is the external AI model that processes this input and generates a response (e.g., text, image, audio). The GenAI Service is often accessed via an Application Programming Interface (API). A key advantage of this API-centric approach is its inherent flexibility, empowering researchers to connect their applications to virtually any GenAI service that offers an API. This adaptability ensures that researchers remain independent of the rapidly evolving model landscape and can adapt or extend their GenAI research applications as new and diverse GenAI models are published by various companies.

The fundamental technical task is to establish a communication channel between the GenAI service via the API and the user frontend, which can be accomplished through different architectural patterns. The most direct architectural pattern connects the frontend (i.e., Qualtrics) straight to the GenAI service. While this approach is straightforward and easier to implement, it also comes with the risk of exposing the secret API key to survey participants, what could lead to unforeseen costs if they misuse it. However, the cost risk can be significantly mitigated since most GenAI services use prepaid credit systems, allowing researchers to limit API key funds to small amounts (please see pages 10–19 in the [web appendix](#) for API key setup). Nevertheless, to avoid the possibility of API key access, an alternative pattern introduces a backend server as a secure intermediary that manages all communication with the GenAI service on behalf of the frontend. The figure below shows the two principal architectures to establish the communication channel between the GenAI service via the API and the user frontend. Subsequent chapters will provide the necessary background on these elements (Fig. 1).

4.1.1. Frontend

A web frontend for GenAI interaction can be seen as any website that allows a user to make an input. While researchers can build custom frontends from scratch (e.g., a mobile application; De Freitas et al., 2025), survey platforms such as Qualtrics offer a practical and powerful option as it avoids the considerable effort of building and hosting a separate interface. The integration of a GenAI model into Qualtrics is achieved by adding a small block of code to a survey question. This code combines three code elements that any website is built with: Hypertext Markup Language (HTML), Cascading Style Sheets (CSS), and JavaScript (Simon, 2023). While HTML defines the content and structure of a website (Berners-Lee & Connolly, 1993), CSS provides the design (Flanagan, 2011), and JavaScript defines the frontend's behavior and interactivity (Kalim, 2013).

For integrating a GenAI service into Qualtrics, JavaScript is the most important coding element as it establishes the communication channel between the frontend and the GenAI service. It takes what a participant types, sends it to the GenAI service, and then displays the AI's output back to the participant. The other two, HTML and CSS, play supporting roles. HTML is used to create the basic structure

Table 2
Conditions for valuable GenAI interactions in research studies.

When GenAI interactions in research studies provide value	
Studying AI as a Research Phenomenon	<ul style="list-style-type: none"> - Investigating AI design, trust, adoption, and interaction patterns - Examining human-AI collaboration effectiveness
Enabling Novel Research Designs	<ul style="list-style-type: none"> - Understanding consumer responses to AI systems (e.g., chatbots, transparency preferences) - Creating impossible interactions (e.g., conversations with simulated future selves)
Enhancing Methodological Rigor	<ul style="list-style-type: none"> - Establishing controlled collaborative settings with AI partners - Simulating interactions difficult or unethical with humans
Scaling Qualitative Methods	<ul style="list-style-type: none"> - Replacing static stimuli with dynamic interactions - Adding AI conditions to test robustness alongside traditional methods
Improving Data Quality & Participant Experience	<ul style="list-style-type: none"> - Adding AI conditions to traditional methods for balancing external validity and experimental control - Conducting hundreds of interviews simultaneously - Bridging qualitative depth with quantitative scale - Enabling 24/7 data collection for global studies - Using AI for initial exploration while humans focus on depth - Increasing engagement through interactive study experiences - Reducing interviewer bias - Enabling follow-up questions and clarifications in online studies - Collecting multimodal data (text, voice, image) - Serving as sophisticated attention checks
When GenAI interactions in research studies do not provide value	
Population Constraints	<ul style="list-style-type: none"> - Studying highly specific groups (e.g., domain experts, niche subcultures) - Target participants unlikely to engage with AI - Sample inherently limited by population characteristics
Human Expertise Essential	<ul style="list-style-type: none"> - Trust and rapport critical to research topic - Cultural context or specialized knowledge required - Researcher’s interpretive skills central to data quality
Methodological Requirements	<ul style="list-style-type: none"> - Absolute experimental control with zero variation needed - Exact replication of previous methodologies required - Observational or ethnographic methods necessary - Non-verbal cues essential to research questions

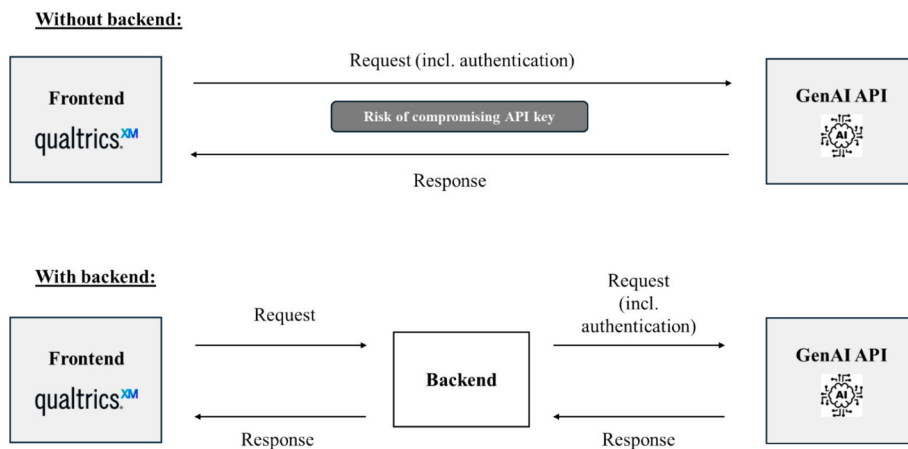


Fig. 1. Principal architecture of a GenAI integration for participant interaction in research studies with and without backend solution (accessing via API).

and text, such as the instructions a participant reads. CSS is then used to control the visual style, like the colors, layout, and fonts. In practice, the code for all three elements is often bundled together in one script and inserted into a single survey question using Qualtrics’s ‘add JavaScript’ feature.

Another crucial feature of using Qualtrics as a frontend is its “Embedded Data” functionality, which allows custom variables to be stored alongside standard survey responses. To implement this, a researcher first navigates to the ‘Survey Flow’ section in Qualtrics. There, they add an ‘Embedded Data’ element and simply type the names for the new variables they wish to create, such as ‘user_prompt’ and ‘AI_response’. Once these fields are defined in the Survey Flow, the embedded JavaScript can be programmed to save information directly into them. For example, after a participant types their prompt, the script would use a simple command to store that text directly into the variable ‘user_prompt’. Similarly, after the script receives the response from the GenAI, it would save it to ‘AI_response’. The result is a complete, automatically logged transcript of the interaction. When the researcher downloads the study data as usual from Qualtrics, the exported spreadsheet will contain new columns labeled ‘user_prompt’ and ‘AI_response’. For each

participant, these columns will hold the full text of their interaction, appearing directly alongside their answers to other questions that the researcher added to the survey (e.g., demographics, behavioral intention, satisfaction measures). This creates a single, unified dataset ready for analysis.

While this procedure works well for text-based output from the GenAI service, some modifications are needed to handle non-textual outputs, such as images or audio files, which cannot be stored directly in Embedded Data fields. For this more specialized case, the workflow involves uploading the generated media to an external cloud storage service. The persistent URL (i.e., Uniform Resource Locator, the address of a specific webpage or file on the internet) for the stored file is then captured and saved into an Embedded Data field, effectively linking the non-text output to the participant's survey data (please see pages 34–36 in the [web appendix](#) for detailed instructions on how to store non-textual data).

4.1.2. GenAI model

The GenAI model is the central component of a GenAI-driven web application, responsible for its core functionality. In contrast to traditional AI models, which primarily analyze existing data for tasks like prediction and classification, GenAI constitutes a broad category of systems capable of creating novel content (Toner, 2023). GenAI models are either offered directly by the individual providers (e.g., OpenAI, Anthropic, Google), or there also exist “AI model Aggregators” like FireworksAI, AIMLAPI, or OpenRouter, which provide a collection of the most relevant GenAI models on their web presence (much like booking a hotel directly on the hotel webpage or booking it via a platform). In any case, selecting the appropriate GenAI model for a study requires the consideration of some key characteristics.

The first and most fundamental characteristic to consider is modality—the format of the input the model receives from the study participant and the output it generates. Although text-to-text interaction is the most common paradigm, the methods described in this paper allow for the integration of a wide range of modalities within Qualtrics. The following table provides an overview of available GenAI models, categorized by their input and output modalities, to illustrate the breadth of possibilities (Table 3).

Beyond modality, a second critical characteristic to consider is the model's specialization and inherent capabilities. Many contemporary GenAI models are augmented with built-in tools that extend their functionality beyond simple content generation. For example, some models can perform real-time web searches to incorporate up-to-date information (OpenAI, 2025), a crucial feature for studies involving current events or the investigation of people's online search behavior (Melumad & Yun, 2025). Others include moderation systems to ensure safe interactions by detecting harmful content (De Freitas et al., 2025) or are optimized for generating computer code (MistralAI, 2025). A researcher should therefore select a model whose interaction modality and functionalities align the best with the corresponding research question or task.

Moreover, the selection involves a practical evaluation of three often-competing factors: performance, speed (latency), and cost. A model's performance can be assessed using objective online resources and public leaderboards, which offer continuously updated benchmarks that compare various models on standardized tests (e.g., <https://artificialanalysis.ai/>; <https://lmarena.ai/>).² However, higher performance often correlates with increased operational costs and higher latency—the time delay between a user's input and the model's response. In a research context, high latency can negatively impact the participant experience, while high costs weigh on the research budget. Consequently, the “best” model is context-dependent. The largest or most capable model is not always the optimal choice. Researchers must balance these trade-offs to select a model that provides the necessary performance for their research question while remaining within acceptable parameters for latency and budget.

Finally, GenAI models can be classified as either open-source (e.g., DeepSeek, LLaMA 3 by Meta or Gemma 2 by Google) or proprietary (e.g., ChatGPT-4 by OpenAI or Gemini 2.5 by Google). Open-source models are models where aspects like the architecture, training methods, or even the model weights themselves are made publicly available (Bi et al., 2024). However, to fully benefit from open-source models, researchers must run them on their own computers or servers, which requires powerful hardware that most researchers don't have access to, especially if they want performance matching commercial models like ChatGPT. Given these practical constraints, most researchers will find it more feasible to connect to proprietary GenAI models (e.g., ChatGPT, Gemini, Claude) through their Application Programming Interface (API). However, for research projects requiring high control, transparency, or customization, open-source models offer distinct advantages. These models can be modified or trained on specific datasets—for example, teaching an AI to conduct specialized interviews using your field's terminology and methods. Moreover, when running on a private server, user-GenAI interactions are not shared with the model developer (please see pages 38–39 in the [web appendix](#) for an additional discussion).

4.1.3. API

An API serves as the gateway through which a software program communicates with other programs, and—in the case of web APIs—with the broader digital ecosystem across the internet (Jin et al., 2018). In our context, it is the crucial link that enables a platform like Qualtrics to send a participant's input to a GenAI model and receive a response. Each request sent via the API is a self-contained package of information. This package includes several key components. First, it contains an API key for authentication—a unique code that identifies the researcher's account for access and billing, much like a credit card held on file at a restaurant. An API key can be generated on the website of a GenAI model provider (please see pages 10–19 in the [web appendix](#) for API key setup). Most providers (e.g., OpenAI, Anthropic) allow prepaid credits for their API usage (e.g., \$20–100) with auto-recharge disabled, which

² For more extensive discussions on measuring model performance and quality see for example Weidinger et al. (2025).

Table 3
Overview of GenAI models categorized by modality.

Input Modality (s)	Output Modality (s)	Description / Common Tasks	Exemplary Models
Text	Text	Generating human-like text, conversation, summarization, and translation	GPT-4, Claude 3 Opus, Gemini 1.5 Pro, Llama 3
Text	Code	Generating computer code from natural language or code prompts	GitHub Copilot, AlphaCode 2, Gemini, CodeLlama
Text	Image	Creating images from textual descriptions	Stable Diffusion 3, Midjourney v7, DALL-E 3, Imagen 2
Text	Video	Creating video clips from textual descriptions	Sora, Runway Gen-3, Make-A-Video
Text	Audio (Speech)	Synthesizing human-like speech from text (Text-to-Speech)	ElevenLabs TTS, Bark, VALL-E X
Text	Audio (Music/Sound)	Generating music or sound effects based on text prompts	MusicLM, Stable Audio 2.0, AudioCraft
Image	Text	Describing images in natural language (Captioning), Analysis	Gemini Series, GPT-4 V, BLIP-2, Florence-2
Image (+ opt. Text)	Image	Modifying existing images based on prompts or styles	Stable Diffusion (img2img, ControlNet), Pix2PixHD
Video	Text / Data	Analyzing video content, generating descriptions or summaries	Gemini Series, Video-LLaMA, various analysis models
Audio	Text	Transcribing spoken language into text	Whisper, Google Cloud Speech-to-Text

allows strict cost controls and ensures that the set budget will not be exceeded. However, not all providers offer these safeguards; Google's Gemini API currently lacks spending caps. In such cases, researchers who still want to use a specific model can turn to AI model aggregators like OpenRouter or AIMLAPI. These services provide access to the same models through their own APIs while offering prepaid credit systems for better cost control. Second, an API call includes a "body", which specifies exactly what the researcher wants the GenAI model to do. This includes defining which specific model to use (e.g., ChatGPT-4 or Gemini 2.5), and providing an instruction on how the model should behave (e.g., "be a friendly collaborator and always provide constructive feedback"), which is called system prompt. Normal users of GenAI models never see the system prompt, which works behind the scenes, but every model has specific instructions that are followed when a user types in their regular prompt. Moreover, the body eventually includes the actual prompt from the study participant (e.g., "Write a slogan for a new eco-friendly sneaker"). This structured format ensures the request is understood and processed correctly by the GenAI model.

From a methodological standpoint, the power of an API lies in its configurability. Critically, APIs address a key concern about GenAI controllability in experimental settings by allowing researchers to adjust parameters like temperature, which governs output determinism. Lower temperature values produce more consistent, predictable responses, while higher values introduce variability. Beyond temperature control, researchers can configure numerous other parameters, such as defining specific brand personas through system prompts or adjusting response length and style. Each model provider (e.g., OpenAI, Google, Anthropic) publishes comprehensive API documentations detailing these configurable options, which researchers can treat as independent variables in experimental designs. This control enables researchers to standardize their methodology, enhance replicability, and test how specific AI characteristics influence participant responses.

4.1.4. Backend

After selecting a GenAI model and understanding its API, the researcher must decide on the architectural pattern for connecting the frontend survey to the GenAI service. They can either connect the frontend survey directly to the GenAI service or route requests through a backend server, which is a private, researcher-controlled server that acts as an intermediary. While direct frontend connections offer simplicity, using a backend is the professional standard for larger-scale studies. This architecture's primary advantage is security, as the API key remains stored on the private server, never exposed to participants' browsers. Though the risk of survey participants actively misusing an API key is minimal, backend routing prevents accidental key discovery or harvesting by automated web scrapers—a particular concern for publicly available surveys.

The choice between direct frontend connection and backend architecture involves balancing simplicity against security requirements. Direct frontend connections work well for rapid prototyping, pilot studies, and research with known participant pools. Cost risks can be prevented by using pre-paid systems as described above. However, backend implementations provide the credential security sometimes required by IRBs or university data policies but they come along with additional implementation complexity. Researchers should select the architecture that aligns with their project's specific context, participant pool, and institutional requirements.

4.1.5. Operational and ethical aspects

Before showcasing the individual implementation steps for the described components, there are some operational and ethical aspects to consider. First, researchers must obtain explicit informed consent from study participants before any AI interaction, clearly stating that participant responses will be processed by an external service. Direct links to the provider's data processing policies should be included as participant inputs will be transmitted to third-party commercial entities (Weisz et al., 2024).

Instructions to the system's behavior (i.e., system prompts) should be carefully designed to avoid soliciting personally identifiable information from participants. When sensitive data is collected separately through the survey platform—researchers must ensure such

information is not transmitted to the GenAI service through embedded data fields or other mechanisms. Anticipating potential data disclosure risks helps maintain participant privacy while collecting necessary interaction data.

Technical failures are inherent to systems dependent on external services and cannot be entirely eliminated. Network interruptions, API outages, or rate limiting can all disrupt the participant experience. Researchers should establish rules for handling such disruptions and check for incomplete or corrupted data in the final data set. Additionally, researchers can test whether participants can connect to the AI service at the very start of the survey (please see page 33 in the [web appendix](#) for the technical instructions on such a connectivity check). This simple check prevents participants from investing time in a study they cannot complete due to network restrictions, allowing researchers to redirect affected participants immediately rather than after they have begun responding to questions.

Finally, documentation is essential for research validity and reproducibility. GenAI service providers may update their models without notice, potentially altering behavior in ways that affect research outcomes. Researchers must record the specific model used (including version numbers when available), all API configuration parameters such as temperature settings and system prompts employed during data collection ([Ganguly et al., 2025](#)). This documentation ensures that results can be appropriately interpreted and potentially replicated. Together, these considerations represent important methodological foundations for responsibly integrating GenAI interactions into research studies.³

4.2. Coding assistants

A remarkable aspect of using GenAI is that the technology itself provides the most powerful means for its own implementation. This empowers researchers, even those with little to no coding experience, to build the very GenAI-driven integrations they need for their studies ([Cui et al., 2025](#)). This is made possible by a new category of specialized AI coding assistants. Unlike general-purpose chatbots like ChatGPT, which only process isolated prompts, these specialized tools have a complete understanding of all the files in a research project codebase. This “project awareness” is a crucial advantage. However, these assistants vary in user-friendliness. While some operate through technical command-line interfaces, tools like Cursor or Windsurf provide familiar point-and-click interfaces similar to standard word processors. Researchers can simply highlight code, click buttons, and chat with the AI assistant.

Cursor, for example, functions as a versatile workbench where code can be created. Its most transformative feature for researchers with limited or no coding experience is the integrated AI chat. A researcher can simply type a request in plain English—such as, “Create a JavaScript for Qualtrics to embed an interaction with ChatGPT”—and the AI translates this into a functional code snippet, which could be integrated into Qualtrics. As seen in the screenshot below, the interface presents the chat on the right panel and generates the corresponding code files in the main window. These files can be saved directly in a folder on the computer, ready for use. In the example below, the coding assistant also automatically created a README file that helps with the further Qualtrics integration ([Fig. 2](#)).

For generating code, these tools offer different ways to manage their integrated AI assistant, which typically involves a trade-off between automation and user control. The most common method is an “Ask” mode, which functions like a conversation. Here, the researcher gives a command to the coding assistant, and the AI proposes the corresponding code. The researcher can then review and approve the provided code, ensuring full control over the process. In contrast, an “Agent” mode offers a more hands-off approach. In this mode, the researcher describes a goal in natural language, and the Agent works autonomously across multiple files to achieve it. This is powerful but involves trusting the AI to complete the project independently.

To further refine the code generation in these coding assistants, researchers can use a feature called Rules ([Cursor, 2025](#)). Think of rules as a permanent set of instructions or a style guide for the AI assistant, which prevents the need to repeat the same directions in every prompt. For a Qualtrics study, a researcher could, for example, establish a general rule like the creation of README files to provide implementation instructions or a project-related rule to ensure data quality and a good participant experience:

When creating new code snippets, always create an accompanying README file that explains their Qualtrics integration. Moreover, always create code that saves the participant’s prompt to an embedded data field named ‘user_prompt’ and the AI’s full response to ‘ai_response’ after every AI interaction. While the participant is waiting for the AI to reply, always display a “Loading...” message. If the connection to the AI fails, display a simple error message to the participant and save the value ‘API_ERROR’ in the ‘ai_response’ field.

Once saved, the AI will automatically incorporate this logic into any future code it generates for the project. This ensures that critical data is never lost and that the participant experience is consistent, without the researcher having to remember the coding assistant. These coding assistants enable researchers—even without coding experience—to generate, test, and debug code connecting Qualtrics with any GenAI model, as shown through step-by-step tutorials for marketing-relevant applications. Before presenting the walk-throughs, understanding effective interaction with AI coding assistants will significantly improve success rates. The table below presents practices that have proven essential ([Table 4](#)).

4.3. Implementation walk-throughs

This section provides one practical implementation walk-through for a GenAI-powered research tool within Qualtrics, using the described coding assistant. Due to space constraints, three further walkthroughs are provided in the [web appendix](#) (pages 23–30), following the same structure as the walkthrough in the manuscript. The examples address common marketing research needs related to

³ For a further discussion on responsible GenAI usage in marketing research see: [Blanchard et al. \(2025\)](#).

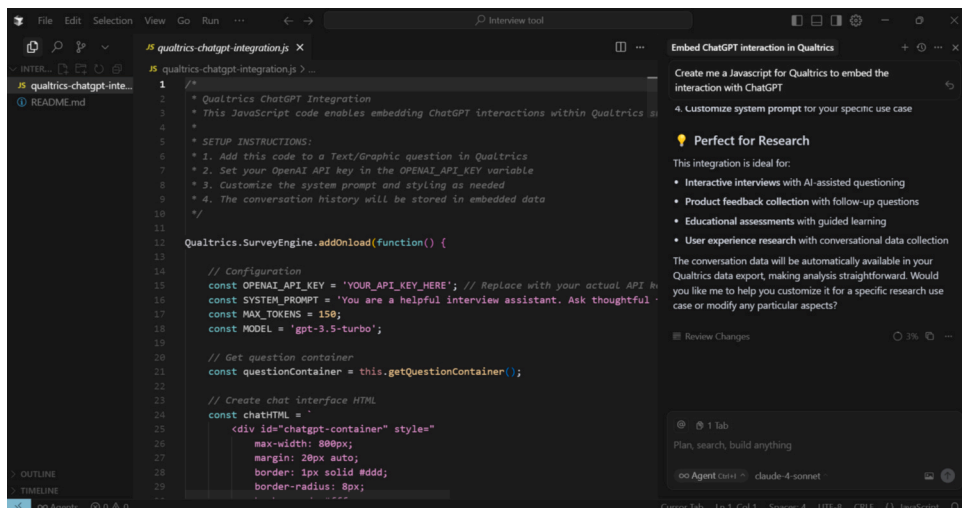


Fig. 2. Example of a coding assistant showing natural language prompt and created script.

Table 4

Best practices when working with coding assistants.

Setup and Implementation

- **Use meta-prompting:** Ask any LLM to help formulate detailed prompts for the coding assistant. Example: "Create a detailed prompt I can give to a coding assistant to build [...] in Qualtrics"
- **Include API documentation:** Always paste the provider's API documentation (found on the provider's website) with the prompt to the coding assistant – the coding assistant needs this exact syntax
- **Follow code markers:** Keep placeholder comments like "//Place your API Key here//" and follow embedded instructions
- **Request documentation:** Ask for a README file with implementation instructions, or set this as a rule to automatically generate documentation with every code output
- **Consolidate if needed:** Request "Combine everything into a single JavaScript file for Qualtrics" if multiple files are generated
- **Test properly:** Use anonymous survey links, not preview mode (which may block features like audio recording) in Qualtrics for testing the provided code

Troubleshooting

- **Use browser console to identify errors:** Open it in your web browser by pressing F12 (or right-click anywhere on the page and select "Inspect"), then click the "Console" tab. This shows what happens behind the scenes when the code runs. Red text indicates errors, yellow text shows warnings (usually not critical), and white/gray text shows normal operations. Look for red error messages that often include line numbers and descriptions like "API key not defined" or "Cannot read property of undefined"
- **Share errors with assistant:** Screenshot console errors and provide to coding assistant: "The code produces this error: [error text]. Please fix it"
- **Be specific about issues:** Describe unexpected behavior precisely (e.g., "The chat displays, but responses don't save to embedded data")
- **Remember variability:** AI-generated code is probabilistic – test thoroughly as the same prompt may produce different results

some of the themes identified in the literature review: understanding how consumers use GenAI to search for online information (Melumad, 2023; Melumad & Yun, 2025; Spatharioti et al., 2023; Xu et al., 2023), conducting in-depth interviews at scale to understand consumer insights (Chopra & Haaland, 2023; Epp & Humphreys, 2025), the effective usage of GenAI as a co-creation tool (Celikutan et al., 2024; Lee & Chung, 2024), and GenAI's power to persuade by creating hyper-individualized output (Hackenburg &

Table 5

Overview of basic implementation steps.

Step	Action	Description
1	Create Qualtrics Survey and Question Container	Create a new project in Qualtrics and add a Text/Graphic question. This question will serve as the container for your AI interface.
2	Get API Credentials	Sign up with a provider (e.g., OpenAI, Anthropic). Generate an API Key in your account settings and copy the provider's API Documentation page.
3	Generate Code	Open an AI Coding Assistant (e.g., Cursor). Paste the API documentation and a prompt: "Create a JavaScript for Qualtrics that sends user input to this API and saves the reply to embedded data".
4	Configure Script	Save the code generated by the assistant. Insert your API Key into the code where the assistant indicated (e.g., const API_KEY = 'your-key-here').
5	Embed Script	Return to your Qualtrics question (Step 1), open the JavaScript editor, and paste your fully configured code.
6	Define Data Fields	In Qualtrics Survey Flow, add an Embedded Data element. Add the specific variable names used in your code (e.g., user_prompt, ai_response) so the data saves correctly.
7	Test Connection	Test the survey. Interact with the AI to ensure it responds and check Data & Analysis to confirm all data is being captured.

Margetts, 2024; Kapoor et al., 2025). All presented applications can be built using the straightforward approach of connecting Qualtrics directly to AI services, making them accessible to researchers with a limited technical background. Subsequently, the potential backend implementation is presented. The examples have been selected to demonstrate the breadth of possibilities, using GenAI as a research method and as a research object. Moreover, different GenAI services are used, demonstrating that the approach can be easily transferred to basically any GenAI service and model. Before the walk-throughs are described in detail, the following table gives an overview of the basic steps that a researcher needs to go through for the implementation (Table 5).

4.3.1. Walk-through: The GenAI search assistant

The emergence of GenAI substantially impacted how people search for information, which represents one of the three main use cases of ChatGPT (Chatterji et al., 2025). Moreover, about 58 % of consumers have already replaced search engines with GenAI tools for product or service recommendations (Capgemini, 2025), and search patterns have shifted from shorter, more navigational search queries to longer, more conversational prompts (Solis, 2025). Additionally, when AI provides synthesized answers, click-through rates plummet to just 8 % as 26 % of users end their search entirely after reading AI responses (Kelly, 2025). For marketers, this creates new challenges but also opportunities, prompting relevant questions about how to adapt. For example, how do consumers search for information, and how do they make decisions when search becomes conversation? What drives engagement in AI-generated search results? How do marketers optimize for AI recommendations? The tool presented below enables researchers to systematically investigate these questions.

Tool components. This application combines two parts: a Qualtrics survey as an interface and a GenAI service that can search the web and provide answers. This example uses OpenAI's GPT model with web search access. Researchers can identify suitable AI models for their needs through simple web searches (e.g., "AI model with web search API" or "GenAI models with internet access"), consulting AI comparison websites, directly asking any AI assistant about available options, or visiting the web pages of AI model aggregators (e.g., OpenRouter, AIMLAPI). To connect these pieces, instructions are needed for how Qualtrics should communicate with the selected GenAI service through its API. These instructions, called API documentation, are freely available in the developer section of any GenAI service provider's website—OpenAI, Google, Anthropic, and others all provide this documentation in a similar format. While these instructions might appear complex initially, they serve as a standardized recipe that the AI coding assistant will follow exactly when generating the required code snippets. Researchers simply copy this documentation from the provider's website (see Fig. 3 below) and paste it into the coding assistant along with instructions describing what they want to build.

Building the tool. With the API documentation ready, researchers now need to tell the coding assistant what to build. These instructions should specify three elements: interface design (e.g., chat window, buttons), functionality (e.g., sending queries, displaying responses), and data storage (which embedded data fields to populate). Rather than writing these from scratch, researchers can use any GenAI model to help create this prompt (i.e., meta-prompting). Below is an example prompt that researchers can adapt or use directly:

"Create a JavaScript snippet for Qualtrics. It should power a chat interface with the HTML elements 'chat-container', 'chat-box', 'user-input', and 'send-btn'. When the user clicks the send button, take the text from 'user-input' and send it to the web search of OpenAI (the documentation is below). Display a 'loading...' message while waiting. Show the AI's response in the chat box. Before sending the API request, store the user's full prompt in the Qualtrics embedded data field named user_prompt. After receiving the response, store the entire

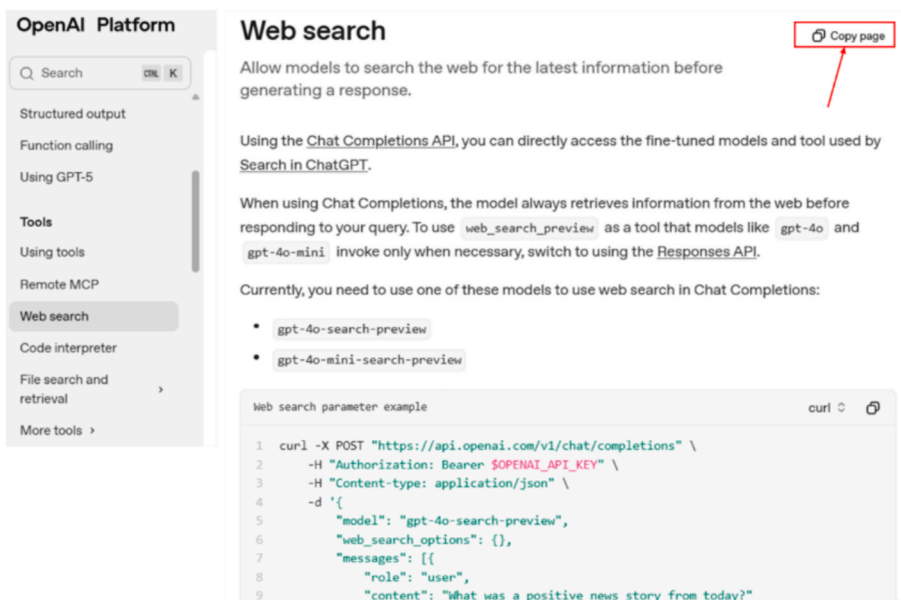


Fig. 3. OpenAI's API documentation.

AI message in the ai_response field. Ensure you include error handling. Integrate the HTML and JavaScript into one script that I can add as JavaScript to a Qualtrics question. Prioritize the robustness and functionality of input and output.”

After providing this prompt, paste the OpenAI API documentation for web search functionality directly below this prompt into the coding assistant.

The coding assistant will create the corresponding code, and the following three straightforward steps are required for implementation:

Configure the Code: Save the generated code as a file on your computer (e.g., web_search.js) and insert the API key from OpenAI into the designated spot (marked as ‘your-openai-api-key-here’ in the code generated by the coding assistant) (Fig. 4).

Prepare Qualtrics: In the Survey Flow section, create two embedded data fields called user_prompt and ai_response. These must appear before the question containing the chat tool. Leave the value of these fields empty.

Add to Survey: Create a Text/Graphic question, open its JavaScript editor following the platform’s standard procedure for adding custom JavaScript (see: <https://www.qualtrics.com/support/survey-platform/survey-module/question-options/add-javascript/>), and paste the entire code from the coding assistant, including the added API key.

Test the survey: When you reach the question where the JavaScript was added, you will see the Chat interface (Fig. 5).

Enhancing the tool. Once the basic tool is working its functionalities can be continuously expanded with simple additional instructions. In the coding assistant’s chat panel, describe the enhancement you want. The assistant will display the proposed changes directly in your existing code in the main editor window, with visual indicators showing additions (typically in green) and deletions (typically in red). Review these inline changes carefully before accepting to ensure core functionality remains intact.

For instance, to track which links participants click within AI responses: “*Modify the script to save the URL of any link the participant clicks on in an embedded data field named clicked_link.*” This enhancement adds tracking functionality—when participants click any link in the AI’s response, that URL is automatically captured and will appear in the downloaded data as a new column, enabling analysis of which sources or suggestions participants found most relevant. Similarly, researchers can modify the chat interface or the AI’s behavior by adjusting the system prompt—instructing it to be more descriptive, add emojis for emotional tone, adopt a specific brand voice, or limit responses to certain word counts—allowing systematic testing of how different AI communication styles influence user engagement and decision-making. Moreover, researchers can consider adding this rule to the coding assistant for developing search applications in general: “*For search applications, always parse and display the search results in a readable format with clear source attribution. Store both the query and the complete response, including metadata.*”

Data collection. The tool captures complete interaction data: what participants asked (user_prompt), the full AI response (ai_response), and any links clicked (clicked_link). This data appears in the standard Qualtrics data files and can be downloaded for analysis. Researchers can analyze search patterns, identify which information participants found most useful, and understand decision-making sequences through these recorded interactions (Fig. 6).

Experimental comparisons and benchmarking. To understand how AI-powered search transforms information seeking, researchers should compare this conversational approach against traditional search engines (Google/Bing with standard result listings). This comparison establishes whether AI synthesis fundamentally changes how users explore information versus self-directed searching.

The response presentation can be also systematically varied, comparing synthesized narratives versus structured bullet points, inline citations versus separate reference lists, concise answers versus comprehensive explorations, and varying levels of confidence indicators. Researchers could also test different AI personas (expert advisor versus neutral assistant), response timing (immediate versus delayed), and visual enhancements (highlighting, relevance scores, source credibility badges).

Key measures should capture search efficiency (time to decision, query count), information quality (accuracy, decision confidence), user experience (perceived helpfulness, trust), and behavioral outcomes (link clicks, final choices). Moreover, researchers could examine whether GenAI surfaces similar or distinctly different results compared to traditional search engines, revealing the technology’s potential to expand discovery beyond conventional information pathways. This design reveals not only whether AI search changes information seeking but also how specific presentation choices shape user trust, comprehension, and decision quality in this new search paradigm.

4.3.2. Using a backend

The presented application will work when following the descriptions above. However, if a researcher wants to manage the communication between the Qualtrics interface and the GenAI model through a backend to protect the API key, the following description shows how researchers can make this transition using AI coding assistance.

Converting to Backend Architecture. The backend server is essentially a separate computer or cloud service. To build this

```
Qualtrics.SurveyEngine.addOnload(function() {
  // Configuration - Replace with your actual OpenAI API key
  const OPENAI_API_KEY = 'your-openai-api-key-here';
  const API_URL = 'https://api.openai.com/v1/chat/completions';

  // Get the question container
```

Fig. 4. Adding an API key to the generated JavaScript code.

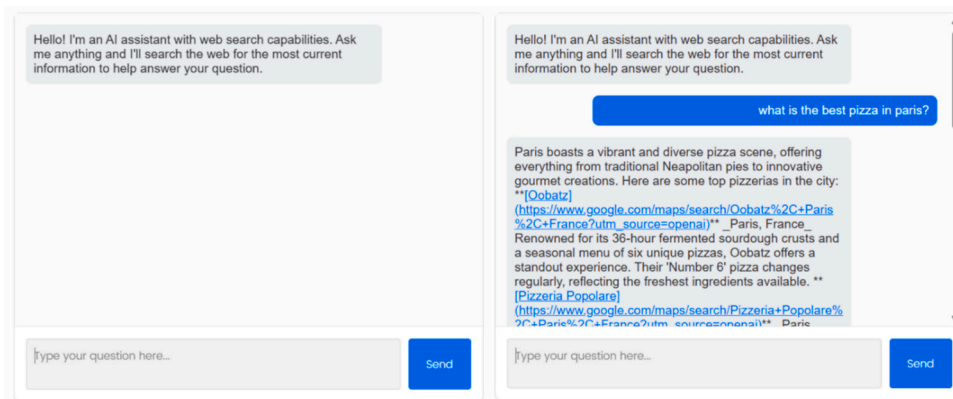


Fig. 5. The web search tool interface in Qualtrics showing user query and AI response.

user_prompt	ai_response	api_error	clicked_link
what is the best pizza in paris?	<p>Paris boasts a vibrant and diverse pizza scene, offering everything from traditional Neapolitan pies to innovative gourmet creations. Here are some top pizzerias in the city:</p> <p>[Oobatz] https://www.google.com/maps/search/Oobatz%2C+Paris%2C+France?utm_source=openai Paris, France Renowned for its 36-hour fermented sourdough crusts and a seasonal menu of six unique pizzas, Oobatz offers a standout experience. Their 'Number 6' pizza changes regularly, reflecting the freshest ingredients available.</p> <p>[Pizzeria Popolare] https://www.google.com/maps/search/Pizzeria+Popolare%2C+Paris%2C+France?utm_source=openai Paris, France Part of the Big Mamma Group, this lively spot serves authentic Neapolitan pizzas with soft, oversized crusts. The classic Margherita and truffle options are particularly popular.</p>		<p>https://www.google.com/maps/search/Pizzeria+Popolare%2C+Paris%2C+France?utm_source=openai</p>
			<p>https://www.google.com/maps/search/Pizzeria+Popolare%2C+Paris%2C+France?utm_source=openai</p>

Fig. 6. Data captured by the search tool in embedded data fields, showing user query, AI response, and clicked link.

intermediary system, researchers can use web frameworks, pre-built software tools that simplify server creation. Flask, which uses the Python programming language, is particularly suitable for research applications because it requires minimal technical setup. The server creates a specific receiving point (i.e., API endpoint, similar to a dedicated email address like /api/search) where survey input arrives from Qualtrics. For security reasons, web browsers normally prevent different websites from communicating directly with each other. Therefore, the server needs special permission settings (i.e., CORS—Cross-Origin Resource Sharing configuration) that explicitly allow Qualtrics and the backend to exchange information. Additionally, the server stores API keys in a protected area separate from the main code (i.e., environment variables). To create this backend system, researchers can use the following two prompts with a coding assistant:

First, to request the server code: “Convert the existing web search tool to use a backend architecture. Create a Python Flask server that: 1) Stores the OpenAI API key securely as an environment variable, 2) Receives search queries from Qualtrics through an /api/search endpoint, 3) Handles the web search requests to the OpenAI server-side, 4) Returns search responses to Qualtrics with proper CORS configuration for Qualtrics domains, 5) Includes error handling and query logging.”

Second, update the Qualtrics code: “Modify the Qualtrics JavaScript to communicate with our backend server instead of OpenAI directly. It should: 1) Send user queries to the backend, 2) Display appropriate loading messages, 3) Handle timeouts gracefully (30 s), 4) Save responses to the same embedded data fields (user_prompt and ai_response), 5) Show user-friendly messages if the server is unreachable.”

The coding assistant will generate both components, creating a secure architecture where participants never access the API key directly.

Step-by-Step Implementation. Researchers can host their backend server at beginner-friendly platforms such as [Render.com](#). The deployment process involves several straightforward steps. First, researchers create a free account on the hosting platform and select “New Web Service.” The Python code must then be stored in a GitHub repository (please see page 37 in the [web appendix](#) for a more detailed explanation on GitHub). This repository is subsequently connected to the hosting service, a process guided by the platform’s interface. The critical security configuration involves storing the API key as an environment variable (typically named OPENAI_API_KEY, when using an OpenAI model) within the hosting platform’s settings interface, rather than embedding it directly in the code where it would be visible. After deployment is initiated by a simple click in the hosting service, the platform generates a public

URL (e.g., <https://search-bot.onrender.com>). This URL serves as the secure connection point that researchers enter in Qualtrics to route survey requests through the backend to the AI service.

Once the server is running, the Qualtrics survey requires updating. The original JavaScript code is replaced with the backend-enabled version generated by the coding assistant. Within this new code, researchers must locate the server URL reference (typically appearing as <https://localhost:5000/api/search>) and replace it with the actual deployed server URL (e.g., <https://search-bot.onrender.com>).

Common deployment challenges. Several common issues may arise during backend implementation that the coding assistant can help resolve. One frequent problem occurs when the server blocks requests from Qualtrics due to security settings. Essentially, the server doesn't recognize Qualtrics as a trusted source. The coding assistant can fix this configuration issue when given a prompt such as "Update the Flask configuration to accept requests from Qualtrics domains." Researchers can ensure proper configuration by providing the coding assistant with the specific Qualtrics web address shown in their browser's address bar, allowing automatic setup for that particular survey platform.

Server overload represents a significant challenge when multiple participants access the study simultaneously. Free hosting tiers have limited processing power and can become overwhelmed, leading to slow responses or crashes. This is particularly problematic with resource-intensive services like image generation. The most practical solution for researchers is to control participant flow through the study platform. On Prolific or MTurk, researchers should release the study in smaller batches (for example, 20–30 participants at a time) rather than opening it to hundreds simultaneously. If the server still overloads, it is required to upgrade the service (please see pages 31–32 in the [web appendix](#) for a discussion on hosting services).

If the server indicates the API key cannot be found, this typically means the environment variable wasn't properly configured. The coding assistant can provide platform-specific instructions with "Show me how to properly set environment variables on [platform name] (e.g. [render.com](#))".

5. Research avenues for GenAI interactions in research studies

The implementation examples presented above and in the [web appendix](#) demonstrate the practical feasibility of integrating GenAI interactions into research studies. The same methodological approach using AI coding assistants can be applied to create virtually any GenAI-powered research instrument by describing it in natural language to coding assistants. Technical barriers that once limited such implementations have largely been removed, opening new possibilities for innovative study designs. The following section discusses some of these possibilities, starting with GenAI implementations for methodological purposes, followed by its integration to investigate AI itself.

First, AI-powered interviews emerge as an exceptionally versatile tool that addresses multiple methodological challenges simultaneously. These interviews can uncover underlying motivations and process variables for subsequent quantitative testing, potentially bridging the traditional divide between qualitative and quantitative research. Their scalability enables researchers to conduct large numbers of interviews that may complement human-led sessions. AI interviews might follow human interviews to build on initial insights, or run in parallel to uncover different patterns due to participants' varying responses to AI versus human interviewers. Indeed, initial research suggests hybrid human-AI approaches may be optimal, leveraging human interviewers for depth while using AI for scale and pattern detection across large samples ([Arora et al., 2025](#)).

However, critical questions remain about optimizing AI interview design and performance. For example, whether participants disclose more sensitive information to AI than human interviewers remains an open empirical question, with potential implications for studying stigmatized behaviors. Additionally, the interaction modality (speaking versus writing) may affect disclosure differently across topics, with spontaneous responses potentially benefiting from speech while complex reflections benefit from writing ([Gaerth et al., 2025](#)). These design parameters await empirical validation to establish best practices for different research contexts.

Moreover, GenAI interviews may provide an elegant solution to encounter demand effects and social desirability bias. Rather than administering scales that explicitly name constructs—thereby priming participants—researchers can conduct neutral conversational interviews about general topics and then analyze transcripts post-hoc for construct presence. For instance, instead of measuring materialism through direct scales, which may trigger socially desirable responding, an AI interviewer can discuss recent purchases, gift-giving, or lifestyle aspirations. The resulting transcripts may reveal materialistic values that can be potentially quantified without alerting participants to this focus. This approach shows whether constructs genuinely emerge in natural discourse or only appear when explicitly prompted. If such an approach is feasible and how it needs to be designed can be element of future research.

Beyond exploratory interviews, GenAI enables entirely new research paradigms that were previously impossible or prohibitively complex to implement. Considering the fundamental challenge of studying collaborative consumption or group decision-making, researchers have traditionally faced enormous logistical hurdles in synchronizing multiple participants for real-time online interactions. GenAI elegantly solves this by simulating collaborators with precise experimental control. For example, researchers can now investigate how people reach a conclusion in group decisions (like group travel planning, household purchasing decisions, or charity allocation of study bonuses). Each participant can engage with AI collaborators programmed with specific personalities, expertise levels, or influence tactics, enabling clean experimental manipulations that would be impossibly messy with human confederates.

Another compelling example of GenAI-enabled research paradigms is temporal manipulation. For example, an extensive psychology study with over 60,000 participants demonstrated that conversations with an AI-simulated future self significantly reduce anxiety ([Pataranutaporn et al., 2024](#)). This finding has profound implications for marketing, as temporal perspective fundamentally shapes decision-making in general ([Sagrignano et al., 2002](#); [Trope & Liberman, 2010](#)), and consumer behavior in particular ([Kyu Kim](#)

et al., 2012). When participants can engage with a vivid, personalized representation of their future selves—one that can discuss the consequences of today's choices, share regrets about missed opportunities, or express gratitude for past decisions—it creates a psychological bridge between present actions and future outcomes. This temporal manipulation paradigm could influence how marketers approach long-term behavior change, from promoting retirement savings and insurance adoption to encouraging sustainable consumption and health-conscious purchasing. The ability to make abstract future consequences feel immediate and personal through AI conversation represents a methodological innovation that was simply impossible before GenAI. While the temporal manipulation seems very powerful, researchers can explore countless alternative paradigms. Imagine participants conversing with versions of themselves raised in different cultures to study how cultural context shapes consumer identity, or chatting with alternate selves who made different career choices to understand professional identity's role in consumption patterns. The implementation of such experimental treatments is limited only by the researcher's creativity, as GenAI can convincingly simulate any counterfactual version of the self.

Turning to GenAI as a research object, the technology itself becomes the phenomenon under investigation. Consider, for example, how GenAI transforms information search. Evidence of 80 million clickstream records shows that ChatGPT directs users differently than traditional search (Kelly, 2025). This raises critical questions for marketers and content creators: How deeply do consumers engage with AI-synthesized search results compared to traditional lists of links? Do they click through to original sources or accept AI summaries at face value? In co-creation and collaboration contexts, AI becomes an active partner in generating content and ideas, prompting different questions: Do individual co-created outcomes get better, but does the collectivity of co-created outcomes fall victim to an average trap (Huang & Rust, 2025)? When sharing AI-co-created content (e.g., on platforms like etsy), do consumers disclose AI involvement? Meanwhile, in consumer-company interactions, as AI increasingly mediates or replaces human touchpoints, researchers must ask: When AI agents make purchasing decisions on behalf of consumers, how does this alter brand relationships and loyalty? How does service recovery differ when the service failure involves an AI rather than a human employee? These examples represent just a fraction of the contexts where GenAI influences marketing-relevant questions.

Finally, researchers can explore additional experimental variations. Response timing, for instance, carries psychological weight—instant responses might suggest pre-formed databases while delays imply thoughtful consideration. Transparency levels offer another avenue, with the recent introduction of “chain-of-thought” displays enabling studies of whether visible reasoning increases or decreases trust (Piper, 2025). Autonomy and agency levels become critical as AI moves from assistant to actor, with researchers able to vary decision-making authority from purely advisory to fully delegated across different product categories and purchase situations. Together, these manipulable dimensions represent multifold research avenues for understanding how GenAI characteristics shape consumer behavior and marketing outcomes.

6. Conclusion

This paper provides marketing researchers with a comprehensive guide for integrating GenAI interactions into research studies. It demonstrates that technical barriers to integrating GenAI interactions into marketing research have effectively disappeared. By understanding the core architectural components (frontend, backend, GenAI service via API) and leveraging the provided templates and resources, researchers without programming expertise can now oversee and implement sophisticated GenAI research tools—from scalable AI interviews to controlled experiments with AI collaborators. The paper equips researchers with the conceptual knowledge to guide implementations using AI coding assistants or to adapt the provided templates directly for their specific needs.

The rapid evolution of GenAI capabilities means that the specific models and implementations described here will inevitably be superseded. However, the underlying approach—recognizing the potential value of GenAI integrations, understanding the core architectural components, knowing how to articulate requirements clearly, and using AI to implement AI—provides a durable foundation for continued advancement. As GenAI increasingly mediates marketplace interactions, from product discovery to customer service to purchase decisions, marketing researchers need to develop the capabilities to study these new realities.

The practical walkthroughs and open-source resources (<https://github.com/QualtriGen>) provide immediate starting points, but more importantly, they illustrate a fundamental shift: researchers can now create experimental paradigms that were previously impossible, bridge qualitative depth with quantitative scale, and study AI-mediated consumer behavior as it actually occurs.

During the preparation of this work the author used Gemini 2.5, and Claude Opus 4.1 in order to copy edit content and generate [supporting materials](#). After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

CRedit authorship contribution statement

Moritz Joerling: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

I want to thank the anonymized researchers that have participated in the group discussions.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ijresmar.2025.12.003>.

Data availability

No data was used for the research described in the article.

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