Received: 17 May 2026 | Accepted: 26 June 2026

DOI: 10.1002/jcpy.70036

METHODS DIALOGUE

JCP Journal of Consumer Psychology · SCP Society for Consumer Psychology

Generative grounded theory (GGT): Inductive theory building in the age of generative AI

Bernd Schmitt[1] | **Shuyi Hao**[2] | **Michel Tuan Pham**[3] | **Reto Hofstetter**[4]

[1]Robert D. Calkins Professor of International Business, Columbia University, New York, New York, USA

[2]Assistant Professor of Marketing, ICN Business School Paris Campus, Puteaux, France

[3]Kravis Professor of Business in Marketing, Columbia University, New York, New York, USA

[4]Institute of Marketing and Consumer Insight, University of St. Gallen, St. Gallen, Switzerland

Correspondence
Bernd Schmitt, Robert D. Calkins Professor of International Business, Columbia University, 665 130th Street, New York, NY 10027, USA.
Email: bhs1@gsb.columbia.edu

Abstract

This paper introduces generative grounded theory (GGT), an AI-enhanced method for inductive theory building that adapts grounded theory—and qualitative research procedures more broadly—to contemporary digital and algorithmic research conditions. GGT integrates generative artificial intelligence (GenAI) into grounded-theory analysis while preserving human interpretive authority and theoretical responsibility. The method specifies a step-by-step process that supports systematic comparison and structured engagement with qualitative data. We demonstrate the method by outlining two new consumer-psychology studies and reanalyzing two established grounded-theory studies. We also address concerns surrounding GenAI use and outline future developments in the use of GenAI for qualitative analyses. GGT enables greater scale and efficiency in working with qualitative data, which are increasingly heterogeneous and multimodal, while supporting rigorous and precise theory construction and enhancing transparency and traceability. GGT can also be extended to other qualitative approaches that rely on similar analytic procedures.

KEYWORDS

CCT, GenAI, GGT, Grounded theory, qualitative methods

INTRODUCTION

Inductive theory building plays a foundational role in consumer psychology, particularly when psychological processes are complex or not yet well captured by existing theoretical frameworks (Lynch et al., 2025). As Fischer and Guzel (2023) note in a *Journal of Consumer Psychology* (*JCP*) Methods Dialogue article, qualitative research can play an important role in theory development. Among inductive approaches, grounded theory has been especially influential as a qualitative method for constructing theory from empirical data through systematic coding, constant comparison, axial coding, theoretical coding, abstraction, and theoretical sampling (Charmaz, 2006; Corbin & Strauss, 2014; Glaser & Strauss, 1967).

In consumer research, this method has been used to understand how consumers perceive, categorize, and evaluate consumption phenomena—such as experiences of fun and special experiences (Oh & Pham, 2022; Sun & Pham, 2026), minimalist consumption (Wilson & Bellezza, 2022), product design (Kumar & Noble, 2016), status-related signaling (Bellezza, 2023), leisure travel (Woodside et al., 2004), and perceived brand corporateness (Reich & Hanson, 2025). Grounded theory has also been used to develop foundational frameworks, such as brand relationship theory (Fournier, 1998), as well as inductive accounts of how consumers experience

Accepted by David B. Wooten, Editor; Associate Editor, Joel Huber

Commentaries on "Generative Grounded Theory (GGT): Inductive Theory Building in the Age of Generative AI" by Geoff Tomaino, David A. Schweidel, Pierre-Yann Dolbec, Eileen Fischer, Andrew N. Smith, Stefano Puntoni, Niels Schillewaert, Joel Huber, Martin Reimann. https://doi.org/10.1002/jcpy.70037

and make sense of innovations (Mick & Fournier, 1998). Meanwhile, consumer culture theory (CCT) scholars have argued that grounded theory is particularly suitable for developing CCT-relevant concepts and frameworks (Belk & Sobh, 2019; Fischer & Otnes, 2006), and it has been used for this purpose (Bardhi & Eckhardt, 2012; Jafari & Goulding, 2013; Pellandini-Simányi & Barnhart, 2024; for recent examples). Finally, grounded theory has supported theory development at organizational and market levels, including research on market orientation, contractual breaches, and platform-enabled market change (Atanasova et al., 2025; Gebhardt et al., 2006; Johnson & Sohi, 2016).

JCP has been a leader in advancing and refining research methods in consumer psychology, especially through its Methods Dialogues, which address both foundational and emerging methodological issues from construct-variable clarity and scale use to neural/physiological methods and AI (Calder et al., 2021; Clithero et al., 2024; Haws et al., 2023; Tomaino et al., 2025). This paper introduces generative grounded theory (GGT), an artificial intelligence (AI)-enhanced method for inductive theory building, which integrates generative AI (GenAI) into the core analytic procedures of grounded theory. GGT's contribution lies in performing analysis at a greater scale and efficiency, particularly when working with large, heterogeneous, and multimodal qualitative datasets. GGT also supports more rigorous and precise theory construction by allowing researchers to engage with alternative interpretations and shift across analytic perspectives. In addition, this new method enhances the transparency and traceability of the research process by making analytic steps more explicit and open to examination. Just as netnography emerged in response to the rise of the internet and online communities (Kozinets 2002), GGT responds to the challenges and opportunities of an AI-mediated research environment.

CONTEMPORARY QUALITATIVE RESEARCH CONDITIONS AND THE ROLE OF GENAI

Qualitative research is increasingly conducted under conditions that differ substantially from those under which grounded theory originally developed. Data in consumer research are becoming more heterogeneous and multimodal, spanning interviews and field notes as well as audio, images, videos, social media posts, and online reviews (Balducci & Marinova, 2018; Bazeley, 2022; Geiger & Ribes, 2011; Liu et al., 2016). These unstructured materials are widely used in experimental and quantitative research because they capture consumers' thoughts, feelings, and evaluations across consumption contexts. Although such data also offer great potential in qualitative research, they also amplify the analytic demands of inductive theory construction. For example, Aboelenien and Arsel (2025) study vegan consumers using a large, heterogeneous corpus combining 21 semi-structured in-depth interviews (45 min–2 h) and 18 ethnographic interviews (5–20 min) conducted at market events, along with 5 years of multi-source secondary data (newspaper articles, blogs, social media posts, podcasts, YouTube videos and comments, books, and documentaries). Their analysis proceeded iteratively between data and theory, including open coding, axial coding, and abstraction as part of intra-textual and inter-textual analyses. Such cases might strain traditional analytic practices, highlighting the need for methodological approaches that can support intensive analytic tasks while preserving core principles of inductive theory construction.

GenAI tools, built on large language models (LLMs), such as ChatGPT, Gemini, Claude, Grok, and DeepSeek, can easily process, summarize, compare, and integrate large amounts of information. Because these systems operate on language, they are well suited for qualitative materials. Examples include interviews, which are widely used in consumer research and are fundamentally linguistic (Arsel, 2017) as well as other narrative materials (e.g., blogs, forums, and online reviews). The use of GenAI tools can also extend to non-textual materials converted into textual form for analytic purposes. Prior work in consumer psychology shows that meaning, categorization, and evaluation are expressed through language and organized in associative and conceptual networks, which can be examined through systematic analyses of semantic structures, conceptual associations, or narrative patterns (Boghrati et al., 2023; Escalas, 2004; Hartmann et al., 2023). Accordingly, GenAI can facilitate qualitative research by processing large volumes of text and surfacing recurring themes, contrasts, and relational patterns that would be challenging to track exhaustively through manual analysis.

Recent research has begun to examine the potential of GenAI in consumer research. In experimental and quantitative research contexts, Tomaino et al. (2025), in a *JCP* Methods Dialogue paper, examine whether and to what extent ChatGPT can perform core stages of the experimental research process, including idea generation, empirical testing, analysis, and manuscript writing. They suggest that while GenAI is adept at certain research components, such as tasks involving synthesis, pattern recognition, and text generation, it remains inadequate at this stage for others and requires careful human oversight to ensure quality, coherence, and theoretical rigor. Similarly, Blanchard et al. (2025) show that GenAI can support multiple stages of the research process, from literature review and study design to data collection and analysis, but they emphasize that its effective use requires a clear understanding of model functioning, limitations, and the need for validation and responsible implementation.

Meanwhile, qualitative researchers have been more critical of GenAI usage, citing epistemological, methodological, and ethical concerns. For example, Jowsey et al. (2025), along with 416 qualitative researchers from 38 countries, explicitly reject GenAI for qualitative research, arguing that it cannot "make meaning," that qualitative analysis should remain distinctly human, and that GenAI use entails ethical harms (e.g., environmental and labor costs). Likewise, based on interviews with consumer culture researchers and qualitative research industry professionals, Epp and Humphreys (2025) conclude that GenAI can only serve a limited, supportive function, but should not be used for "deep theoretical analysis to generate novel insights." Carlsen and Ralund (2022) similarly note that automated discovery can weaken immersion, comparison, and theoretical sampling when analytic control shifts away from the researcher. More generally, the use of GenAI risks creating what Quattrociocchi et al. (2025) call "epistemia"—a situation in which linguistic plausibility replaces rigorous epistemic evaluation, producing a sense of vague knowing without genuine insight.

However, prior work has also shown that computational tools can support grounded-theory analysis when qualitative corpora become large or difficult to manage. Nelson's (2020) computational grounded theory uses computational techniques for inductive theory development, but it does so mainly through computer-led pattern discovery (e.g., topic modeling). Emerging evidence also suggests that GenAI can support key qualitative analysis tasks, such as descriptive coding, pattern identification, and conceptual synthesis, when used appropriately (Sinha et al., 2024; Wachinger et al., 2024; Yan et al., 2024; Yue et al., 2025).

What is missing is a systematic, step-by-step process that clarifies how GenAI can best be used in qualitative analysis. GGT provides such a methodological framework. It builds on prior work on computer-assisted data analysis while extending scale and efficiency, theoretical rigor and precision, as well as transparency and traceability. In particular, GGT supports systematic comparison across large, diverse, and multimodal qualitative corpora, thereby enabling more comprehensive pattern detection and comparative analysis. It also provides rigorous theory construction by facilitating the generation, evaluation, and refinement of alternative conceptualizations, relationships, and boundary conditions during inductive analysis. Finally, GGT enhances transparency and traceability by externalizing and explicitly documenting coding decisions, comparative steps, and refinements, making the process of theory construction more traceable and thus more accountable.

The remainder of the paper proceeds as follows. We first discuss the core concepts and analytic procedures of grounded theory. We then briefly describe its value and challenges and present the seven-step process of GGT, including methodological guardrails that govern its responsible use. To illustrate the application of GGT in consumer research, we apply it to two new consumer-psychology projects and reanalyze two published grounded-theory studies. Finally, we address key epistemological, methodological, and ethical concerns and outline future directions for the use of GenAI in qualitative analysis.

GROUNDED THEORY: CORE CONCEPTS AND ANALYTIC PROCEDURES

Grounded theory originated in the 1960s as an inductive method in response to research traditions centered on deductive hypothesis-testing, offering an alternative for generating theory from data rather than testing theory against it (Glaser & Strauss, 1967). As part of its methodological contribution, grounded theory has introduced a set of analytic concepts and terminologies used across qualitative research, which

TABLE 1 Variants of grounded theory.

Dimension	Classic (Glaserian)	Reformulated (Straussian)	Constructivist (Charmazian)
Analytic Logic	Inductive emergence through constant comparison across data	Systematic category development through coding, comparison, and specification of relationships	Iterative, interpretive comparison across data and emerging categories
Role of Prior Theory	Minimized; prior theory largely avoided to prevent "forcing"	Used as heuristic guidance in coding and category development	Used as a sensitizing/enabling lens; iteratively engaged and subject to revision
Researcher Role	Analyst maintaining analytic openness to data	Active analyst structuring and organizing categories	Reflexive interpreter engaging with and shaping categories
Coding Structure	Open and theoretical coding; flexible and non-prescriptive	Open, axial, and selective coding; structured and prescriptive	Iterative coding with evolving categories and ongoing refinement
Theoretical Outcome	Substantive theory emerging from data	Structured explanatory model with specified relationships	Interpretive theoretical account grounded in data within a broader theoretical lens

we also use in the AI-enhanced approach in this paper (see Appendix S1 for a glossary of key terms). Several variants of grounded theory have emerged, for example, classic, Glaserian grounded theory (Glaser & Strauss, 1967), the reformulated, Straussian variant (Corbin & Strauss, 2014), and the Charmazian constructivist approach (Charmaz, 2006). They all share a common comparative, inductive process, but they also differ, as shown in Table 1. The key differences concern analytic logic, the role of prior theory, the researcher's role, coding structure, and the nature of the theoretical outcome. In addition to these three major variants, numerous modified and hybrid approaches exist in practice, including the Gioia methodology and case-based theory building (Eisenhardt, 1989; Gioia et al., 2013), which incorporate elements such as structured data representation or more explicitly defined research questions while retaining an overall inductive and comparative orientation.

Despite these differences, several core analytic principles and processes can be identified (Hallberg, 2006; Thornberg & Charmaz, 2014), which form the basis for GGT. First, theory construction begins with close engagement with empirical materials rather than prior specification of constructs or hypotheses. Second, analysis proceeds through constant comparison: incidents, codes, and emerging categories are compared to refine conceptual distinctions and ensure internal coherence. Third, data collection is guided by theoretical sampling, such that new cases (e.g., individual samples) are selected to add insight, help refine categories, or explain, challenge, and qualify developing ideas, rather than to achieve representativeness or support statistical inference. Fourth, memo writing supports the shift from description to abstraction by documenting analytic decisions, unresolved questions, and evolving interpretations. Finally, analysis continues until theoretical saturation is reached, when additional data no longer yield novel conceptual properties or relationships.

Grounded theory thus typically follows a process that moves from coding the data to higher levels of conceptual abstraction. It begins with initial, open coding, where researchers engage closely with the data and explore multiple possible analytic directions. As recurring patterns and distinctions surface, focused coding prioritizes the most theoretically relevant coding, facilitating the development of categories and specifying the relationships among them. As analysis progresses, at higher levels of abstraction, theoretical concepts emerge and eventually reach saturation, when additional data and coding no longer yield new conceptual properties. Memo writing occurs throughout the process, supporting comparison, reflection, and theoretical integration at every stage of analysis.

From a philosophy-of-science perspective, grounded theory, in particular, the constructivist approach, aligns with recent methodological arguments in consumer psychology that emphasize inductive and abductive theory construction. Janiszewski and Van Osselaer (2022) and Lynch et al. (2025) argue that theory development requires an iterative cycle of generating, refining, and evaluating explanations before formal testing is possible. Although their focus is primarily on experimental research, Lynch et al.'s (2025) "phenomenon-to-construct" theory construction follows a similar logic to constructivist grounded theory. Constructivist formulations emphasize that grounded theory is not simply discovered in the data but is constructed through interaction between the researcher and empirical materials (Charmaz, 2006). Although fundamentally inductive, the constructivist approach also incorporates abductive reasoning, particularly when researchers encounter surprising or puzzling observations that demand explanation (Thornberg & Charmaz, 2014). Interpretive rigor is maintained by requiring that theoretical claims remain tied to the data and show integration across categories.

GROUNDED THEORY BUILDING: ITS VALUES AND CHALLENGES

Grounded theory plays an important role in consumer research, particularly in supporting inductive theory building. Janiszewski and Van Osselaer (2022) characterize consumer research as involving a division of labor in which qualitative research primarily contributes to theory construction, while quantitative research primarily contributes to theory testing. Although this distinction, in our opinion, simplifies the diversity of research practices in the field, it underscores the central role of inductive theory building in consumer research. As we will show, some influential constructs and theories have been developed through inductive analysis. At the same time, the rigor of inductive theory building depends critically on the researcher's ability to code the data, compare across cases, evaluate alternative interpretations, and iteratively refine categories—procedures that place substantial processing demands on researchers and require great cognitive flexibility.

Recent work in consumer research demonstrates both the value of grounded-theory procedures for inductive theory building and the level of analytic effort it requires. For example, Wilson and Bellezza (2022) employed inductive coding and constant comparison to identify three core dimensions of consumer minimalism—number of possessions, sparse aesthetic, and mindfully curated consumption—which subsequently informed scale development. The dimensions were developed from a heterogeneous qualitative corpus including books, films, television shows, blogs, press articles, exhibitions, store visits, Google image searches of minimalist spaces, and open-ended survey responses from both self-identified minimalists and lay consumers recruited. All these materials were jointly coded using open, selective, and theoretical coding. Similarly, Reich and Hanson (2025) used sequential qualitative analysis to conceptualize brand corporateness. Drawing on verbatim transcripts from video- and audio-recorded focus groups, they iteratively analyzed the data to identify core and peripheral dimensions that capture consumers' unfavorable evaluations of brands as organizational entities. To identify alternative forms of status signaling using grounded theory, Bellezza (2023) drew on a large, heterogeneous corpus (e.g., academic articles and books, conference materials, media articles, museum exhibitions, documentaries, and ethnographic visits to luxury stores). Through systematic coding, the corpus was distilled into 710 initial open codes, refined into 255 unique codes, clustered into 20 higher-order concepts, and integrated into six dimensions of alternative status signaling. These examples illustrate that the theoretical contributions of grounded theory rest on repeated comparison across a diverse range of data that allows for progressive abstraction from descriptive codes to higher-order theoretical constructs.

Grounded theory has also been used to specify the psychological structure of consumer experiences. Oh and Pham (2022) analyzed interviews and narrative accounts of such experiences using iterative coding and constant comparison to develop a "liberating-engagement" theory of fun, which characterizes fun as the joint experience of hedonic engagement and perceived freedom from constraints. Similarly, analyzing a large corpus of consumer narratives and in-depth interviews, Sun and Pham (2026) identified uniqueness, meaningfulness, and authenticity as the core psychological pillars of what makes consumption experiences feel special. In both articles, theory construction relied on comparison, progressive abstraction through memo writing, and integration of categories into a coherent explanatory model that can be examined in subsequent empirical testing.

Finally, grounded theory as a method has been explicitly advocated by some CCT researchers (Belk & Sobh, 2019; Fischer & Otnes, 2006). In line with this view, Bardhi and Eckhardt (2012) drew on a grounded-theory approach in their study of access-based consumption in car sharing, developing categories through iterative comparison across cases. Pellandini-Simányi and Barnhart (2024) similarly began their analysis with grounded-theory procedures in examining collective ignorance and spiraling risk in the Hungarian mortgage market, before extending the analysis to related thematic analyses. Likewise, Jafari and Goulding (2013) applied a grounded-theory approach in their study of globalization, reflexivity, and self-projects, using constant comparison, memo writing, and iterative coding to build their conceptualization.

While being valuable, grounded theory places heavy demands on researchers' limited information-processing capacities (Bettman, 1979). It requires holding multiple and sometimes competing interpretations in mind, revisiting earlier coding decisions, and continuously evaluating whether new observations refine, qualify, or overturn emerging categories. As the volume and heterogeneity of qualitative evidence increase, these demands strain researchers' attention and memory capacities (Shiffrin, 1976), reflecting fundamental constraints of human cognition (Marois & Ivanoff, 2005). A key constraint is therefore not the availability or quality of rich qualitative data, but the capacity to process, compare, and abstract from such data reliably under cognitively taxing conditions.

This constraint also introduces methodological risks concerning the reliability and validity of grounded theory building. One challenge is cognitive isolation: word-by-word coding across voluminous transcripts and repeated within-corpus comparison, often by a single researcher or small team, can cause self-reinforcing interpretations or confusion, leading researchers to become "lost within the minutia of data" (Allan, 2003). Concepts may remain underexposed to competing explanations, as traditional, Glaserian, grounded theory approaches discourage early literature reviews to avoid "contamination" (Lynch & Egan, 2013). Consequently, the methodology risks drifting toward internal consistency that is insufficiently stress-tested.

A second challenge follows from biased perspectives, including disciplinary bias, as grounded theory cannot fully remove the researcher's background from analysis (Lynch & Egan, 2013). For example, researchers trained in psychology may be more likely to code in terms of cognition, goals, or affect, whereas researchers in sociocultural analysis may more readily foreground identity work, symbolic boundaries, or consumption practices. Such biases are often not conscious and difficult to detect during manual analysis, especially because researchers themselves engage in documentation and memo writing. This does not render grounded theory arbitrary; rather, it highlights that the method is not perspective-neutral, and thus it is important to make the analysis process transparent and accountable to ensure that conceptual claims are supported by the evidence.

We next present GGT, a GenAI-enhanced approach for conducting grounded-theory and related qualitative analytic procedures. Core grounded-theory procedures, such as coding, constant comparison, abstraction, theoretical sampling, and saturation, guide analysis and ensure that interpretive decisions remain explicit and reviewable. In the spirit of constructivist approaches, GGT also allows extant theories to inform analysis.

GGT: METHODOLOGY AND PROCESS

GGT outlines how GenAI can be used across grounded-theory analytic steps through a structured, seven-step process. In practice, this involves using widely available GenAI systems (e.g., ChatGPT, Claude, DeepSeek) via a chatbot interface or an application programming interface (API) that provides automated access to the model, where researchers provide structured prompts for qualitative data analysis.

The seven steps of GGT

Figure 1 presents GGT as a seven-step framework. It follows the core logic of grounded theory while enabling analysis at a greater scale and supporting more efficient and systematic comparison beyond unaided manual analysis. The outputs of each step serve as the basis for the inputs for the next. Although organized into steps, GGT is iterative and recursive: researchers may move back and forth between structuring, coding, clustering, abstraction, and integration. In GGT, prompting is treated as part of the analytic method because prompt formulation determines what the system attends to and what becomes available for extraction, comparison, and theory development. The framework differentiates prompts by the analytic function corresponding to each step. Importantly, GGT is not a rigid procedure but a flexible set of analytic support system. Researchers may choose to use GenAI only for selected steps, depending on the research question and analytic needs. Likewise, researchers may opt for only using certain procedures within each step (i.e., certain prompt components) and even combining multiple steps into a single extended prompt in some cases.

The goal of Step 1, GenAI-mediated corpus formation, is to assemble the data corpus after defining the research question, phenomenon, and scope. While qualitative approaches differ in the extent to which research questions are determined in advance, GGT assumes that an initial research question or focal phenomenon is selected prior to corpus formation to guide data collection. Depending on the research focus, data sources may include interviews, field notes, observation records, and/or online sources such as blogs, reviews, pictures, or videos. Researchers may also provide GenAI with sampling constraints for online sources and governance criteria (e.g., documenting provenance). Using *corpus-curation prompts*, GenAI helps to identify candidate sources, assess data sources (e.g., their quality or relevance), and, where appropriate, retrieve or compile them (e.g., when materials are publicly available online). GenAI can also clean the data and document provenance. In this context, GenAI functions as a research assistant supporting the systematic identification, retrieval, and organization of relevant data sources. Researchers may also use GenAI to support data generation, for example, by assisting in the design of interview questions and

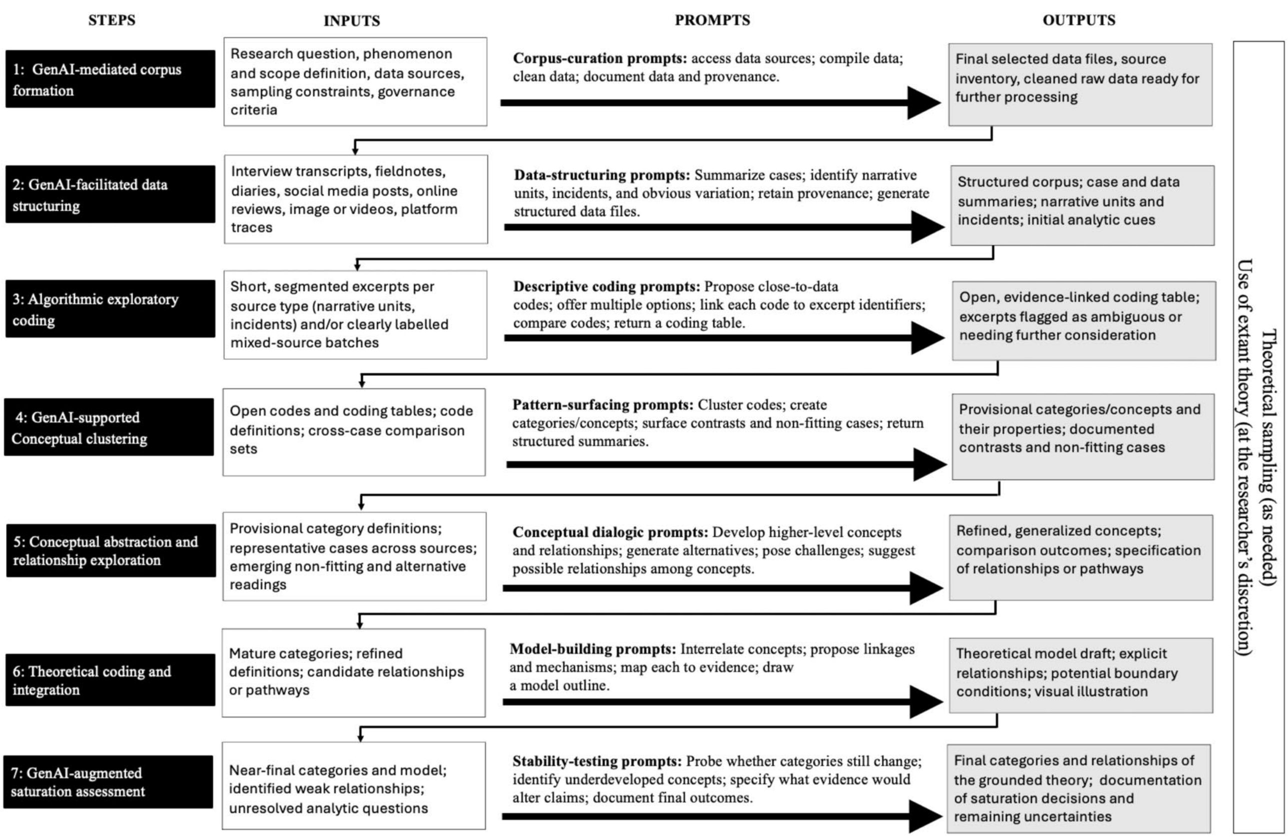

FIGURE 1 GGT process.

conducting structured or semi-structured interview interactions, or, where appropriate, by generating synthetic qualitative inputs such as "digital twins," that is, AI-generated consumer personae designed to simulate plausible perspectives or experiences (see Appendix S2 for a discussion of digital twins and their use in current consumer research). The outputs of Step 1 consist of the resulting "cleaned" data files and data inventories (e.g., descriptions of the information, data sources, and collection methods, and any transformations or filtering procedures applied). These outputs then serve as inputs for Step 2.

The goal of Step 2, GenAI-facilitated data structuring, is to prepare the corpus for coding in subsequent steps. Through *data-structuring prompts*, researchers review and organize data before coding. GenAI helps summarize cases individually, describe what is present, identify narrative units (e.g., analytically relevant incidents of text or images), note obvious variations in the data, and preserve provenance labels. This step results in a structured corpus with case and data summaries, narrative units and incidents based on the data sources, and suggestions of initial analytic cues.

Step 3, algorithmic exploratory coding, constitutes the initial analytic step of GGT's grounded theory development. It generates descriptive codes at the excerpt level through constant comparison across excerpts. Specifically, *descriptive coding prompts* instruct the system to generate close-to-data codes that reflect what is explicitly stated or shown, offer more than one plausible code when appropriate, and link each code to an excerpt identifier and supporting text. The outputs can take the form of an evidence-linked coding table as well as excerpts considered ambiguous or needing further consideration. Researchers may revise, merge, split, or remove codes, often by comparing codes across cases and incidents, with GenAI support. In traditional grounded theory, coding decisions and other analytic issues throughout the process are documented in memos; in GGT, they are captured in the GenAI interaction record, providing a consolidated and traceable audit trail.

Step 4, GenAI-supported conceptual clustering, organizes descriptive codes into provisional categories through comparison across coded excerpts. *Pattern-surfacing prompts* ask the system to cluster related codes, surface contrasts and points of divergence, and flag non-fitting cases. Based on the researcher's judgment and input, clustering may proceed iteratively and be revised as needed. The outputs include provisional categories and their descriptive properties (i.e., attributes, working definitions, and boundaries) as well as documented contrasts and non-fitting cases. At this step, the researcher may also choose to engage in theoretical sampling by collecting additional data to further examine emerging categories.

Step 5, conceptual abstraction and relationship exploration, further develops and refines the categories based on the outputs of Step 4. At this step, *conceptual dialogic prompts* generate higher-level abstract and consolidated categories, as well as refined comparisons across categories. Importantly, the GenAI may be prompted to suggest possible relationships among concepts or pathways. As noted earlier, grounded theory differs regarding the use of external theory (i.e., existing conceptual frameworks, constructs, or theoretical perspectives from the literature). At the researcher's discretion, prompts may be used to bring in phenomenon-related extant theory.

Step 6, theoretical coding and integration, consolidates the categories and their relationships in a theoretical model. *Model-building prompts* ask the system to suggest precise linkages and mechanisms and to map each linkage to supporting evidence. In this context, GenAI can act as a co-theorist by proposing, refining, and linking conceptual relationships within the emerging model, while the researcher reviews and evaluates the GenAI outputs. GenAI may also help generate a visual representation of the emerging model. Such conceptual model building, especially regarding theoretical linkages, may involve temporal, causal, part-whole, or contextual relationships, consistent with axial coding in Straussian grounded theory (Corbin & Strauss, 2014). The outputs may include a full draft of the theoretical model with explicit relationships and potential boundary conditions. The theoretical model and its concepts may be related to extant theory if theory-related prompts were used as part of the prior and present steps.

Step 7, GenAI-augmented saturation assessment, the final step, assesses theoretical completeness and stability. *Stability-testing prompts* are used to evaluate whether additional analysis—such as re-running coding and comparison with alternative prompts, introducing new or extreme cases through theoretical sampling, or systematically probing contrasts and boundary conditions—yields any new concepts, properties, or relationships. This step assesses whether the model continues to change because of these probes, whether any concepts remain underdeveloped or unstable, and what specific kinds of new evidence would be required to revise category definitions or proposed linkages. In this context, GenAI acts as an auditor by systematically probing the emerging model by testing whether alternative analyses or additional data would significantly alter its conceptual structure. Outputs encompass the final conceptual categories and relationships of the grounded-theory model, along with explicit documentation of the tests conducted to assess saturation and remaining uncertainties, such as caveats, boundary conditions, and limitations of the model.

Overall, GGT preserves the core analytic process of grounded theory while specifying how GenAI can provide analytic support. Step 1 corresponds to phenomenon framing and the establishment of an initial sampling frame that informs later theoretical sampling. Step 2 aligns with data preparation and early data engagement without substantive coding. Steps 3 and 4 correspond to initial/open coding and focused coding through systematic comparison, including attention to non-fitting cases. Step 5 captures further theory development regarding relationships among concepts. Step 6 corresponds to theoretical coding and integration, where relationships, mechanisms, and boundary conditions are specified. Step 7 aligns with theoretical saturation and closure decisions, making explicit the criteria used to assess stability and conclude the analysis.

Theoretical sampling and use of extant theory

Along the seven-step GGT process, researchers may use theoretical sampling and extant theory for abductive theory construction. Theoretical sampling involves collecting new data based on emerging concepts and theory. Rather than aiming for representativeness, predefined sample size, or specific demographic targets, theoretical sampling is driven by whether additional data is expected to contribute new conceptual insight, help refine categories, explore variation, or qualify developing ideas (Glaser & Strauss, 1967). As illustrated on the right side of Figure 1, GGT treats theoretical sampling as a data-collection process that can be employed at different stages of analysis as needed. As provisional categories emerge, stabilize, and are clustered, researchers can explore gaps, unresolved contrasts, or boundary conditions through targeted collection or retrieval of additional data. GenAI can support theoretical sampling by identifying and accessing relevant new data sources. In addition, it can be used to generate synthetic qualitative inputs (e.g., digital twins) as part of theoretical sampling, although such inputs should be treated as supplementary and interpreted carefully (see Appendix S2).

Furthermore, extant theory can also be incorporated within GGT. In classic grounded theory, prior theory is treated with caution because premature theoretical framing can constrain discovery and lead researchers to force data into existing conceptual categories. Nonetheless, researchers may use prior extant theory related to the phenomenon carefully in the later stages of the GGT process when provisional categories and relationships have already emerged through coding and clustering. During those steps, extant theory related to the phenomenon may be used as an abductive resource. It can help sharpen conceptual distinctions, clarify underlying mechanisms, evaluate alternative explanations, and specify boundary conditions, thus contributing to the refinement of the emerging theory. In addition, in line with the constructivist approach of grounded theory, at the researcher's discretion, a broader external theory that is not directly related to the phenomenon may be used as an enabling lens (Dolbec et al., 2021).

As with other procedures of the seven analytic steps of GGT, theoretical sampling and the use of extant theory are implemented through prompts. Table 2 shows examples of prompts that may be used at each step, as well as for theoretical sampling and the incorporation of extant theory.

Methodological guardrails

GGT also proposes methodological guardrails that specify GenAI involvement across the steps. These guardrails are implemented through prompt-design criteria that structure how GenAI contributes to specific analytic tasks. In addition, GGT is grounded in a core epistemological position: interpretive authority, theoretical judgment, and responsibility for the research process remain fully with the researcher. Decisions regarding the research question, theoretical relevance, analytic direction, and the evaluation of competing explanations are not delegated to GenAI. Rather, GenAI produces bounded, task-specific outputs that are evaluated and integrated by the researcher.

These guardrails respond directly to concerns raised in Blythe et al.'s (2025) commentaries on Tomaino et al.'s (2025) *JCP* Methods Dialogue paper, particularly regarding the opportunities, risks, and governance challenges associated with GenAI in consumer research. Whereas Blythe et al. (2025) highlight general broad field-level recommendations in appropriate GenAI use—such as asking, training, and checking systems; strategic prompting; and preserving researcher agency and ethical standards—GGT outlines operational criteria tailored to inductive theory building. Specifically, it defines three criteria for using GenAI throughout the analytical process: task-boundedness, explicit evidence anchoring, and a comparative orientation, ensuring rigor and relevance of the outputs.

First, *task-boundedness* requires prompts to be tightly aligned with clearly specified analytic tasks (e.g., "perform descriptive coding of these excerpts" or "identify contrasts across cases") because overly general prompts (e.g., "create a theory from these data") tend to yield generic summaries that are not usable for grounded theory construction (Shah, 2024). This constraint thus ensures that GenAI outputs can be mapped onto grounded-theory specific analytic contributions (e.g., coding, comparisons, abstractions, and integration).

Second, *evidence anchoring* requires that GenAI outputs be clearly tied to the empirical materials from which they are derived. This criterion enables verification and reduces the risk of model hallucination, leaving out relevant evidence, or simply conforming to the prompt's framing—a concern analogous to demand characteristics in experimental research (McCambridge et al., 2012). Because LLM outputs are sensitive to framing and initial inputs (e.g., anchoring effects), systematic reference to source material helps to ensure that interpretations are grounded in the data (Lou & Sun, 2026).

The implementation of evidence anchoring depends on the analytic task. For example, coding and clustering (Steps 3–4), it involves linking incidents, codes, and

TABLE 2 Examples of prompts.

Step & prompt type	Example prompts
1. Corpus curation prompts	"Based on [research question], suggest appropriate qualitative data sources I should collect" "Help me design interview questions to explore: [research question]" "Generate [number] synthetic interview responses reflecting diverse perspectives on: [research topic] using [procedure]" "Clean, organize, and convert the following raw data into a usable corpus" "Document the provenance of each data source (origin, type, collection method)" "Assess the quality and relevance of these sources for the research question"
2. Data-structuring prompts	"Summarize each of the following interview excerpts into key points" "Describe what is present in each case without interpretation" "Break [insert interview text] into meaningful segments or incidents for analysis" "Organize [segments or incidents] into a structured table with case identifiers" "Identify and summarize obvious variations across cases or excerpts in this dataset (e.g., differences in tone, content, or context)" "Transform the content [picture, video] into text. Provide a description of the context of [picture, video]"
3. Descriptive coding prompts	"Generate close-to-data codes for the following [data]" "Provide multiple possible codes for each excerpt" "Link each code to specific supporting text" "Compare codes across these cases and identify similarities" "Refine this list of codes by merging or splitting where appropriate" "Provide a list of all codes. Identify identical codes"
4. Pattern-surfacing prompts	"Group these codes into higher-level coding categories" "Identify patterns and contrasts across these coding categories" "Flag any codes that do not fit well into existing categories" "Propose labels and definitions for each category" "Suggest alternative ways to cluster these codes" "Highlight subtle differences between similar codes"
5. Conceptual dialogic prompts	"Propose [number of] higher-order concepts based on these categories" "Suggest relationships between these concepts" "Generate alternative theoretical interpretations of the conceptualization" "Indicate what evidence in the data supports or challenges each concept" "Describe possible processes or sequences reflected in this data"
6. Model-building prompts	"Integrate these concepts into a coherent theoretical model" "Propose underlying relations connecting the concepts in the model" "Map each proposed relationship to supporting evidence from the data" "Refine the model by clarifying concept definitions, boundaries, and linkages"
7. Stability-testing prompts	"Assess whether additional data would likely change this model" "Show the data that each part of the model is based on" "Identify limitations and weaknesses of the concepts in the proposed model(s)" "Suggest what types of data would challenge or refine this theory" "Re-evaluate this model using a [different/specific] interpretive lens" "Summarize remaining uncertainties of this theory"
Theoretical sampling prompts (as needed)	"Which additional [data, participants] should be sampled to test these concepts?" "Suggest extreme or deviant cases that would help stress-test this model" "What [contexts, conditions, groups] that are underrepresented could be sampled?" "What [data] from which [participant samples] would help differentiate between these competing interpretations?" "Propose follow-up interview questions and data that can be collected to deepen these emerging concepts"
Use of extant theory prompts (at the researcher's discretion)	"Use [broad theory] as an enabling lens during the analysis of the data related to [research question]" "Identify patterns or relationships using [broad theory] as an enabling lens, while ensuring that categories remain grounded in the data" "Identify relevant theories related to [research question] and summarize their key constructs and proposed relationships" "Evaluate whether the observed patterns are consistent with [theory]. Cite specific data segments that support or contradict [theory]" "Use [theory] to reinterpret the current conceptualization. Specify what changes and what remains unchanged" "Compare alternative theoretical frameworks ([theory A], [theory B]) and assess which provides a better account of the observed patterns"

categories to excerpt identifiers, that is, specific references to particular units of data (e.g., interview ID × paragraph number, post ID × timestamp) along with supporting data. In theoretical integration (Step 6), it requires mapping each proposed linkage to a defined group of excerpts that jointly illustrate a relationship, mechanism, or contrast across cases. In saturation assessment (Step 7), it focuses on specifying what new excerpt-level evidence would revise or challenge a category or relationship and applying explicit criteria for saturation. In theoretical sampling, anchoring includes documenting provenance and demonstrating relevance before the material is admitted to the corpus and subjected to coding and comparison. Similarly, when synthetic inputs (e.g., digital twins) are used, their construction procedures should be made transparent.

Finally, *comparative orientation* requires that prompts generate comparative options rather than a single output. It aligns with the principle of constant comparison in grounded theory analysis (Glaser & Strauss, 1967). For instance, in Step 2, this can involve identifying variations across data files. In Steps 3–4, it can take the form of generating candidate codes and identifying contrasts as well as non-fitting cases. During abstraction (Step 5), researchers can use prompts to identify rival interpretations and specify what evidence would support, revise, or disconfirm different alternatives. Finally, in Steps 6–7, the prompts can be designed to evaluate alternative models, specify boundary conditions, and identify conditions that may challenge the model.

In sum, task-boundedness keeps prompts focused on specific analytic operations. Evidence anchoring ensures that the outputs are tied to data. Comparative orientation requires the consideration of alternatives rather than converging prematurely on a single interpretation. Beyond these operational guardrails, researchers can also determine the level of autonomy granted to GenAI. In GGT, GenAI can be used in a more supportive or more autonomous manner, ranging from assisting with specific analytic operations (e.g., suggesting codes or retrieving data) to engaging in structured analytic interaction (e.g., proposing alternative interpretations) or even executing multiple analytic steps with limited intervention. The degree of autonomy may vary across steps based on analytical needs and the observed quality and reliability of GenAI outputs. In all cases, the researcher remains responsible for interpreting the outputs and making all analytic decisions.

ILLUSTRATING GGT IN PRACTICE

To demonstrate how GGT can be used in consumer research, we present three illustrations. First, we apply the seven-step GGT process to conduct a consumer-psychology research project. Second, we illustrate how the theoretical output of GGT changes based on extant theoretical lenses. Third, we revisit two published grounded-theory investigations—Oh and Pham's (2022) liberating engagement theory of consumer fun and Sun and Pham's (2026) theory of special consumption experiences—to show how GGT can replicate their inductive analyses. For all analyses, we used ChatGPT (OpenAI; model: GPT-5.2).

Illustrating the seven-step GGT process

The first illustration uses the seven-step GGT process to conduct a new qualitative consumer-psychology research project on body adornment. Hao and Schmitt (2026) present a general conceptual framework that defines various body transformations ranging from exercise and fitness procedures to cosmetic interventions and cosmetic surgery. The goal of the research presented here is to develop a grounded theory on one aspect of body transformation—creative decoration or styling of the body, including tattoos, piercings, or radical hairstyles. The illustration shows how GGT supports inductive theory building by integrating GenAI while maintaining researcher supervision. A detailed description of the illustration is provided in Appendix S3.

Step 1: GenAI-mediated corpus formation

The analysis began with the construction of an initial qualitative corpus consisting of two data sources. First, we generated 15 digital-twin interviews with responses to open-ended questions about current body adornment, motivations for body adornment, and the relationship between body adornment and identity. Second, we gathered a corpus of 180 forum discussions (e.g., Reddit and Trustpilot posts) related to individuals' body adornment experiences, such as tattoos, piercings, and radical hair coloring. GenAI was prompted to assess data relevance to the focal phenomenon (body adornment) and document data provenance (elicited vs. naturally occurring). The key researcher decision was to combine digital-twin interviews and forum discussions, treating digital twins as a supplementary source rather than as a substitute for human-provided data.

Step 2: GenAI-facilitated data structuring

In the second step, GenAI was used to support data structuring. Prompts instructed the model to summarize each digital-twin interview, structure forum discussions into narrative incidents and units (e.g., the accounts of getting a piercing to provoke others or getting a full arm tattoo to appear more fashionable), and identify obvious points of variation (e.g., permanence vs. reversibility, visibility vs. concealment). The outputs included case-level summaries for all digital twins and incident-level summaries of forum discussions. The researcher made two critical decisions: retaining narrative units close to participants' language and avoiding any early abstraction or theoretical labeling, so that subsequent coding remained grounded in the data.

Step 3: Algorithmic exploratory coding

Next, GenAI was instructed to conduct close-to-data exploratory coding. Prompts asked the model to generate descriptive codes tied directly to excerpts and, when necessary, to propose multiple plausible codes for the same incident. This resulted in a large set of open codes (e.g., *reclaiming something, expressing inner self, feeling resolved, restoring familiarity, adjusting to new appearance, feeling more "me," feeling proud afterward, choosing placement for visibility, maintaining controlled appearance*). More examples are given in Appendix S3. The researcher accepted redundancy at this stage and refrained from integrating codes prematurely, removing only those that were clearly non-descriptive or irrelevant to the phenomenon (<12 % across the two datasets).

Step 4: GenAI-supported conceptual clustering

The open codes derived from the previous step were then subjected to conceptual clustering. GenAI was prompted to cluster related codes, surface contrasts and non-fitting cases, and suggest higher-order candidate categories. This process yielded three broad categories: (1) motivations and identity, (2) feelings, emotions, and concerns, and (3) practices and bodily choices. A key researcher decision at this stage was to treat these categories as provisional, serving as the basis for further abstraction and relationships or typologies explorations.

Step 5: Conceptual abstraction and relationship exploration

In this step, GenAI was asked to refine and propose higher-order concepts as well as conceptual models and to specify what codes confirm and disconfirm each candidate model. This led to the abstraction of a process model linking motivations, practices, and outcomes. Specifically, self-body identity misalignment motivates bodily intervention, which in turn shapes embodied affect and ultimately leads to restored alignment. At this stage, the researcher made two decisive analytic choices: (1) deciding on a process model that integrates elements of two candidate pathways over a typological classification of body-adornment motives, and (2) engaging in theoretical sampling to assess whether new data would support or disconfirm the model. We generated nine additional digital-twins interviews based on a screener that only focused on those who had altered or managed their bodies due to perceived misalignment between their body and sense of self. Digital twin participants were then given a set of prompts designed to elicit accounts of experiences of misalignment, responses related to body adornment, and subsequent self-perception.

Step 6: Theoretical coding and integration

The emerging process model was subjected to theoretical integration here. The extant body-transformation theoretical framework by Hao and Schmitt (2026) was introduced abductively to assess the emerging account's conceptual compatibility. Rather than replacing the grounded model, this extant framework enriched the process model identified in the earlier step by goals (e.g., decoration, restoration, or rebodying) and choice structure (e.g., levels of permanence, expansiveness, and invasiveness) of the interventions as potential elements shaping how the core process unfolds. The researcher deliberately retained parsimony by treating these elements as refinements of the bodily-intervention stage rather than as additional constructs. Importantly, the goals and choice structure were verified to be supported by the data.

Step 7: GenAI-augmented saturation assessment

Finally, GenAI was used in a bounded role to assist with saturation assessment. Prompts asked the model to evaluate whether additional data would alter the core process or introduce new mechanisms, and to specify what kinds of evidence would require revising the model. These checks indicated stability of the identity-repair process across data sources and two rounds of sampling. Thus, we conclude that saturation was reached, with remaining variation treated as boundary conditions rather than gaps in the analysis.

Final grounded theory: Body adornment as identity alignment

The final grounded theory conceptualizes body adornment as a self-regulation process of identity repair. This illustration, therefore, provides an in-depth theoretical account of one aspect of body transformation, namely body adornment. When experiencing misalignment between their sense of self and their bodily appearance, consumers, as agents in control, engage in bodily interventions and make specific adornment choices. These interventions generate embodied affect (e.g., more positive feelings about one's appearance), which functions as the central mechanism through which self–body alignment is restored. The outcome is a recalibration of how the self is experienced in and through the body, which then serves as a new reference point for future body adornment decisions. This psychological process is robust across different forms of body adornment and indicates that adornment is not reducible to mood regulation or impression management.

Illustrating alternative theoretical lenses in GGT

The second illustration aims to show how the theoretical output of GGT for the same research question varies when different theoretical lenses are applied, depending on the researcher's own background. To do so, we conducted a qualitative study focused on consumers' engagement in technology-mediated forms of companionship and intimacy (e.g., AI chatbots, game-based romantic characters). As in the prior illustration, the purpose of this illustration was not to advance a definitive substantive theory but to demonstrate the role of theoretical lenses in GGT analysis.

We first generated a corpus of open-ended interview digital twins. Digital twins were prompted to respond as individuals who had engaged in such forms of synthetic companionship, using everyday language and reflecting on their motivations and experiences. The resulting corpus was treated as primary qualitative data for subsequent grounded-theory analysis following the GGT framework. We then ran five parallel analyses on the same dataset, each analysis providing GenAI with a different theoretical lens (or none) and asking it to construct a grounded theory with three concepts. The five lens settings were: (1) a no-theory benchmark without any guiding theoretical lens, (2) emotion theories in consumer psychology, (3) goal-based consumer psychology, (4) identity work in consumer culture research, and (5) practice theory in consumer culture research. Across all analyses, GenAI was instructed to perform the same analytic tasks (descriptive coding, clustering, abstraction, integration, and saturation probing) and received the same data; given the lens settings, we expect GenAI to engage in "enabled theorizing" (Dolbec et al., 2021).

As Appendix S4 shows, all five GenAI outputs converge on a similar underlying pattern: synthetic intimacy offers relationship-like benefits while containing the interpersonal costs of human relating. The benchmark non-theory condition, Relational Cost Regulation, is closest to this core account with its three constructs: low social threat, asymmetric reciprocity (responsiveness without indebtedness), and cognitive–emotional structure (including clear signals and a sense of emotional progression). Based on conceptual dialogue prompting, the results also suggest a common process where reduced social threat allows interactions to unfold with limited reciprocal obligation, which leads to predictable patterns of exchange. These constructs, and the mechanism linking them, provide theoretical insights beyond existing papers about or related to digital companions that focus on digital self-extension, perceived similarity, and loneliness (Belk, 2013; De Freitas et al., 2026; Gelbrich et al., 2023).

The four alternative lenses offer different perspectives but do not substantially alter the core pattern. The emotional theories lens, Affective Appraisal and Emotion Regulation, specifies the underlying affective mechanism (benign appraisal and instrumental down-regulation of distress), while the goal-based lens, Goal-Compatible Affiliation, reframes the same cost containment as enabling affiliation that fits competing goals and preserves self-regulation. In the CCT context, the identity lens, Identity Work, interprets the low-surveillance context as a safe space for narrative reconstruction and symbolic recognition, whereas the practice theory lens, Relational Practice, shifts attention to the routinized, materially enabled practices—availability, reduced competence demands, and repeated cycles of emotional relief—that stabilize synthetic intimacy in everyday life.

In sum, although the five analyses differ in their theoretical emphasis framing, they produce distinct yet related perspectives on the focal phenomenon. Consistent with the constructivist view (Charmaz, 2006), this result illustrates how GGT may generate multiple, data-anchored grounded theories from the same qualitative material. Depending on one's epistemological view, this may be viewed as a strength or a limitation. We suggest maintaining metatheoretical self-awareness and, pragmatically, advise conducting subsequent experimental testing to further investigate the resulting grounded theories and their concepts and relationships.

Reanalyzing established grounded-theory studies

Using GGT, we reanalyzed two published grounded-theory studies: Oh and Pham's (2022) liberating engagement theory of consumer fun and Sun and Pham's (2026) theory of special consumption experiences. We used the OpenAI API to execute GGT analyses across multiple conditions and repeated runs. Appendix S5 shows the methodological details.

The prompt structure we used is aligned with GGT's analytic process and methodological guardrails. Appendix S5 (Prompt Structure 1a) shows the prompt structure for the Oh and Pham (2022) re-analysis. GenAI was explicitly instructed to conduct multiple grounded-theory operations (e.g., descriptive coding, contrast identification, abstraction, model linkage, saturation probing) in a single analytic execution. However, the researchers specified the research question and the output format, matching the structure of Oh and Pham's (2022) fun theory to enable better comparison between the GGT output and the original theory. As input data, we used either the original narratives analyzed in the study or digital twins. The digital twins (N=100) included synthetic personae with demographics representative of the U.S. population. To generate open-ended responses, digital twins received instructions closely mirroring those used in the original studies. As a benchmark condition, we also instructed GenAI to create a theory of fun without using the GGT process (see Appendix S5, Prompt Structure 1b). The same process was also adopted for the re-analysis of Sun and Pham's (2026), with only the output format adjusted to reflect the original theory (three higher-order psychological pillars and four to seven sub-concepts for each pillar).

Each condition (GGT with original data, GGT with synthetic personae data, no GGT) was run ten times. For each run, we computed the cosine similarity (i.e., a vector-based measure of similarity between textual representations) ranging between 0 (no/low similarity) and 1 (perfect/high similarity) between the theory output generated by GenAI and the theory reported in the focal article (see Appendix S5, Write-up 1 and Write-up 2 for the respective original theories). In addition, the Appendix S5 also documents the final theory outputs produced by GenAI. Overall, GenAI appears to replicate the focal theories, although component labels sometimes differed, and performance appeared to be stronger in the GGT conditions than in the no-GGT conditions.

Figure 2 reports the cosine-similarity results across conditions. In the benchmark condition, GenAI—even without the grounded-theory prompt structure—still generated theories that overlapped with the published theoretical accounts. The similarity coefficient was 62.5% for the Oh and Pham (2022) theory of fun, and 59% for the Sun and Pham (2026) theory of special experiences. This suggests that GenAI can, on its own, with simple prompts, produce meaningful theories about these two consumption phenomena, even without following grounded theory procedures. One possible explanation for the moderate performance of the non-GGT benchmark condition could be that the original theories of Oh and Pham (2022) and Sun and Pham (2026) align with the large-scale data on which GenAI models are trained. Thus, unstructured GenAI may be less effective in reproducing more novel or counterintuitive grounded theories. More importantly, however, structuring the analysis using GGT increased similarity. In the Oh and Pham (2022) reanalysis, similarity increased to 81.9% when GGT was applied to the original narratives and to 83.1% when GGT used synthetic personae. In the Sun and Pham (2026) reanalysis, similarity rose to 85.4% with the original data and to 78.4% with digital twins.

A closer check of the GenAI process generated in the GGT conditions indicates that GenAI performed the core analytic processes specified by GGT methodology. The process outputs showed a track of open coding, with low-level conceptual labels attached to the data; constant comparison, as categories were contrasted and refined, and became more abstract; and saturation checking, reflected in explicit assessments that additional data or comparisons no longer yielded substantively new conceptual insights.

Notably, the two re-analyses in this illustration provide a conservative test of how GGT processes can yield coherent theoretical structure, even in the absence of human input. Unlike the human-GenAI collaboration outlined earlier in the paper and shown in the first two illustrations, GenAI here executed the full grounded-theory procedure as an independent analytic agent without stepwise expert human intervention. We expect that more active researcher involvement might further increase similarities between the GGT theories and the original theories. However, such expert intervention was not appropriate in the present context, as any researcher would bring prior knowledge of the domain and existing studies, which could unintentionally steer the analysis toward theory-conforming outcomes.

What these illustrations show

These illustrations have three implications. First, GGT can support grounded-theory analysis from beginning to end while retaining interpretive authority and theoretical responsibility with the researcher. Second, GGT outcomes are not theory-neutral: different theoretical lenses can analyze the same data and generate distinct yet related grounded theories. Third, GGT re-analyses yield theory outputs that more closely match established grounded theories than unstructured prompting, underscoring that GGT can serve not only to build new theory but also to reconstruct and, potentially, audit existing qualitative work.

CONCERNS, CRITIQUES, AND RESPONSES

The use of GenAI in qualitative research has prompted a wide range of concerns and critiques across epistemological, methodological, and ethical domains. In this section, we first review the main sources of resistance to GenAI in qualitative research and place them in the context of broader debates in the philosophy of science. We then outline a governance-based response, reframing GenAI not as a substitute for qualitative reasoning but as a bounded analytic aid within established inductive procedures. Finally, we evaluate GGT against prevailing standards in consumer research, showing that GGT can enhance rigor, theoretical development, and transparency.

Epistemological, methodological, and ethical concerns of GenAI

The first set of concerns is epistemological. Critics argue that GenAI lacks human embodiment, lived experience, and reflexive intentionality—capacities that are often assumed to be essential for qualitative inquiry conceived as a mode of *Verstehen*. For example, Thompson et al. (2023) highlights that many consumer phenomena are constituted through meaning, experience, and interpretation, and thus require close engagement between researcher, participant, and phenomenon. In line with this view, based on interviews with CCT and qualitative experts, Epp and Humphreys (2025) argue that GenAI lacks embodied experience, contextual immersion, epistemic grounding, and historical situatedness. Quattrociocchi et al. (2025) discuss a set of "epistemic fault lines" between human and model judgment: differences in grounding (world-involving perception and social contact vs. text-only inputs), parsing (interpretive sense-making vs. token-level segmentation), experience (episodic and intuitive models vs. learned association), motivation (goal- and stake-sensitive inquiry vs. optimization without intrinsic aims), causal reasoning (intervention-oriented explanation vs. correlational regularities), metacognition (monitoring uncertainty and withholding judgment vs. compelled completion), and value (normative commitment and accountability vs. output without intrinsic responsibility).

The second set of concerns is methodological. GenAI systems risk producing hallucinated content and smoothing over ambiguity, sometimes generating seemingly coherent but unsupported outputs (Lund et al., 2023; Methnani et al., 2023; Omar et al., 2025). They may also reproduce biases and stereotypes present in training data, overrepresent dominant perspectives, or omit contextually important details (Akter et al., 2021; Arora et al., 2023; Nguyen & Welch, 2026). These tendencies create verification burdens: researchers must assess both incorrect outputs (false positives) and missing or omitted evidence (false negatives) (Curry et al., 2024; Friedman et al., 2025). Additional concerns include limited transparency in output generation and reductionist accounts instead of in-depth engagement with primary data.

The third set of concerns is ethical. These include issues of data privacy, consent, authorship, and accountability, especially when sensitive qualitative materials are processed using commercial GenAI systems (Andreotta et al., 2022; Moulaei et al., 2025). Broader critiques also point to environmental costs and the political economy of AI infrastructures as reasons for caution (Wu et al., 2022), including the "exploitative, colonialist and extractivist practices in which big AI corporations engage" (Jowsey et al., 2025). Moreover, scholars have emphasized that LLMs can introduce and amplify biases (e.g., cultural and gender biases) stemming from systemic imbalances in their training data (Dahal, 2024; Mehta et al., 2025).

These concerns have been expressed forcefully by behavioral researchers, particularly those operating within interpretive traditions. As noted earlier, 416 experienced qualitative researchers from 38 countries recently signed a manifesto-like open letter rejecting GenAI for reflexive thematic analysis and other qualitative approaches, citing the aforementioned epistemological, methodological, and ethical concerns (Jowsey et al., 2025). In a detailed rebuttal, Friese (2025) argues that the manifesto's categorical rejection of GenAI rests on a series of conceptual and methodological misunderstandings. The author situates GenAI use within established views of distributed cognition, arguing that reflexive qualitative analysis has long relied on external cognitive support (e.g., memos, visual artifacts,

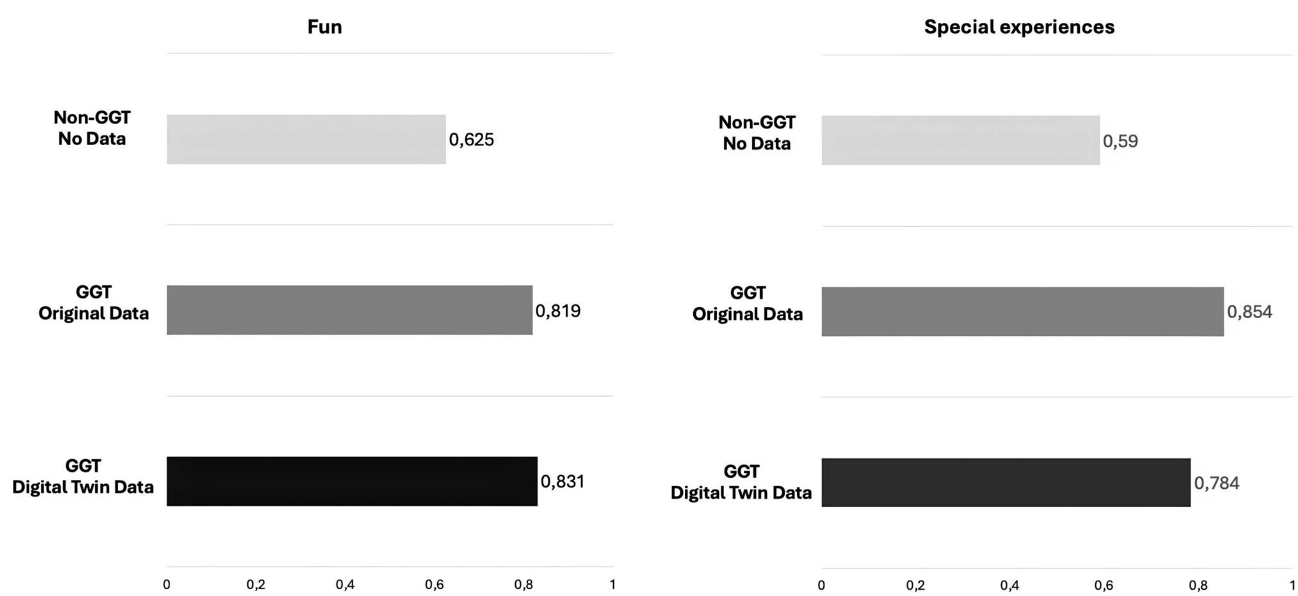

FIGURE 2 Similarities between GenAI-Generated Theories and Theories in Original Studies. Synthetic personae data were collected using https://www.insightable.ch/ (N=100 each). For the data from the paper, the first 100 narratives/data points were used. Prompts were executed 10 times per approach using gpt-5.2 via the OpenAI API.

theoretical lenses) and that AI-generated outputs can function similarly when used critically. The response further notes that risks of bias are greatest when outputs are detached from data but can be mitigated when analysis remains explicitly anchored in empirical material (e.g., through retrieval-augmented analysis). Finally, Friese (2025) challenges the moral claim that abstinence is the only responsible response to the environmental and labor costs of AI. The author argues instead for proportionality, responsible use, and collective regulation, cautioning that categorical rejection risks methodological conservatism that limits engagement with emerging analytic tools.

At a broader level, a common thread across these debates is that GenAI is often evaluated through an inherited philosophical lens that sharply separates "scientific explanation" (*Erklären*) from "interpretive understanding" (*Verstehen*). This opposition was influential in earlier philosophy-of-science debates; for example, it shaped debates and mobilized opposition against positivist verificationism and reductionism (Ayer, 1959), or falsificationism (Popper, 1959), and later culminated in the Chinese Room thought experiment (Searle, 1980). However, the arguments from these debates are less central in contemporary philosophy of science, which increasingly relies on cognitive science and neuroscience and treats explanation and understanding as more continuous and mutually informative than categorically opposed (Clithero et al., 2024; Pinker, 1997). Accordingly, recent work has shifted from strict dualisms that separate explanation from understanding and instead emphasizes continuity and complementarity. For example, Dennett (2017) advances an evolutionary account of mind in which cognition and consciousness emerge from biological and cultural evolution and generate meaningful, adaptive behavior without possessing intrinsic understanding in a phenomenological or hermeneutic sense. Thus, the sharp opposition between scientific explanations and human understanding appears historically contingent rather than philosophically grounded. When applied uncritically, such dichotomies risk becoming ideological by serving a protectionist function that preserves inherited methodological boundaries rather than enabling open, integrative inquiry for knowledge generation.

The critiques of GenAI in qualitative research often conflate two separate questions: whether GenAI "thinks" like humans and therefore can replace human qualitative researchers, and whether GenAI can participate in qualitative analysis. Much of the epistemological resistance to GenAI implicitly assumes the former, whereas GGT is built on the latter premise. Qualitative analysis does not require that every analytic operation involve lived experience, embodiment, or reflexive intentionality. Grounded theory has long relied on structured analytic procedures (e.g., coding, constant comparison, theoretical sampling, abstraction, memo writing, and saturation) that guide how interpretations are generated and assessed, even though the procedures themselves do not "understand" meaning. When GenAI is incorporated within these procedures, its outputs can expand the range of analytic alternatives while preserving the standards of qualitative inquiry.

In addition, many of the methodological risks associated with GenAI, such as hallucination, bias amplification, premature coherence, and selective omission, are not unique to AI. Since the classic work by Tversky et al. (1982), decision research has documented numerous human biases. Baron (2008) alone documented 53 biases. More recent synthesis work shows that these biases also shape professional decision-making across management, finance, medicine, and law (Berthet, 2022). Qualitative researchers are therefore also susceptible to such biases, such as the anchoring-and-adjustment effect and the confirmation bias (Jain et al., 2021; Nickerson, 1998). Because analytic decisions are often implicit, such bias may not easily be detectable. Under explicit governance, GenAI can externalize analytic steps and preserve decision traces, making interpretations more contestable rather than less.

Ethical concerns similarly call for governance, for example, the development of evolving "living guidelines" (Davison et al., 2024), rather than exclusion of GenAI (Schlagwein & Willcocks, 2023). Issues of privacy, consent, and accountability hinge on how GenAI is used, disclosed, and constrained within the research process, not on its categorical prohibition. As with other analytic tools, ethical responsibility for interpretation and representation of GGT remains with the researcher. In sum, the central question is not whether GenAI should be fully accepted or rejected, but whether its use meets the field's shared standards and criteria of evaluation.

Standards for evaluating GenAI-enhanced methods in consumer research

In a recent editorial, the editorial team of the *Journal of Consumer Research* (JCR) reaffirmed that the field's shared goal is "to improve our scientific understanding of consumer behavior" (Urminsky et al., 2025). Similarly, *JCP* emphasizes its commitment to "scientific standards and expectations." *JCP* states on its website:

> JCP is committed to publishing research with the highest standards in scholarship and scientific practices. In particular, the Journal is committed to (a) a high degree of transparency in how the research was actually conducted, (b) a high degree of reproducibility of the reported findings, and (c) a strict respect of the ethical research standards set forth by the American Psychological Association.

These statements highlight a longstanding challenge, and at the same time a core principle, for consumer research: how research should be evaluated, especially in a field characterized by methodological pluralism, including qualitative research alongside experimental and quantitative works—an issue further complicated by the emergence of GenAI. Pham (2023) and Pham and Oh (2021) argue that consumer research should be evaluated by how well it advances a set of epistemic criteria. These include veridicality (faithful engagement with empirical reality), transparency (clarity about analytic procedures and decisions), precision (conceptual clarity and abstraction), generalizability (the capacity for insights to extend beyond a single context), relevance (connection to meaningful consumer phenomena), and insight (the generation of non-obvious understanding). Similar to Janiszewski and Van Osselaer (2022) and Lynch et al. (2025), Pham (2013) cautions against overly narrow epistemologies, privileging deductive, hypothesis-testing approaches at the expense of inductive and phenomenon-driven theorizing.

Complementing the above criteria, Fischer and Guzel (2023) outline criteria specifically for qualitative research that emphasize conversational clarity (clearly specifying the theoretical conversation addressed), procedural transparency (making data collection and analysis visible to ensure trustworthiness and reasonable conclusions), contextual grounding (linking claims closely to rich empirical evidence), conceptual caliber (offering insightful, coherent, and plausible theoretical contributions), and conceptual transferability (extending insights beyond the focal context to relevant settings). While recognizing the distinctive features of qualitative inquiry, these criteria align with broader epistemic standards, particularly by emphasizing procedural transparency and the systematic linking of interpretive claims to empirical evidence.

GGT aligns closely with these core evaluative standards in consumer research. It structures qualitative analysis through explicit, step-by-step procedures that make analytic decisions visible and open to scrutiny, while ensuring clear linkage between coding, categories, and the underlying data. By doing so, GGT allows for procedural transparency and strong empirical anchoring, while also supporting conceptual development, comparison, and the articulation of boundary conditions. GGT also enables analysis with larger and more diverse corpora and facilitates systematic consideration of alternative interpretations, including those informed by different theoretical lenses. Finally, GGT provides a shared vocabulary and prompting structure and makes analytic delegation explicit and traceable. In sum, GGT aligns with established standards for evaluating consumer research and strengthens rigor, transparency, and traceability in qualitative theory construction.

FUTURE DIRECTIONS FOR GENAI IN QUALITATIVE ANALYSIS

From a technical perspective, the current implementation of GGT relies on prompting a general-purpose base model through a conversational interface. Base model here refers to a LLM trained on broad, internet-scale corpora (e.g., web text, books, and other publicly available sources), without additional task-specific training. In this sense, the model acts as a "best-informed grounded theorist," drawing on a wide range of qualitative research practices as encoded in its training data, although the composition and potential biases in its training data remain largely unknown. Yet, the scope of such training data can be partially inferred from the types of large-scale web corpora commonly used in model development (e.g., Common Crawl, FineWeb2). At this point, most analyses are likely to use such a base model via a chat-based interface. However, alternative implementations such as API-based workflows (i.e., application programming interface allowing automated, large-scale processing) may enable greater scalability and automation when working with larger or more complex datasets. Beyond scalability, such efficiencies may also lower the time and cost associated with qualitative analysis, thereby reducing barriers to conducting resource-intensive qualitative research. This enables greater accessibility and broader participation across institutions with differing levels of research support, particularly where budgetary constraints limit large-scale qualitative analyses.

Future developments are likely to expand the range of possible implementations. One important direction is supervised fine-tuning, which trains a base model on curated prompt–output pairs defined by the researcher, thereby aligning outputs more closely with specific analytic tasks (Brand et al., 2023; Dong et al., 2024; Prottasha et al., 2022). In GGT, this could involve training the model on examples of high-quality coding schemes, category structures, or theory-building steps. Related approaches include few-shot prompting (providing a small number of examples within the prompt to guide output) and retrieval-augmented generation (linking the model to external documents or datasets during analysis). Recent work in machine learning shows that such approaches can improve task performance and consistency by incorporating domain-specific information, thereby reducing the risk of hallucination (Lewis et al., 2020; Liu et al., 2023). However, these approaches also carry trade-offs: adaptation (e.g., fine-tuning) embeds biases and assumptions from training and task-specific data, which may potentially distort pretrained representations and increase dependence on these data sources (Bommasani et al., 2021). Accordingly, model configuration should be treated as methodological decisions that require transparency and methodological justification.

Beyond individual prompts, future research may explore more advanced forms of human–GenAI collaboration, including increasingly integrated and automated analytic workflows. Recent studies show that GenAI can support multiple stages of qualitative analysis, including coding, theme development, and validation, while leaving interpretation to human researchers (Nyaaba et al., 2026; Pueschel et al., 2026; Sinha et al., 2024). Building on this, GenAI could also support systematic comparison of alternative interpretations, automated checks for consistency, and evidence grounding across large corpora.

As GenAI systems become increasingly agentic (Bandi et al., 2025; Plaat et al., 2025), with AI serving not only as assistant but as agent (Patil et al., 2026), a further possibility is that qualitative analyses may shift soon toward a more autonomous form. For example, GenAI may operate as a principal analytic agent executing multiple, or even all, analytic steps in a single run. In such settings, models can generate grounded-theory structures, thematic frameworks, or sets of tensions without stepwise researcher prompting. The replication studies in this paper approximate such an approach, as GenAI was tasked with executing multiple analytic steps in a single run and produced theory structures that closely aligned with those of the original studies. While promising, this also raises questions about human researcher oversight, process transparency, and appropriate usage. Future research is needed to examine when more autonomous GenAI-driven analysis enhances insight generation and when more interactive, researcher-guided approaches remain necessary.

The increasing integration of GenAI into qualitative research also introduces risks. One risk is the potential for "cognitive surrender," whereby researchers may over-rely on AI-generated outputs without sufficient critical evaluation (Shaw & Nave, 2026), echoing the broader concerns about the erosion of human autonomy and critical thinking in AI-mediated environments (Krook, 2025). Mitigating this risk may involve procedural safeguards, such as requiring researchers to independently generate alternative interpretations, explicitly justify acceptance or rejection of AI-generated outputs, or use GenAI in auditor-like roles that challenge initial interpretations. Additional risks include the amplification of biases present in training data, as well as forms of cultural homogenization that can narrow the range of perspectives reflected in AI outputs (Cheong et al., 2025). These risks are not unique to GGT but are inherent to the use of GenAI more broadly. Addressing them requires continued reflection on the appropriate division of labor between human researchers and GenAI systems.

While GGT is explicitly grounded in grounded-theory methodology, many qualitative approaches in consumer research use similar analytic procedures that share core grounded-theory procedures. Across traditions, qualitative analysis often proceeds through iterative engagement with data, progressive abstraction, and the development of conceptual categories that capture patterns (e.g., themes or tensions in CCT research). While the presence of such shared procedures does not imply that these approaches constitute grounded theory, they nonetheless incorporate a common set of analytic building blocks of grounded-theory operations. GGT can therefore be understood not only as a GenAI-enhanced method for conducting grounded theory but as a structured, modular framework that operationalizes a set of widely used qualitative procedures. GGT components and procedures, particularly prompt structures, can therefore be adapted and integrated into other qualitative analyses. Consequently, qualitative researchers should utilize selected components of GGT as needed or develop related GenAI-enhanced approaches, extending the benefits of structured and transparent analysis beyond grounded theory.

In sum, GGT points to broader opportunities for GenAI-enhanced methods across qualitative traditions, whether grounded theory, phenomenology, hermeneutics, or other forms of qualitative analysis. These developments are consistent with emerging work on increasingly autonomous, closed-loop research systems in marketing, in which generative AI iteratively supports hypothesis generation, testing, and refinement (Hermann, 2025).

CONCLUSION

This paper introduces GGT as an AI-enhanced method for inductive theory building in consumer research. GGT specifies how GenAI can be incorporated into grounded-theory analysis while preserving the interpretive standards of this inductive qualitative method. Rather than being purely a technical aid, GGT contributes bounded analytic inputs, while researchers retain responsibility for theoretical evaluation. By anchoring GenAI use in grounded theory's established procedures—coding, constant comparison, abstraction, theoretical sampling, and saturation—GGT shows how grounded theory can be conducted efficiently, comprehensively, and transparently. It is particularly useful in settings where researchers must engage with complex, heterogeneous, and multimodal qualitative materials. More generally, GGT advances the core scientific values of transparency, reproducibility, and accountability.

In introducing a recent JCR special section on AI, Schmitt (2025) poses a deliberately provocative question: "Are we the last generation of human consumer researchers?" Rather than treating this as a dystopian prediction of human displacement, the question invites reflection more generally on how GenAI should be used in consumer research, to what degree, and with how much autonomy. GGT speaks directly to this challenge for grounded theory and qualitative research that uses its procedures by offering a structured approach to integrating GenAI into analysis while maintaining researcher responsibility for interpretation and theory development.

To conclude, qualitative research has much to gain from thoughtful engagement with language-based analytic tools such as GenAI. Rather than merely accommodating GenAI within existing research practices, GGT shows how inductive theory building and qualitative inquiry can be strengthened using GenAI tools.

DATA AVAILABILITY STATEMENT

Data and analyses that support the findings of this study are detailed in the corresponding Appendices. Additional information is available from the corresponding author upon reasonable request.

ORCID

Bernd Schmitt https://orcid.org/0000-0001-7339-1987
Shuyi Hao https://orcid.org/0000-0001-6736-9214
Michel Tuan Pham https://orcid.org/0000-0002-0717-5191
Reto Hofstetter https://orcid.org/0000-0002-6048-3927

REFERENCES

Aboelenien, A., & Arsel, Z. (2025). Surviving as a vegan in a world of omnivores: Relational fractures in shared practices. *Journal of Consumer Research*, *56*, ucaf052. https://doi.org/10.1093/jcr/ucaf052

Akter, S., McCarthy, G., Sajib, S., Michael, K., Dwivedi, Y. K., D'Ambra, J., & Shen, K. N. (2021). Algorithmic bias in data-driven innovation in the age of AI. *International Journal of Information Management*, *60*, 102387. https://doi.org/10.1016/j.ijinfomgt.2021.102387

Allan, G. (2003). A critique of using grounded theory as a research method. *Electronic Journal of Business Research Methods*, *2*(1), 1–10.

Andreotta, A. J., Kirkham, N., & Rizzi, M. (2022). AI, big data, and the future of consent. *AI & Society*, *37*(4), 1715–1728. https://doi.org/10.1007/s00146-021-01262-5

Arora, A., Barrett, M., Lee, E., Oborn, E., & Prince, K. (2023). Risk and the future of AI: Algorithmic bias, data colonialism, and marginalization. *Information and Organization*, *33*(3), 100478. https://doi.org/10.1016/j.infoandorg.2023.100478

Arsel, Z. (2017). Asking questions with reflexive focus: A tutorial on designing and conducting interviews. *Journal of Consumer Research*, *44*(4), 939–948. https://doi.org/10.1093/jcr/ucx096

Atanasova, A., Eckhardt, G. M., & Laamanen, M. (2025). Platform cooperatives in the sharing economy: How market challengers bring change from the margins. *Journal of the Academy of Marketing Science*, *53*(2), 419–438. https://doi.org/10.1007/s11747-024-01042-9

Ayer, A. J. (1959). *Logical positivism*. Simon and Schuster.

Balducci, B., & Marinova, D. (2018). Unstructured data in marketing. *Journal of the Academy of Marketing Science*, *46*(4), 557–590. https://doi.org/10.1007/s11747-018-0581-x

Bandi, A., Kongari, B., Naguru, R., Pasnoor, S., & Vilipala, S. V. (2025). The rise of agentic ai: A review of definitions, frameworks, architectures, applications, evaluation metrics, and challenges. *Future Internet*, *17*(9), 404.

Bardhi, F., & Eckhardt, G. M. (2012). Access-based consumption: The case of car sharing. *Journal of Consumer Research*, *39*(4), 881–898.

Baron, J. (2008). *Thinking and deciding*. Cambridge University Press.

Bazeley, P. (2022). Designing for multimodal data and mixed methods within a qualitative framework. In *The SAGE handbook of qualitative research design* (pp. 604–617). SAGE Publications.

Belk, R. W. (2013). Extended self in a digital world. *Journal of Consumer Research*, *40*(3), 477–500.

Belk, R., & Sobh, R. (2019). No assemblage required: On pursuing original consumer culture theory. *Marketing Theory*, *19*(4), 489–507. https://doi.org/10.1177/1470593118809800

Bellezza, S. (2023). Distance and alternative signals of status: A unifying framework. *Journal of Consumer Research*, *50*(2), 322–342. https://doi.org/10.1093/jcr/ucac049

Berthet, V. (2022). The impact of cognitive biases on professionals' decision-making: A review of four occupational areas. *Frontiers in Psychology*, *12*, 802439. https://doi.org/10.3389/fpsyg.2021.802439

Bettman, J. (1979). *An information processing theory of choice*. Addison-Wesley Publishing Company.

Blanchard, S. J., Duani, N., Garvey, A. M., Netzer, O., & Oh, T. T. (2025). New tools, new rules: A practical guide to effective and responsible generative AI use for surveys and experiments in research. *Journal of Marketing*, *89*(6), 119–139. https://doi.org/10.1177/00222429251349882

Blythe, P. A., Kulis, C., McGraw, A. P., Haenlein, M., Hewett, K., Yoo, K., & Huber, J. (2025). Comments on "AI and the advent of the cyborg behavioral scientist". *Journal of Consumer Psychology*, *35*(2), 316–328.

Boghrati, R., Berger, J., & Packard, G. (2023). Style, content, and the success of ideas. *Journal of Consumer Psychology*, *33*(4), 688–700. https://doi.org/10.1002/jcpy.1346

Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., Arora, S., von Arx, S., Bernstein, M. S., Bohg, J., Bosselut, A., Brunskill, E., Brynjolfsson, E., Buch, S., Card, D., Castellon, R., Chatterji, N. S., Chen, A., Creel, K., Davis, J. Q., Demszky, D., & Liang, P. (2021). On the opportunities and risks of foundation models. *arXiv Preprint* arXiv. https://doi.org/10.48550/arXiv.2108.07258

Brand, J., Israeli, A., & Ngwe, D. (2023). *Using LLMs for market research*. Harvard Business School Marketing Unit Working Paper.

Calder, B. J., Brendl, C. M., Tybout, A. M., & Sternthal, B. (2021). Distinguishing constructs from variables in designing research. *Journal of Consumer Psychology*, *31*(1), 188–208. https://doi.org/10.1002/jcpy.1204

Carlsen, H. B., & Ralund, S. (2022). Computational grounded theory revisited: From computer-led to computer-assisted text analysis. *Big Data & Society*, *9*(1), 80146. https://doi.org/10.1177/20539517221080146

Charmaz, K. (2006). *Constructing grounded theory: A practical guide through qualitative analysis*. SAGE Publications.

Cheong, I., Caliskan, A., & Kohno, T. (2025). Safeguarding human values: Rethinking US law for generative AI's societal impacts. *AI and Ethics*, *5*(2), 1433–1459.

Clithero, J. A., Karmarkar, U. R., Nave, G., & Plassmann, H. (2024). Reconsidering the path for neural and physiological methods in consumer psychology. *Journal of Consumer Psychology*, *34*(1), 196–213. https://doi.org/10.1002/jcpy.1397

Corbin, J., & Strauss, A. (2014). *Basics of qualitative research: Techniques and procedures for developing grounded theory*. SAGE Publications.

Curry, N., Baker, P., & Brookes, G. (2024). Generative AI for corpus approaches to discourse studies: A critical evaluation of ChatGPT. *Applied Corpus Linguistics*, *4*(1), 100082. https://doi.org/10.1016/j.acorp.2023.100082

Dahal, N. (2024). How can generative AI (GenAI) enhance or hinder qualitative studies? A critical appraisal from South Asia, Nepal. *The Qualitative Report*, *29*(3), 722–733.

Davison, R. M., Chughtai, H., Nielsen, P., Marabelli, M., Iannacci, F., van Offenbeek, M., & Panteli, N. (2024). The ethics of using generative AI for qualitative data analysis. *Information Systems Journal*, *34*(5), 1433–1439.

De Freitas, J., Oğuz-Uğuralp, Z., Uğuralp, A. K., & Puntoni, S. (2026). AI companions reduce loneliness. *Journal of Consumer Research*, *52*(6), 1126–1148.

Dennett, D. C. (2017). *From bacteria to Bach and back: The evolution of minds*. WW Norton & Company.

Dolbec, P. Y., Fischer, E., & Canniford, R. (2021). Something old, something new: Enabled theory building in qualitative marketing research. *Marketing Theory*, *21*(4), 443–461.

Dong, G., Yuan, H., Lu, K., Li, C., Xue, M., Liu, D., Wang, W., Yuan, Z., Zhou, C., & Zhou, J. (2024). How abilities in large language models are affected by supervised fine-tuning data composition. In *Proceedings of the 62nd annual meeting of the Association for Computational Linguistics* (pp. 177–198). Long Papers.

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review*, *14*(4), 532–550.

Epp, A. M., & Humphreys, A. (2025). Collaborating with generative AI in consumer culture research. *Journal of Consumer Research*, *52*(1), 32–48. https://doi.org/10.1093/jcr/ucaf014

Escalas, J. E. (2004). Narrative processing: Building consumer connections to brands. *Journal of Consumer Psychology*, *14*(1–2), 168–180. https://doi.org/10.1207/s15327663jcp1401&2_19

Fischer, E., & Guzel, G. T. (2023). The case for qualitative research. *Journal of Consumer Psychology*, *33*(1), 259–272.

Fischer, E., & Otnes, C. C. (2006). Breaking new ground: Developing grounded theories in marketing and consumer behavior. In R. W. Belk (Ed.), *Handbook of qualitative research methods in marketing* (pp. 19–30). Edward Elgar Publishing.

Fournier, S. (1998). Consumers and their brands: Developing relationship theory in consumer research. *Journal of Consumer Research*, *24*(4), 343–373. https://doi.org/10.1086/209515

Friedman, C., Owen, A., & VanPuymbrouck, L. (2025). Should ChatGPT help with my research? A caution against artificial intelligence in qualitative analysis. *Qualitative Research*, *25*(5), 1062–1088. https://doi.org/10.1177/14687941241297375

Friese, S. (2025). *Response to: "We reject the use of generative artificial intelligence for reflexive qualitative research" (SSRN scholarly paper No. 5690262)*. Social Science Research Network.

Gebhardt, G. F., Carpenter, G. S., & Sherry, J. F. (2006). Creating a market orientation: A longitudinal, multifirm, grounded analysis of cultural transformation. *Journal of Marketing*, *70*(4), 37–55. https://doi.org/10.1509/jmkg.70.4.037

Geiger, R. S., & Ribes, D. (2011). Trace ethnography: Following coordination through documentary practices. In *Proceedings of the 44th Hawaii international conference on system sciences* (pp. 1–10). IEEE.

Gelbrich, K., Kerath, A., & Chun, H. H. (2023). Matching digital companions with customers: The role of perceived similarity. *Psychology & Marketing*, *40*(11), 2291–2305.

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational Research Methods*, *16*(1), 15–31.

Glaser, B., & Strauss, A. (1967). *The discovery of grounded theory: Strategies for qualitative research*. Aldine Publishing Company.

Hallberg, L. R.-M. (2006). The "core category" of grounded theory: Making constant comparisons. *International Journal of Qualitative Studies on Health and Well-Being*, *1*(3), 141–148. https://doi.org/10.1080/17482620600858399

Hao, S., & Schmitt, B. (2026). Body transformations: A conceptual framework and roadmap for future research. *Journal of the Association for Consumer Research*. https://doi.org/10.1086/742486

Hartmann, J., Bergner, A., & Hildebrand, C. (2023). MindMiner: Uncovering linguistic markers of mind perception as a new lens to understand consumer–smart object relationships. *Journal of Consumer Psychology*, *33*(4), 645–667. https://doi.org/10.1002/jcpy.1381

Haws, K. L., Sample, K. L., & Hulland, J. (2023). Scale use and abuse: Towards best practices in the deployment of scales. *Journal of Consumer Psychology*, *33*(1), 226–243. https://doi.org/10.1002/jcpy.1318

Hermann, E. (2025). *Self-driving labs: The new frontier for generative-AI-driven marketing research*. Business Horizons.

Jafari, A., & Goulding, C. (2013). Globalization, reflexivity, and the project of the self: A virtual intercultural learning process. *Consumption Markets & Culture*, *16*(1), 65–90.

Jain, G., Nayakankuppam, D., & Gaeth, G. J. (2021). Perceptual anchoring and adjustment. *Journal of Behavioral Decision Making*, *34*(4), 581–592. https://doi.org/10.1002/bdm.2231

Janiszewski, C., & Van Osselaer, S. M. J. (2022). Abductive theory construction. *Journal of Consumer Psychology*, *32*(1), 175–193. https://doi.org/10.1002/jcpy.1280

Johnson, J. S., & Sohi, R. S. (2016). Understanding and resolving major contractual breaches in buyer–seller relationships: A grounded theory approach. *Journal of the Academy of Marketing Science*, *44*(2), 185–205. https://doi.org/10.1007/s11747-015-0427-8

Jowsey, T., Braun, V., Clarke, V., Lupton, D., & Fine, M. (2025). *We reject the use of generative artificial intelligence for reflexive qualitative*. Social Science Research Network.

Kozinets, R. V. (2002). The field behind the screen: Using netnography for marketing research in online communities. *Journal of Marketing Research*, *39*(1), 61–72. https://doi.org/10.1509/jmkr.39.1.61.18935

Krook, J. (2025). When autonomy breaks: The hidden existential risk of AI. *AI & Society*, *23*, 1–14.

Kumar, M., & Noble, C. H. (2016). Beyond form and function: Why do consumers value product design? *Journal of Business Research*, *69*(2), 613–620. https://doi.org/10.1016/j.jbusres.2015.05.017

Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Küttler, H., Lewis, M., Yih, W. T., Rocktäschel, T., Riedel, S., & Kiela, D. (2020). Retrieval-augmented generation for knowledge-intensive NLP tasks. *Advances in Neural Information Processing Systems*, *33*, 9459–9474.

Liu, P., Yuan, W., Fu, J., Jiang, Z., Hayashi, H., & Neubig, G. (2023). Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *ACM Computing Surveys*, *55*(9), 1–35. https://doi.org/10.1145/3560815

Liu, X., Singh, P. V., & Srinivasan, K. (2016). A structured analysis of unstructured big data by leveraging cloud computing. *Marketing Science*, *35*(3), 363–388. https://doi.org/10.1287/mksc.2015.0972

Lou, J., & Sun, Y. (2026). Anchoring bias in large language models: An experimental study. *Journal of Computational Social Science*, *9*(1), 11. https://doi.org/10.1007/s42001-025-00435-2

Lund, B. D., Wang, T., Mannuru, N. R., Nie, B., Shimray, S., & Wang, Z. (2023). ChatGPT and a new academic reality: Artificial intelligence-written research papers and the ethics of the large language models in scholarly publishing. *Journal of the Association for Information Science and Technology*, *74*(5), 570–581. https://doi.org/10.1002/asi.24750

Lynch, J., & Egan, J. (2013). Grounded theory: Help or hindrance for consumer behaviour? 46th Academy of Marketing Conference. https://westminsterresearch.westminster.ac.uk/item/q29vw/grounded-theory-help-or-hindrance-for-consumer-behaviour.

Lynch, J., van Osselaer, S. M., & Torres, P. (2025). Insiders only: Are our ideas about what makes "good theory" holding us back? *Journal of Consumer Research*, *56*, ucaf069. https://doi.org/10.1093/jcr/ucaf069

Marois, R., & Ivanoff, J. (2005). Capacity limits of information processing in the brain. *Trends in Cognitive Sciences*, *9*(6), 296–305. https://doi.org/10.1016/j.tics.2005.04.010

McCambridge, J., De Bruin, M., & Witton, J. (2012). The effects of demand characteristics on research participant behaviours in non-laboratory settings: A systematic review. *PLoS One*, *7*(6), e39116. https://doi.org/10.1371/journal.pone.0039116

Mehta, S. D., Paul, S., Awiti, E., Young, S., Zulaika, G., Otieno, F. O., Phillips-Howard, P. A., Mason, L., & Bhaumik, R. (2025). Evaluation of large language models within GenAI in qualitative research. *Scientific Reports*, *15*(1), 34993. https://doi.org/10.1038/s41598-025-18969-w

Methnani, J., Latiri, I., Dergaa, I., Chamari, K., & Saad, H. B. (2023). ChatGPT for sample-size calculation in sports medicine and exercise sciences: A cautionary note. *International Journal of Sports Physiology and Performance*, *1*, 1–5. https://doi.org/10.1123/ijspp.2023-0109

Mick, D. G., & Fournier, S. (1998). Paradoxes of technology: Consumer cognizance, emotions, and coping strategies. *Journal of Consumer Research*, *25*(2), 123–143. https://doi.org/10.1086/209531

Moulaei, K., Akhlaghpour, S., & Fatehi, F. (2025). Patient consent for the secondary use of health data in artificial intelligence (AI) models: A scoping review. *International Journal of Medical Informatics*, *198*, 105872. https://doi.org/10.1016/j.ijmedinf.2025.105872

Nelson, L. K. (2020). Computational grounded theory: A methodological framework. *Sociological Methods & Research*, *49*(1), 3–42. https://doi.org/10.1177/0049124117729703

Nguyen, D. C., & Welch, C. (2026). Generative artificial intelligence in qualitative data analysis: Analyzing—Or just chatting? *Organizational Research Methods*, *29*(1), 3–39. https://doi.org/10.1177/10944281251377154

Nickerson, R. S. (1998). Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology*, *2*(2), 175–220.

Nyaaba, M., SungEun, M., Apam, M. A., Acheampong, K. O., Dwamena, E., & Zhai, X. (2026). Human–AI collaborative inductive thematic analysis: AI-guided analysis and human interpretive authority. *arXiv Preprint* arXiv.

Oh, T. T., & Pham, M. T. (2022). A liberating-engagement theory of consumer fun. *Journal of Consumer Research*, *49*(1), 46–73. https://doi.org/10.1093/jcr/ucab051

Omar, M., Nassar, S., Hijazi, K., Glicksberg, B. S., Nadkarni, G. N., & Klang, E. (2025). Generating credible referenced medical research: A comparative study of OpenAI's GPT-4 and Google's Gemini. *Computers in Biology and Medicine*, *185*, 109545. https://doi.org/10.1016/j.compbiomed.2024.109545

Patil, R. K., Rice, D. H., & Janiszewski, C. (2026). Human–AI partnerships: Living and working with AI assistants, AI agents, and AI companions. *Journal of Consumer Psychology*, *25*, jcpy.70025. https://doi.org/10.1002/jcpy.70025

Pellandini-Simányi, L., & Barnhart, M. (2024). The market dynamics of collective ignorance and spiraling risk. *Journal of Consumer Research*, *51*(4), 698–718.

Pham, M. T. (2013). The seven sins of consumer psychology. *Journal of Consumer Psychology*, *23*(4), 411–423. https://doi.org/10.1016/j.jcps.2013.07.004

Pham, M. T. (2023). Are scientific practices improving in consumer research? A glass half-full and half-empty. *Marketing Letters*, *34*(3), 375–382. https://doi.org/10.1007/s11002-023-09679-2

Pham, M. T., & Oh, T. T. (2021). On not confusing the tree of trustworthy statistics with the greater forest of good science: A comment on Simmons et al.'s perspective on preregistration. *Journal of Consumer Psychology*, *31*(1), 181–185. https://doi.org/10.1002/jcpy.1213

Pinker, S. (1997). *How the mind works*. W. W. Norton & Company.

Plaat, A., van Duijn, M., Van Stein, N., Preuss, M., van der Putten, P., & Batenburg, K. J. (2025). Agentic large language models, a survey. *Journal of Artificial Intelligence Research*, *84*, 1203.

Popper, K. (1959). *The logic of scientific discovery*. Routledge.

Prottasha, N. J., Sami, A. A., Kowsher, M., Murad, S. A., Bairagi, A. K., Masud, M., & Baz, M. (2022). Transfer learning for sentiment analysis using BERT-based supervised fine-tuning. *Sensors*, *22*(11), 4157.

Pueschel, J., Hao, S., & Schmitt, B. (2026). Understanding luxury shaming: A multi-study exploration using qualitative inquiry and generative AI. *Journal of Business Research*, *206*, 115996. https://doi.org/10.1016/j.jbusres.2026.115996

Quattrociocchi, W., Capraro, V., & Perc, M. (2025). Epistemological fault lines between human and artificial intelligence (No. arXiv:2512.19466; Version 1). *arXiv*. https://doi.org/10.48550/arXiv.2512.19466

Reich, B. J., & Hanson, S. (2025). Brand corporateness: Measurement and symbolic meaning of an unfavorable brand association. *Journal of Consumer Research*, *52*(3), 597–618. https://doi.org/10.1093/jcr/ucae069

Schlagwein, D., & Willcocks, L. (2023). 'ChatGPT et al.': The ethics of using (generative) artificial intelligence in research and science. *Journal of Information Technology*, *38*(3), 232–238.

Schmitt, B. (2025). GenAI and consumer research: Are we the last generation of human consumer researchers? *Journal of Consumer Research*, *52*(1), 1–3. https://doi.org/10.1093/jcr/ucaf015

Searle, J. (1980). Minds, brains, and programs. *Behavioral and Brain Sciences*, *3*(3), 417–457. https://doi.org/10.1017/S0140525X00005756

Shah, C. (2024). From prompt engineering to prompt science with human in the loop. *arXiv*. https://doi.org/10.48550/arXiv.2401.04122

Shaw, S. D., & Nave, G. (2026). Thinking-fast, slow, and artificial: how AI is reshaping human reasoning and the rise of cognitive surrender. Available at SSRN 6097646.

Shiffrin, R. M. (1976). Capacity limitations in information processing, attention, and memory. In W. K. Estes (Ed.), *Handbook of learning and cognitive processes: Vol. 4. Attention and memory* (pp. 177–236). Psychology Press.

Sinha, R., Solola, I., Nguyen, H., Swanson, H., & Lawrence, L. (2024). The role of generative AI in qualitative research: GPT-4's contributions to a grounded theory analysis. *Proceedings of the Symposium on Learning Design and Technology*, *56*, 17–25. https://doi.org/10.1145/3663433.3663456

Sun, J. J., & Pham, M. T. (2026). What makes consumption experiences feel special? A multimethod integrative analysis. *Journal of Consumer Research*, *52*(5), 849–872.

Thompson, C. J., Mick, D. G., Van Osselaer, S. M. J., & Huber, J. (2023). Commentaries on "the case for qualitative research". *Journal of Consumer Psychology*, *33*(1), 273–282. https://doi.org/10.1002/jcpy.1299

Thornberg, R., & Charmaz, K. (2014). Grounded theory and theoretical coding. In U. Flick (Ed.), *The SAGE handbook of qualitative data analysis* (pp. 153–169). SAGE Publications.

Tomaino, G., Cooke, A. D., & Hoover, J. (2025). AI and the advent of the cyborg behavioral scientist. *Journal of Consumer Psychology*, *35*(2), 297–315.

Tversky, A., Kahneman, D., & Slovic, P. (1982). *Judgment under uncertainty: Heuristics and biases*. Cambridge University Press.

Urminsky, O., Eckhardt, G. M., Goldenberg, J., Meloy, M. G., & Spiller, S. A. (2025). Improving our scientific understanding of consumer behavior. *Journal of Consumer Research*, *51*(5), 867–870. https://doi.org/10.1093/jcr/ucae074

Wachinger, J., Bärnighausen, K., Schäfer, L. N., Scott, K., & McMahon, S. A. (2024). Prompts, pearls, imperfections: Comparing ChatGPT and a human researcher in qualitative data analysis. *Qualitative Health Research*, *25*, 44669. https://doi.org/10.1177/10497323241244669

Wilson, A. V., & Bellezza, S. (2022). Consumer minimalism. *Journal of Consumer Research*, *48*(5), 796–816. https://doi.org/10.1093/jcr/ucab038

Woodside, A. G., MacDonald, R., & Burford, M. (2004). Grounded theory of leisure travel. *Journal of Travel & Tourism Marketing*, *17*(1), 7–39. https://doi.org/10.1300/J073v17n01_02

Wu, C.-J., Raghavendra, R., Gupta, U., Acun, B., Ardalani, N., Maeng, K., Chang, G., Aga, F., Huang, J., & Bai, C. (2022). Sustainable AI: Environmental implications, challenges and opportunities. *Proceedings of Machine Learning and Systems*, *4*, 795–813. https://doi.org/10.48550/arXiv.2111.00364

Yan, L., Echeverria, V., Fernandez-Nieto, G. M., Jin, Y., Swiecki, Z., Zhao, L., Gašević, D., & Martinez-Maldonado, R. (2024). Human-AI collaboration in thematic analysis using ChatGPT: A user study and design recommendations. *Extended Abstracts of* *the CHI Conference on Human Factors in Computing Systems*, *25*, 1–7. https://doi.org/10.1145/3613905.3650732

Yue, Y., Liu, D., Lv, Y., Hao, J., & Cui, P. (2025). A practical guide and assessment on using ChatGPT to conduct grounded theory: Tutorial. *Journal of Medical Internet Research*, *27*, e70122. https://doi.org/10.2196/70122

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Schmitt, B., Hao, S., Pham, M. T., & Hofstetter, R. (2026). Generative grounded theory (GGT): Inductive theory building in the age of generative AI. *Journal of Consumer Psychology*, *00*, 1–21. https://doi.org/10.1002/jcpy.70036