Beyond Assistance: A Role-Based Conceptual Framework for Generative and Agentic Artificial Intelligence in Case-Based Management and Governance Research

Rosario Faraci[*], *Rosaria Ferlito*[**]

Received May 24, 2026 – Accepted June 30, 2026

Abstract

The use of artificial intelligence (AI) in qualitative management research has so far been framed predominantly as assistance: a researcher interacting with generative AI during the design or analysis of a case study. Yet methodological discussions still offer limited understanding of how qualitatively different forms of AI involvement reconfigure the production of theoretical insight in case-based research. The existing differentiation remains stage-bound and tool-centred; what is missing is a systematic coupling of AI roles to forms of theorising and to specific validity threats.

Drawing on a review of 139 documents, the authors develop a four-role conceptual framework, AI as Discoverer, Selector, Co-Constructor and Generator. Each role is examined through affordance theory, theorising from cases and sociomaterial perspectives in order to analyse how different forms of AI involvement influence theorising, interpretation and engagement with empirical material.

The study's contribution lies less in naming four roles than in coupling them to forms of theorising and to role-specific validity threats. AI involvement cannot be treated as a uniform methodological condition: different roles raise different implications for contextual understanding, methodological rigor, researcher oversight and the empirical status of research material. We advance six propositions linking each

[*] Full Professor Dipartimento di Economia e Impresa, Università di Catania. Email: faraci@unict.it ID ORCID: 0000-0003-1070-7301

[**] Ricercatrice a tempo determinato. Dipartimento di Scienze Economiche e Giuridiche dell'Università degli Studi di Enna "Kore". Email: rosaria.ferlito@unikore.it ID ORCID: 0000-0002-8320-3940

Corporate Governance and Research & Development Studies, n. 1/2026
(ISSNe 2723-9098, Doi: 10.3280/cgrds1-2026oa23327)

AI role to conditions of legitimacy, characteristic validity threats and disclosure requirements, and we illustrate the framework through a corporate-governance research scenario. The paper closes with role-sensitive guidance for authors, reviewers and editors of governance and R&D case research.

Keywords: case study; qualitative research; artificial intelligence; affordance theory; sociomateriality; theorising.

Sommario

L'uso dell'intelligenza artificiale (IA) nella ricerca qualitativa in ambito manageriale è stato finora inquadrato prevalentemente come assistenza ossia un ricercatore interagisce con l'IA generativa durante la progettazione o l'analisi di un caso di studio. Tuttavia, il dibattito metodologico offre ancora una comprensione limitata di come forme qualitativamente diverse di coinvolgimento dell'IA riconfigurino la produzione di conoscenze teoriche nella ricerca basata su casi studio. La differenziazione esistente rimane legata alle fasi del processo e centrata sullo strumento. Ciò che manca è un collegamento tra i ruoli dell'IA, le forme di teorizzazione e le specifiche minacce alla validità.

Sulla base di una revisione di 139 documenti, gli autori sviluppano un framework concettuale a quattro ruoli: IA come *Discoverer* (Scopritore), *Selector* (Selezionatore), *Co-Constructor* (Co-costruttore) e *Generator* (Generatore). Ciascun ruolo viene esaminato attraverso la teoria dell'*affordance*, la teorizzazione a partire dai casi e le prospettive sociomateriali, al fine di analizzare come le diverse forme di coinvolgimento dell'IA influenzino la teorizzazione, l'interpretazione e l'interazione con il materiale empirico.

Il contributo dello studio risiede meno nella definizione dei quattro ruoli, quanto piuttosto nel loro collegamento a specifiche forme di teorizzazione e a minacce alla validità proprie di ciascun ruolo. Il coinvolgimento dell'IA non può essere trattato come una condizione metodologica uniforme: ruoli diversi comportano implicazioni diverse per la comprensione contestuale, il rigore metodologico, la supervisione da parte del ricercatore e lo status empirico del materiale di ricerca. Gli autori avanzano sei proposizioni che collegano ciascun ruolo dell'IA a condizioni di legittimità, minacce caratteristiche alla validità e requisiti di trasparenza, illustrando il framework attraverso uno scenario di ricerca sulla corporate governance. Il paper si conclude con indicazioni operative, sensibili al ruolo dell'IA, rivolte ad autori, revisori ed editor della ricerca su casi di governance e R&D.

Parole chiave: casi studio; ricerca qualitative; intelligenza artificiale; teoria dell'affordance; sociomaterialità; teorizzazione.

1. Introduction

The case study has been described as both the most flexible and the most debated research strategy in management scholarship (Yin, 2018; Eisenhardt and Graebner, 2007; Welch *et al.*, 2019). Its persistent appeal lies in the capacity to investigate complex, context-sensitive and processually dynamic phenomena that cannot be fully captured by standardized indicators (Gummesson, 2017; Cornelissen, 2017). Its legitimacy, however, continues to depend on the rigor, transparency and reflexivity with which researchers design, conduct and theorise from cases (Hoorani *et al.*, 2019; Lindgreen *et al.*, 2021; Pillai *et al.*, 2024). Theoretical insight in case research is therefore closely tied to methodological judgment: researchers actively interpret, select and construct theoretically meaningful evidence.

Against this background, artificial intelligence (AI) is acquiring relevance in management research methodology at remarkable speed. Generative AI tools such as ChatGPT, Claude and Gemini are now routinely employed by doctoral candidates and senior scholars alike for tasks ranging from idea generation to thematic analysis (Naeem *et al.*, 2025). An emerging stream of methodological research has begun to formalize such uses. Naeem and Thomas (2025), in particular, proposed a seven-stage prompt-based protocol that researchers can follow when employing ChatGPT to construct a qualitative case study, from contextual understanding to the configuration of units of analysis. Their work is careful and stage-sensitive, and it already differentiates where the chatbot is involved and where it is not. It nevertheless addresses one specific configuration: a single human researcher employing a non-autonomous chatbot as a co-constructor of a case study built around real empirical material.

However, the methodological frontier is moving rapidly beyond this co-constructive configuration. Three further possibilities are emerging. First, agentic AI systems, autonomous, goal-oriented systems able to plan, retrieve information and execute multi-step tasks with limited human intervention (Acharya *et al.*, 2025; Sapkota *et al.*, 2025), can support the discovery of candidate cases by scanning news archives, regulatory filings, social media and academic databases. Second, when combined with retrieval-augmented generation, agentic systems can support the selection of candidate cases by evaluating them against theoretically relevant criteria. Third, the documented capacity of large language models (LLMs) to produce realistic narratives and to simulate "silicon" participants (Argyle *et al.*, 2023; Hämäläinen *et al.*, 2023; Hullman *et al.*, 2026) raises the more radical possibility of generating synthetic cases for theoretical or pedagogical use.

These four functions, discovery, selection, co-construction and generation, are not interchangeable. They draw on different AI capabilities, operate at different stages of the case research lifecycle, present different validity threats and align with different approaches to theorising from cases (Welch *et al.*, 2019; Welch *et al.*, 2022). They also imply different degrees of methodological delegation between human researchers and AI systems. We do not claim that the literature is silent on these distinctions; protocols such as Naeem and Thomas (2025) and discussions of AI-grounded theory (Odacioglu *et al.*, 2022) and of synthetic respondents (Argyle *et al.*, 2023; O'Grady, 2025) already separate AI for analysis from AI as a producer of quasi-empirical data. What remains underdeveloped is a synthesis that couples these roles systematically to the forms of theorising they serve and to the specific validity threats they introduce. As a result, the debate still oscillates between enthusiasm for AI-assisted research (Naeem and Thomas, 2025) and well-founded but undifferentiated caution about algorithmic theorising (Lindebaum and Ashraf, 2024; Lindebaum *et al.*, 2023).

The aim of this paper is to provide that synthesis. Consequently, our research questions are:

(1) *what distinct roles can generative and agentic AI assume in case-based management research*;

(2) *under what methodological conditions can each role contribute to, or undermine, the theoretical depth and contextual richness that distinguish case-based research?*

We answer these questions by developing a four-role conceptual framework: AI-as-Discoverer, AI-as-Selector, AI-as-Co-Constructor and AI-as-Generator. The review was not intended to catalogue AI applications descriptively, but to identify recurrent methodological functions attributed to generative and agentic AI within the case research process.

Each role is analysed through three theoretical lenses: affordance theory (Leonardi, 2011; Faraj & Azad, 2012; Li *et al.*, 2023; Yang *et al.*, 2024; Lin *et al.*, 2025); Welch *et al.*'s (2019, 2022) typology of theorising from cases; and the sociomateriality literature (Faraj *et al.*, 2018; Kellogg *et al.*, 2020; Pachidi *et al.*, 2021).

The analysis combines systematic review procedures with an abductive conceptual synthesis, from which we derive six propositions on the conditions of legitimacy, validity threats and disclosure requirements specific to each role and to their combination.

The paper makes three contributions. Theoretically, it moves beyond the binary "human researcher versus AI tool" frame and repositions case-based research as a sociotechnical practice in which qualitatively different AI roles carry different methodological consequences; rather than filling an empty conceptual space, it offers a structured synthesis and extension of emerging streams.

Methodologically, it supplies conceptual categories and evaluative criteria that authors, reviewers and editors can use to interrogate AI involvement in case-based papers.

Practically, it translates these criteria into role-sensitive disclosure guidance for corporate-governance and R&D case research, where the credibility of board, succession, ESG and innovation evidence depends acutely on transparency about how cases were found, chosen, interpreted and, increasingly, generated.

The paper proceeds as follows. Section 2 reviews the conceptual background and clarifies the generative–agentic distinction. Section 3 describes the review process, the coding protocol and the analytical approach. Section 4 develops the four-role framework and a worked governance illustration. Section 5 discusses theoretical and practical implications, articulates six propositions, and considers limitations and a future research agenda. Section 6 concludes.

2. Conceptual background

2.1 Case-based research and approaches to theorising

Case-based research has developed through different methodological traditions that can be broadly grouped into three overlapping but distinct approaches. The positivist approach, exemplified by Yin (2018) and Eisenhardt (1989), conceives of the case as a focused empirical site for theory building or testing through replication logic. The interpretive approach, advanced by Stake (1995), views the case as a phenomenon whose meaning is socially constructed and must be understood through engagement with participants' lived experience. The abductive and process-oriented approach, associated with Gioia, Corley and Hamilton (2013), Langley (1999) and Cornelissen (2017), emphasises the emergence of theoretical categories from rich qualitative material through abductive iteration.

Welch *et al.* (2019) integrated this diversity into four forms of theorising from cases, inductive theory-building, interpretive sensemaking, natural experiment and contextualised explanation, which differ in how they combine contextualisation and causal explanation and therefore rely on different evaluative criteria.

Later contributions emphasised contextualised explanation in particular, through process research, historical methods, the extended case method and configurational theorising (Welch *et al.*, 2022). This distinction is decisive for our argument: the methodological legitimacy of an AI-supported practice cannot be assessed independently of the form of theorising adopted.

A practice that is acceptable within a comparative, theory-driven design may be methodologically inconsistent within an interpretive or processual one. The introduction of AI therefore raises different questions depending on:
(i) how cases are identified and selected;
(ii) how theoretical categories are developed;
(iii) what counts as legitimate empirical evidence.

2.2 Artificial intelligence in qualitative management research

Recent methodological discussions have introduced AI into qualitative management research primarily as analytical support. Naeem *et al.* (2023) proposed a step-by-step process of thematic analysis to develop conceptual models, later extended to AI-supported thematic analysis (Naeem *et al.*, 2025) and to a seven-stage protocol for AI-assisted case study development (Naeem and Thomas, 2025). Odacioglu, Zhang and Allmendinger (2022) proposed an "AI grounded theory" combining topic modeling with grounded theory across fifty-one case studies of project collaboration. These contributions differ methodologically but share an assumption: AI is positioned as a tool supporting the researcher during coding, interpretation or analytical organisation.

A second stream examines the broader implications of algorithmic theorising. A core concern is that predictive optimization and automated pattern recognition may progressively displace explanation, interpretation and theoretical judgment in qualitative inquiry (Lindebaum *et al.*, 2023; Lindebaum and Ashraf, 2024). Related work highlights the growing dependence of management theory on computational artefacts (Glaser *et al.*, 2024) and the persistent tension between AI augmentation and the automation of human judgment (Raisch and Krakowski, 2021). These contributions converge on a single question: how the growing use of AI may influence explanation, interpretation and theory development.

A third stream addresses synthetic data generated by LLMs. Recent studies show that LLMs can simulate responses and generate material resembling empirical patterns observed in human populations (Argyle *et al.*, 2023; Hämäläinen *et al.*, 2023), opening possibilities for exploratory analysis, simulation and pedagogy. The same literature identifies serious limits. AI-generated participants may reproduce biases in training data and inadequately represent marginalised groups (O'Grady, 2025); and simulations cannot automatically be treated as behavioural evidence, since their apparent realism often rests on assumptions that are difficult to verify empirically (Hullman *et al.*, 2026). Synthetic material therefore raises a prior question about what can legitimately count as empirical evidence. These debates are well developed in adjacent science-and-technology-studies and critical-data-studies scholarship; we draw on them selectively while keeping our focus on management research, and we flag this boundary explicitly in Section 5.

These streams of literature show that AI is progressively extending beyond analytical assistance and beginning to influence broader stages of knowledge production in qualitative research. Yet one important issue remains underdeveloped: the emergence of agentic AI systems in research methodology. The several applications and implications of agentic AI analyse by Acharya, Kuppan and Divya (2025) and the conceptual taxonomy by Sapkota, Roumeliotis and Karkee (2025) confirm that the agentic paradigm is maturing rapidly in healthcare, finance and robotics. Its translation into management research methodology, however, remains conceptually undertheorised.

2.3 Working with machines: a sociomaterial framing

A final stream derives from organisation theory and sociomaterial perspectives on algorithmic systems (Orlikowski and Scott, 2008; Faraj *et al.*, 2018; Kellogg *et al.*, 2020; Pachidi *et al.*, 2021). Faraj, Pachidi and Sayegh (2018) identify four properties of learning algorithms, black-boxed performance, comprehensive digitisation, anticipatory quantification and hidden politics, and show how they alter coordination, control and professional expertise. Subsequent work suggests that algorithmic systems increasingly shape what counts as legitimate knowledge (Pachidi *et al.*, 2021) and participate in evaluative, classificatory and interpretive activities once reserved for human experts (Kellogg *et al.*, 2020).

Although developed for organisations, these dynamics may increasingly characterise qualitative and case-based research as AI systems participate in discovery, selection, interpretation and generation. To move beyond high-level appeals to sociomateriality, we use Leonardi's (2011) notion of imbrication, the interlocking of human and material agencies, as a mechanism that differs systematically across roles: in the Discoverer and Selector roles, material agency is comparatively dominant and operates upstream and out of sight in ranking and retrieval pipelines, whereas in the Co-Constructor role human and material agencies imbricate turn by turn within the researcher's view, and in the Generator role material agency substitutes for, rather than imbricates with, empirical reality. This mechanism-level reading allows AI-supported case research to be analysed as a sociotechnical configuration, and it is what the affordance and theorising-from-cases lenses are used to specify in Section 4.

3. Methodology

This study adopts a structured literature review approach to examine how generative and agentic AI are being incorporated into case-based management research (Snyder, 2019). Generative AI refers to large language models that produce text, code or other content in response to prompts; they are powerful but non-autonomous, operating within a turn-by-turn interaction in which the human sets goals, supplies material and evaluates output. Agentic AI refers to systems that wrap such models in mechanisms for autonomy, planning, memory, tool use and retrieval, enabling them to pursue a goal across multiple steps with limited human intervention (Acharya *et al.*, 2025; Sapkota *et al.*, 2025). The two are not opposed: agentic systems typically rely on generative models as their reasoning core, but they add the capacity to act in an information environment rather than only to respond within a dialogue.

In the present study, the review was not intended to provide a descriptive overview of the literature, but to identify recurring forms of AI involvement in case research and to develop a conceptual framework grounded in the analysis of prior studies. To enhance transparency and replicability, the review process followed the PRISMA protocol (Page *et al.*, 2021).

The review focused on studies addressing the use of AI in case-based and qualitative management research, with particular attention to methodological functions associated with case discovery, case selection, co-construction and synthetic case generation.

3.1 Search strategy and Screening

The primary search was conducted in March 2026 using Elsevier's Scopus, which offers broad multidisciplinary coverage of peer-reviewed journals (Snyder, 2019). The search covered 2018–2026 in order to capture the recent emergence of generative and agentic AI. The following Boolean expression was applied to the TITLE-ABS-KEY fields:

("case study" OR "case research" OR "case method" OR "case-based") AND ("artificial intelligence" OR "generative AI" OR "large language model" OR "LLM" OR "ChatGPT" OR "agentic AI" OR "synthetic data" OR "synthetic case") AND (management OR organization OR governance OR strategy OR business).

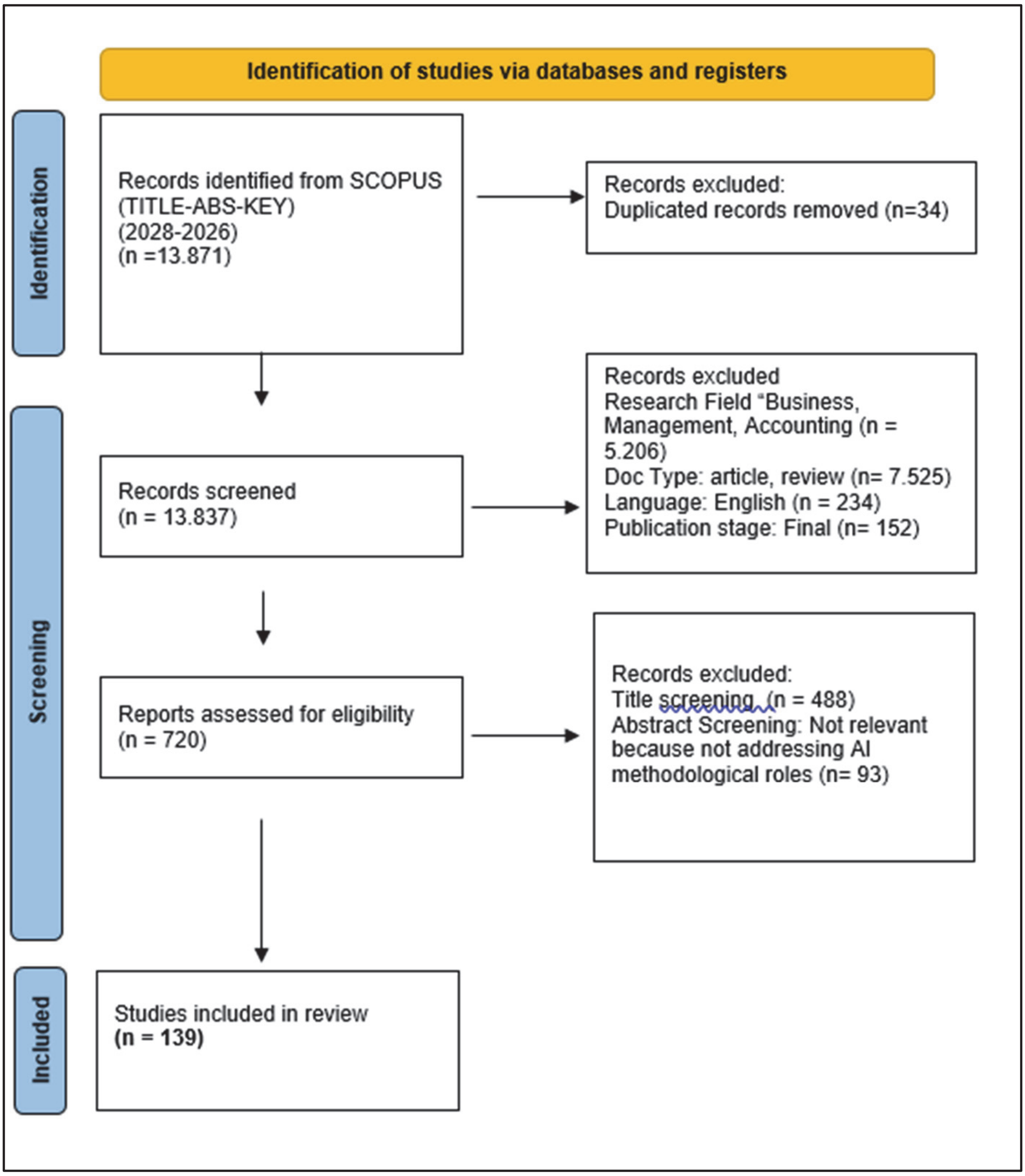
The query returned 13,837 records. Before screening, duplicates have been removed from the final set of results (records excluded n=34).

Only articles and review were included (records excluded n=7.525). Non-English publications or documents without an English abstract were also excluded from the analysis (records excluded n=234). The selected subject area was "Business, Management and Accounting" (records excluded n=5.206). Restricting the database search to this subject area necessarily excludes foundational work published in human–computer interaction venues (e.g., Hämäläinen *et al.*, 2023), in technical AI outlets (e.g., Acharya *et al.*, 2025; Sapkota *et al.*, 2025) and in general-science journals (e.g., O'Grady, 2025). To address this limitation, backward and forward citation searches (snowballing) were conducted during the review process to identify a limited number of highly relevant adjacent studies. These contributions were incorporated into the conceptual analysis to complement the management corpus, particularly with regard to agentic AI and synthetic data, while remaining analytically distinct from the studies retrieved through the original database search. The publication stage was "Final" (records excluded n=152).

The remaining studies were screened through title and abstract analysis in order to exclude contributions clearly unrelated to the methodological use of AI in case-based or qualitative management research. At the title screening stage, 488 records were excluded as out of scope, while a further 93 studies were removed after abstract screening because they did not address methodological aspects of case research or did not include an abstract. Instead we considered the studies that discuss AI as a methodological resource in research activities and show explicit relevance to case research design, data generation, analysis or theorising. Technical contributions without methodological implications for management research were excluded, together with literature reviews addressing AI only as a substantive research topic.

This process resulted in a final sample of 139 studies subjected to full-text analysis. Figure 1 summarises the screening and selection process.

Figure 1: PRISMA Protocol



Source: Our elaboration

3.2 Documents analysis

The analysis was conducted manually through iterative reading and comparison of the selected studies. The authors independently examined the papers and progressively compared interpretations in order to identify recurring methodological patterns and refine the emerging conceptual distinctions. This process supported the development of a shared interpretation of how AI intervenes in different stages of case-based research.

In detail, firstly, all 139 documents were read in full. We then distinguished between two subsets by full-text reading: the 81 core studies are those that attribute at least one explicit methodological function to AI within case-based or qualitative inquiry (or, for the adjacent agentic-AI and synthetic-data literatures, a function directly transferable to it). These studies inform the construction of the roles. The remaining 58 contextual studies supply the theoretical frame, affordance theory, sociomateriality, theorising from cases, and the augmentation-automation debate, and are not coded into roles. In addition, a small number of interdisciplinary studies identified through citation-based snowballing were incorporated into the conceptual analysis. Although not retrieved through the original subject-area filter, these studies provided important insights into agentic AI capabilities and synthetic data generation and were used to enrich the emerging framework.

The second step examined the methodological implications associated with each category. The unit of analysis was the methodological function attributed to AI within a study, not the study as a whole; a single study could therefore instantiate more than one function. Coding combined a deductive starting scheme with inductive refinement. The initial scheme was organized around stages of the case research lifecycle (identification, selection, interpretation, generation) derived from Eisenhardt (1989), Yin (2018) and Welch *et al.* (2019). Through iterative reading these stages were refined into the four conceptual categories AI-as-Discoverer, AI-as-Selector, AI-as-Co-Constructor and AI-as-Generator. Two authors independently coded the studies. The small number of disagreements, concentrated at the Discoverer–Selector and Co-Constructor–Generator boundaries, was resolved through discussion and used to sharpen the operational definitions reported in Table 1.

The distribution of coded functions was as follows: Co-Constructor (34), Generator (26), Discoverer (18) and Selector (15); because 12 studies were double-coded, assignments (93) exceed the 81 studies. The relative weight of the categories is itself informative: the Co-Constructor role rests on consolidated management evidence, whereas the Discoverer and Selector roles draw more heavily on adjacent agentic-AI literature, a point we treat as a limitation.

The final step connected the emerging categories with the theoretical foundations discussed in Section 2. Affordance theory supported the examination of what each AI function enables and constrains. The literature on theorising from cases provided the basis for assessing whether each function is compatible with different forms of case-based theorising. Sociomateriality supported the interpretation of how AI may alter the relationship between human judgment, technological mediation and knowledge production.

Table 1: Coding Scheme

Role	Capability	Operational coding definition	Exemplar Studies	Num. of articles
Discoverer	Agentic (autonomy, planning, retrieval)	AI scans dispersed sources to surface candidate cases before field engagement	Acharya *et al.* (2025); Sapkota *et al.* (2025); Naeem *et al.* (2023)	18
Selector	Agentic (retrieval-augmented evaluation, ranking)	AI evaluates and prioritises candidate cases against theoretically defined criteria	Acharya *et al.* (2025); Sapkota *et al.* (2025); Naeem & Thomas (2025)	15
Co-Constructor	Generative (prompt-based dialogue)	AI participates in coding, framing and interpretation through iterative human-AI exchange	Naeem *et al.* (2023, 2025); Naeem & Thomas (2025); Odacioglu *et al.* (2022)	34
Generator	Generative (simulation, narrative production)	AI produces synthetic cases or participants not derived from observed settings	Argyle *et al.* (2023); Hämäläinen *et al.* (2023); Hullman *et al.* (2026); O'Grady (2025)	26

Source: Our elaboration

The framework presented in Section 4 emerged through comparison between the reviewed studies and the theoretical foundations (Table 2).

Table 2: Analytical Process

	Analytical phase	Focus of the analysis	Outcome
1	**Reading of the selected studies**	Examination of how AI is used within the research process	Identification of recurring forms of AI involvement
2	**Comparative interpretation of the studies**	Analysis of similarities and differences in methodological functions	Progressive distinction between AI roles
3	**Conceptual refinement**	Iterative refinement and resolution of boundary disagreements	Four conceptual categories
4	**Connection with theoretical foundations**	Interpretation through affordance theory, theorising from cases and sociomateriality	Four-role conceptual framework

Source: Our elaboration

4. The four AI roles in case-based management research

The analysis revealed four distinct forms of AI involvement in case-based management research: AI-as-Discoverer, AI-as-Selector, AI-as-Co-Constructor and AI-as-Generator. These four roles differ in the stage of the research process in which AI intervenes, the degree of researcher delegation involved, and the implications they generate for theorising from cases.

The framework is a conceptual representation of methodological functions that AI may assume during the development of case-based research. Some roles primarily support the identification and organisation of empirical material, whereas others intervene more directly in interpretation, theoretical reasoning or the generation of synthetic research material. In detail, Discovery and Selection depend primarily on agentic capabilities, autonomous scanning of dispersed sources, retrieval-augmented evaluation, planning and ranking across large corpora. Co-construction and generation depend primarily on generative, prompt-based capabilities, the production and refinement of interpretations or narratives within an interaction governed by the researcher. Therefore, agentic roles externalise judgment into autonomous information-processing pipelines that are harder to inspect, whereas generative roles keep the human in the interactional loop but expose the researcher to fluent, persuasive output.

The following sections discuss each role by examining the methodological possibilities it enables, the forms of researcher-AI interaction it introduces, and the challenges it raises for validity, interpretation and theoretical depth in case-based management research.

4.1 AI as Discoverer

AI as Discoverer refers to the use of AI systems to support the identification of potentially significant cases before field engagement and data collection begin.

In traditional case research, identification has depended on researchers' prior knowledge, professional networks, media visibility and familiarity with specific settings (Eisenhardt, 1989; Yin, 2018). Recent developments in generative and agentic AI introduce new forms of automated retrieval and organisation of empirical material (Sapkota *et al.*, 2025; Naeem *et al.*, 2023; Naeem *et al.*, 2025; Naeem and Thomas, 2025).

From an affordance perspective, AI-supported discovery increases researchers' capacity to access and organise heterogeneous material and expands the scale and speed at which relevant information can be surfaced

(Leonardi, 2011; Faraj and Azad, 2012; Yang *et al.*, 2024). In governance and R&D research, this can facilitate the identification of episodes associated with theoretically relevant conditions, governance crises, CEO succession events, ESG controversies, innovation breakthroughs, thereby supporting the early stages of theoretical sampling (Eisenhardt, 1989; Welch *et al.*, 2022). In affordance terms, however, the affordance is asymmetric: it strengthens breadth of access far more than depth of contextual understanding, which is why it predicts compatibility with comparative designs but not with interpretive ones.

Sociomaterially, the imbrication of agencies here is upstream and largely invisible: access becomes mediated by digital infrastructures, retrieval systems and ranking, so the visibility of a phenomenon depends not only on the researcher's sensitivity but on the structure, accessibility and ranking of digitally available information (Orlikowski and Scott, 2008; Faraj *et al.*, 2018; Pachidi *et al.*, 2021).

The role is therefore most compatible with approaches relying on comparison, replication logic and contextual variation (Welch *et al.*, 2019; 2022) and least compatible with interpretive approaches, where selection and interpretation depend on direct familiarity with the setting (Stake, 1995; Cornelissen, 2017). The principal threat is visibility bias: AI-supported discovery privileges organisations and events already prominent in digital environments, underrepresenting less documented or marginal contexts, and systems trained on dominant textual patterns may reproduce established assumptions and reduce exposure to genuinely novel situations (Lindebaum *et al.*, 2023; Glaser *et al.*, 2024). Researchers who rely heavily on it may also enter the field with thinner contextual familiarity than qualitative case research has traditionally required (Hoorani *et al.*, 2019; Pillai *et al.*, 2024). Use of the Discoverer role thus demands deliberate attention to source diversity, contextual understanding and oversight.

4.2 AI as Selector

Once candidates have been identified, researchers must decide which are theoretically relevant. Case selection has traditionally relied on theoretical sampling, replication logic, polar types and the identification of particularly informative empirical situations (Eisenhardt, 1989; Eisenhardt & Graebner, 2007; Stake, 1995; Yin, 2018). AI-as-Selector refers to the use of agentic, retrieval-augmented AI to support the evaluation and prioritisation of candidate cases according to theoretically defined criteria.

Unlike the Discoverer, which mainly surfaces material, the Selector intervenes directly in evaluative judgment, supporting ranking and comparative assessment through retrieval-augmented generation, semantic matching and multi-step reasoning (Acharya *et al.*, 2025; Sapkota *et al.*, 2025; Naeem and Thomas, 2025). From an affordance perspective it increases the capacity to compare, classify and prioritise candidates against explicit criteria; more finely, affordance theory predicts that this capacity is realised only to the extent that the relevant theoretical criteria can be made machine-legible, a condition met by structured comparative schemas but violated by criteria that depend on tacit, emergent judgment.

Sociomaterially, the imbrication tightens: algorithmic systems actively participate in organising and prioritising information through ranking and categorisation (Faraj *et al.*, 2018; Kellogg *et al.*, 2020; Pachidi *et al.*, 2021), so selection becomes contingent on how theoretical criteria are translated into prompts, categories and computational representations.

The role aligns most closely with designs based on explicit theoretical schemas and cross-case comparison (Welch *et al.*, 2019) and benefits interpretive and grounded-processual approaches least, since theoretical sensitivity there develops through engagement rather than predefined categories (Stake, 1995; Gioia *et al.*, 2013; Cornelissen, 2017). The Selector also entails a more substantial delegation of judgment than the Discoverer.

Its main methodological threats are the loss of theoretical nuance resulting from the translation of complex constructs into machine-readable criteria, the marginalisation of anomalous or surprising cases that deviate from dominant patterns, and the partial opacity of the reasoning embedded in ranking processes (Lindebaum *et al.*, 2023; Lindebaum and Ashraf, 2024). Therefore, the responsible use requires explicit specification of criteria, oversight, and reflection on how the system participates in evaluative judgment.

4.3 AI as Co-Constructor

AI as Co-Constructor is the most developed role in the methodological literature on AI-supported qualitative research. Existing contributions describe research configurations in which researchers interact with AI systems during different stages of the research process, including research design, theoretical framing, coding activities and interpretation (Naeem *et al.*, 2023). AI contributes to the construction, refinement and interpretation of case-based research material through iterative exchanges involving prompting, evaluation and revision (Naeem & Thomas, 2025). Interaction with AI may help researchers externalise implicit assumptions, examine alternative interpretations and explore theoretical perspectives that might otherwise remain overlooked. Within case-based research, the AI as Co-Constructor therefore operates primarily as a form of AI-assisted interpretation rather than as a mechanism for autonomous methodological judgment.

The methodological implications differ from the previous two roles. Whereas Discoverer and Selector involve increasing forms of delegation in the identification and prioritisation of cases, the Co-Constructor maintains researchers at the centre of interpretative activity. For this reason, it fits more naturally with a broader range of approaches to theorising from cases, including inductive, interpretive and grounded-processual traditions (Gioia *et al.*, 2013; Welch *et al.*, 2022).

From an affordance perspective it broadens the capacity to organise, compare and reinterpret material (Leonardi, 2011; Yang *et al.*, 2024). Socio-materially, this is the role where imbrication is most visible and most balanced, unfolding turn by turn within the researcher's field of view (Faraj *et al.*, 2018; Pachidi *et al.*, 2021). That visibility is also the source of its characteristic threat: automation and confirmation bias. Fluent, coherent and theoretically plausible output may invite premature interpretive closure (Lindebaum and Ashraf, 2024), and the mere externalisation of prompts and exchanges does not by itself constitute methodological reflexivity. Coding support and theoretical exploration may benefit from interaction, but ethical reflection, contextual interpretation and contribution development continue to rely on the researcher's judgment and field sensitivity (Naeem and Thomas, 2025; Hoorani *et al.*, 2019). Therefore, the rigor of this role depends not on the volume of human-AI interaction but on the researcher's capacity to contest, reject and revise AI-generated interpretations.

4.4 AI as Generator

AI as Generator represents the most controversial form of AI involvement in case-based research because it allows the production of cases not derived directly from observed empirical settings. Existing contributions suggest that large language models may reproduce patterns resembling organisational situations and empirical distributions (Hämäläinen *et al.*, 2023).

The literature describes three uses that must be kept analytically distinct, because their status differs sharply. A first and widely accepted application concerns pedagogical purposes, where synthetic cases, vignettes, and scenarios are developed as teaching materials to stimulate discussion in classroom settings or executive education programmes (Gummesson, 2017; Naeem and

Thomas, 2025; Glaser *et al.*, 2024). In this context, no claim of empirical correspondence is made, and the legitimacy of such use is generally unquestioned.

A second application involves exploratory and simulation-oriented purposes. Here, generated cases are employed to investigate counterfactual situations and theoretical boundary conditions by examining alternative organisational configurations that are difficult or impossible to observe directly (Langley, 1999; Argyle *et al.*, 2023; Hullman *et al.*, 2026). The legitimacy of this use depends on the explicit acknowledgement of the synthetic nature of the material and on framing any resulting insights as hypotheses or conceptual propositions rather than empirical findings.

A third and more problematic application arises when AI-generated material is presented as if it constituted observed evidence about real organisations. We consider this quasi-empirical use to be methodologically illegitimate, except under highly restricted circumstances that are clearly specified, transparently justified, and independently verifiable (cf. Hullman *et al.*, 2026; O'Grady, 2025).

Therefore, AI-generated cases should not be regarded as empirical evidence in the conventional sense. Their use can be considered legitimate for pedagogical and exploratory purposes, whereas any evidentiary role requires explicit disclosure and conditions that are transparent and independently verifiable. Even under such circumstances, however, their evidentiary value remains partial and should be interpreted with caution.

From an affordance perspective, AI as Generator broadens researchers' capacity to explore hypothetical organisational configurations and controlled variations of empirical conditions (Leonardi, 2011; Faraj & Azad, 2012). Sociomaterial perspectives, however, emphasise that generated material remains affected by training data, algorithmic mediation and statistically recurrent textual patterns (Faraj *et al.*, 2018; Pachidi *et al.*, 2021). Generated cases therefore reflect the distributions, absences and biases embedded within training infrastructures.

Several methodological challenges emerge from this form of AI involvement. AI-generated cases may complicate the distinction between empirical material and theoretically constructed narratives, particularly when generated material is presented in forms resembling qualitative evidence. In addition, statistically recurrent textual patterns may produce standardised organisational narratives and reduce exposure to unexpected empirical variation (Hullman *et al.*, 2026). Existing work on silicon sampling also raises concerns regarding the representation of marginalised populations and underrepresented organisational contexts within generated material (O'Grady, 2025). More broadly, the use of generated cases raises questions concerning evidentiary legitimacy and contextual validity within case-based theorising.

4.5 Combining AI roles in case-based research

In practice, case-based research is unlikely to rely on a single role. To make the framework concrete for governance and R&D readers, and to address the concern that the illustrations remained abstract, consider a comparative, multiple-case study of how corporate boards respond to ESG controversies in listed firms, a question squarely within this journal's remit. The four roles would manifest in different stages of the research process.

In the Discoverer role, an agentic system scans regulatory filings, enforcement actions, financial news, NGO reports, and social media to identify listed firms that have experienced a material ESG controversy followed by an observable board-level response. By doing so, AI can assemble a much larger pool of candidate cases than a single researcher could realistically compile through manual searches.

In the Selector role, retrieval-augmented systems support the ranking of candidate cases according to theoretically defined criteria, such as controversy severity, variation in board independence and composition, and the identification of polar types suitable for replication logic. This allows researchers to construct a comparative case set that is theoretically informative (Eisenhardt and Graebner, 2007; Welch *et al.*, 2019).

The Co-Constructor role becomes relevant during the analysis of board minutes, proxy statements, disclosures, and interviews. In this phase, researchers interact with generative AI to externalise interpretations, develop and challenge first-order codes, and test alternative explanations of board behaviour, while retaining full authority over the interpretive process (Gioia *et al.*, 2013; Naeem and Thomas, 2025).

Finally, the Generator role emerges after the empirical analysis has been completed. Synthetic counterfactual scenarios, for example, considering how the same controversy might have unfolded under a differently composed board, can be generated to explore boundary conditions and develop executive-education teaching cases. Such generated material remains explicitly labelled as non-empirical and is kept analytically separate from the observed evidence.

This sequence also surfaces governance-specific risks that a domain-general treatment would miss. Visibility bias in the Discoverer role tilts the sample toward large, scandal-prone listed firms, underrepresenting private and family firms whose governance dynamics differ markedly. Evaluative delegation in the Selector role can flatten precisely the nuances, informal board influence, ownership structure, interlocking directorates, that governance theory treats as decisive. And synthetic governance cases, if not clearly flagged, risk being mistaken for evidence about real board behaviour, with consequences for cumulative knowledge in a field where evidence is already hard to obtain. The order in which roles enter the process matters too: generated material introduced before empirical engagement may anchor researchers on model-produced representations, whereas generated cases introduced after empirical inquiry can support counterfactual exploration and theoretical refinement (Argyle *et al.*, 2023; Hullman *et al.*, 2026).

More generally, interpretive approaches grounded in situated understanding derive limited benefit from Selector and Generator configurations, both of which abstract from empirical context, whereas comparative and theoretically structured approaches integrate them more readily (Welch *et al.*, 2019; 2022). Co-Constructor configurations keep researchers more directly involved in interpretation, whereas Discoverer and Selector configurations rely more extensively on retrieval, filtering and ranking. The capacity to evaluate, contest and revise AI-generated outputs is therefore central to methodological transparency, and connects the framework to the augmentation–automation debate (Raisch and Krakowski, 2021): automation may expand the capacity to process information while simultaneously raising questions about interpretative authority and the place of human judgment in case-based theorising. Table 3 summarises the comparison.

Table 3: Comparative overview of AI roles in case-based management research

Dimension	AI as Discoverer	AI as Selector	AI as Co-Constructor	AI as Generator
Capability Type	Agentic	Agentic	Generative	Generative
Research phase	Case identification	Case selection	Interpretation and analysis	Simulation and exploration
Primary affordance	Access to dispersed empirical material	Comparison and prioritisation of cases	Reflexive and interpretive support	Exploration of hypothetical configurations
Imbrication of agencies	Upstream, largely invisible	Tight, criteria-mediated	Visible, turn-by-turn	Substitutive (no empirical referent)
Theorising from cases	Comparative and context-oriented approaches	Theoretically structured comparison	Broad applicability across approaches	Limited fit with interpretive approaches
Researcher delegation	Moderate	High	Limited	Extensive
Main methodological concerns	Visibility bias; limited contextual familiarity	Reduction of theoretical nuance; opacity	Automation bias; superficial reflexivity	Ambiguous empirical status; limited contextual validity

Source: Our elaboration

5. Discussion

The growing diffusion of generative and agentic AI within management research is transforming how qualitative approach is designed, conducted and interpreted. Existing methodological contributions have mainly examined AI as a support instrument for coding, thematic analysis and data interpretation (Odacioglu *et al.*, 2022; Naeem *et al.*, 2023; Naeem *et al.*, 2025; Naeem & Thomas, 2025), while organisation studies have increasingly highlighted the influence of algorithmic systems on knowledge production (Kellogg *et al.*, 2020; Lindebaum *et al.*, 2023).

However, current discussions remain largely focused on collaborative forms of AI-assisted interpretation and analysis. The framework developed in this study extends this perspective by differentiating four roles through which AI occurs in case-based management research: Discoverer, Selector, Co-Constructor and Generator. The value added is not the discovery of an empty conceptual space, but a structured synthesis that gives reviewers, editors and authors a vocabulary and a set of criteria for interrogating AI involvement that the field currently lacks.

In doing so, the study shows that AI intervene through discovery, selection and the generation of hypothetical or quasi-empirical material (Hämäläinen *et al.*, 2023; Acharya *et al.*, 2025; Sapkota *et al.*, 2025). Therefore, AI involvement represents a differentiated set of configurations associated with distinct forms of delegation, mediation and researcher control (Raisch & Krakowski, 2021; Faraj *et al.*, 2018; Pachidi *et al.*, 2021).

The review also indicates that the four roles are not methodologically equivalent. Their implications vary according to how theoretical insight is developed from cases and how researchers relate to empirical settings during the research process. Comparative and theoretically structured approaches may integrate agentic Discoverer and Selector configurations more extensively, particularly when broader sets of candidate cases and explicit comparison criteria are required (Eisenhardt, 1989; Eisenhardt & Graebner, 2007). Interpretive methodology (Stake, 1995; Cornelissen, 2017), grounded theory (Gioia *et al.*, 2013) and processual approaches (Langley, 1999), by contrast, continue to rely strongly on situated understanding and engagement with empirical material.

The framework further shows that the four roles redistribute methodological activities differently across the research process (Gioia *et al.*, 2013; Lindgreen *et al.*, 2021). Discoverer configurations remake access to empirical material through retrieval and exploration activities supported by AI systems (Acharya *et al.*, 2025; Sapkota *et al.*, 2025). Selector configurations occur directly in evaluative judgment through filtering and prioritisation activities (Eisenhardt & Graebner, 2007; Welch *et al.*, 2019). Co-Constructor configurations influence interpretation and analytical refinement through iterative interaction between researchers and AI systems (Naeem *et al.*, 2023; Naeem *et al.*, 2025; Naeem & Thomas, 2025). Generator configurations introduce a more substantial shift because they allow the production of AI-generated material not directly derived from empirical observation (Argyle *et al.*, 2023; Hämäläinen *et al.*, 2023; Hullman *et al.*, 2026).

Our study also extends sociomaterial perspectives on knowledge production (Orlikowski & Scott, 2008; Faraj & Azad, 2012; Faraj *et al.*, 2018). AI systems participate in the retrieval, organisation, interpretation and generation of research material, while training data, ranking systems and filtering processes figure the visibility and accessibility of empirical phenomena (Kellogg *et al.*, 2020; Pachidi *et al.*, 2021; Lindebaum & Ashraf, 2024). The production of theoretical insight becomes mediated by interactions between researchers' judgments, computational systems and digitally available information infrastructures.

Finally, the study contributes to ongoing discussions concerning AI augmentation and automation in management research (Raisch & Krakowski, 2021). Existing discussions often frame AI adoption as a broad tension between human and automation (Glaser *et al.*, 2024; Lindebaum & Ashraf, 2024). Our review instead suggests that different AI roles involve different implications for qualitative inquiry. Rather than framing AI adoption as a binary choice between acceptance and rejection, the framework highlights the importance of evaluating how different forms of AI involvement influence contextual understanding, interpretative authority and theoretical development throughout the research process.

5.1 Propositions

The previous analysis suggests that the implications of AI involvement vary with the role performed and the form of theorising guiding the design. The following six propositions synthesise the framework. Their number and content now correspond exactly to the four roles plus an alignment and an integrative proposition, correcting the earlier mismatch between the propositions announced and those developed.

Proposition 1 (alignment). The methodological legitimacy of any AI role in case-based research depends on its alignment with the form of theorising guiding the design; misalignment between role and theorising weakens, rather than strengthens, the theoretical contribution.

Proposition 2 (Discoverer – visibility bias). Because AI-as-Discoverer mediates access through digital infrastructures and ranking, its use biases case identification toward digitally salient organisations and events; this threat is most acute for interpretive and contextualised theorising and is mitigated only by deliberate attention to source diversity and contextual familiarity.

Proposition 3 (Selector – evaluative delegation). AI as Selector delegates evaluative judgment to semantic matching and ranking; the resulting loss of theoretical nuance is proportional to the tacit, context-dependent knowledge required by the chosen form of theorising, and is contained only when selection criteria are explicitly specified, auditable and contestable.

Proposition 4 (Co-Constructor – reflexivity). AI as Co-Constructor preserves the researcher's interpretive centrality but introduces automation and confirmation bias; its contribution to rigorous theorising depends on the researcher's capacity to contest, reject and revise fluent AI-generated interpretations, not on the volume of human-AI interaction.

Proposition 5 (Generator – epistemic status). The contribution of AI-as-Generator is legitimate only when the epistemic status of synthetic material is explicitly declared and bounded: synthetic cases may support pedagogical and exploratory purposes, but cannot be treated as empirical evidence except under narrowly specified, transparently justified and verifiable conditions.

Proposition 6 (integrative – governance). As generative and agentic AI become more deeply embedded across the case research lifecycle, qualitative rigor, and the credibility of governance and R&D case evidence in particular, depends increasingly on role-sensitive disclosure, researcher oversight and reflexive evaluation of how AI participates in discovery, selection, interpretation and generation.

5.2 Implications for governance and R&D research practice

The framework offers a basis for discussing AI involvement without treating AI use as a generic condition, and it has concrete consequences for this journal's readership. For authors, distinguishing discovery, selection, interpretation and generation enables precise disclosure: a governance case study should state which roles were used, with which systems, and with what human oversight, rather than relying on a blanket acknowledgement of "AI assistance". For reviewers and editors, the four roles supply targeted questions. In Discoverer configurations, which organisational contexts, private firms, emerging-market boards, smaller innovators, remained weakly represented in the digitally accessible sources? In Selector configurations, how was theoretical relevance translated into prompts, ranking criteria and categories, and can that translation be inspected? In Co-Constructor configurations, what evidence is there that the researcher contested rather than merely accepted AI-generated interpretations? In Generator configurations, is synthetic material clearly demarcated from empirical evidence, and is its use pedagogical, exploratory or, problematically, quasi-empirical?

Because operational procedures for these roles remain underdeveloped, we suggest that disclosure expectations be made role-specific in author guidelines and review criteria. This would allow governance and R&D scholarship to harness AI's reach while protecting the contextual depth, evidentiary discipline and transparency on which the credibility of board, succession, ESG and innovation case evidence depends.

5.3 Limitations and future research

This study presents some limitations. First, and most importantly, only a limited number of reviewed studies directly examine agentic AI within research methodology. Accordingly, the Discoverer and Selector roles are developed partly through a limited number of adjacent studies identified through citation-based snowballing, rather than exclusively through consolidated management applications. While this interdisciplinary enrichment broadens the framework, transferability cannot be assumed, since neighboring fields often operate on more structured data, clearer evaluative criteria and more stable classification tasks than the ambiguous and progressively emergent situations characteristic of qualitative case research. This is reflected in the coding distribution (Table 1) and is not a presentational artefact: empirical exemplars of these two roles within management case research are still sparse, and part of our contribution is precisely to import insights from neighboring fields.

Second, the framework remains conceptual and has not yet been applied to actual research projects. Future studies could analyze published AI-supported case studies to examine which roles are effectively used, how they are combined, and which problems recur, ideally within governance and R&D settings, where the worked illustration in Section 4.5 could be operationalized.

Third, detailed methodological guidance currently exists mainly for the Co-Constructor role, through the protocols proposed by Naeem *et al.* (2025).

Equivalent procedures for Discoverer, Selector and Generator roles, including standards for synthetic-case disclosure, remain to be developed. A further, deliberate boundary is that we have engaged the science-and-technology-studies and critical-data-studies debates on synthetic data only selectively; a fuller integration of that scholarship is a promising avenue for anchoring the Generator role more deeply.

In addition, the review relies on a single database (Scopus) and on the "Business, Management and Accounting" subject area. Although these choices enhanced transparency and ensured coherence with the focus of the study, they may have excluded relevant methodological discussions published in adjacent disciplines. Likewise, grey literature and non-indexed sources were not systematically considered. Future research could broaden coverage by incorporating additional databases and interdisciplinary sources.

6. Conclusion

This study examined how generative and agentic AI may assume four methodological roles within case-based management research: Discoverer, Selector, Co-Constructor and Generator. The framework shows that different forms of AI participation emerge at different stages of the research process and influence theorising, interpretation and engagement with empirical material in several ways.

The study contributes to current methodological debates by moving beyond the idea of AI as a generic analytical support tool and by providing a more differentiated vocabulary for discussing AI-supported case research.

Moreover, its contribution is not only this identification of four roles but their systematic coupling to forms of theorising and to role-specific validity threats, expressed in six propositions and translated into disclosure guidance of direct use to governance and R&D scholars.

As generative and agentic AI become increasingly present within qualitative research activities, greater attention to the role performed by AI systems may become essential for preserving the interpretative and contextual depth that characterises case-based management research.

References

Acharya D.B., Kuppan K., & Divya B. (2025). Agentic AI: Autonomous intelligence for complex goals. A comprehensive survey. *IEEE Access*, 13: 18912-18936. DOI: 10.1109/ACCESS.2025.3532853

Argyle L.P., Busby E.C., Fulda N., Gubler J.R., Rytting C., & Wingate D. (2023). Out of one, many: Using language models to simulate human samples. *Political Analysis*, 31(3): 337-351. DOI: 10.1017/pan.2023.2

Cornelissen J. P. (2017). Preserving theoretical divergence in management research: Why the explanatory potential of qualitative research should be harnessed rather than suppressed. *Journal of Management Studies*, 54(3): 368-383. DOI: 10.1111/joms.12210

Eisenhardt K.M. (1989). Building theories from case study research. *Academy of management review*, 14(4): 532-550. DOI: 10.5465/amr.1989.4308385

Eisenhardt K.M., & Graebner M.E. (2007). Theory building from cases: Opportunities and challenges. *Academy of management journal*, 50(1): 25-32. DOI: 10.5465/amj.2007.24160888

Faraj S., & Azad B. (2012). The materiality of technology: An affordance perspective. *Materiality and organizing: Social interaction in a technological world*, 237(1): 237-258. DOI: 10.1093/acprof:oso/9780199664054.003.0012

Faraj S., Pachidi S., & Sayegh K. (2018). Working and organizing in the age of the learning algorithm. *Information and organization*, 28(1): 62-70. DOI: 10.1016/j.infoandorg.2018.02.005

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. DOI: 10.1177/1094428112452151

Glaser V. L., Sloan J., & Gehman J. (2024). Organizations as algorithms: A new metaphor for advancing management theory. *Journal of Management Studies*, 61(6): 2748-2769. DOI: 10.1111/joms.13033

Gummesson, E. (2017). *Case theory in business and management*. SAGE Publications Ltd, DOI: 10.4135/9781473920811

Hämäläinen P., Tavast M., & Kunnari A. (2023). Evaluating large language models in generating synthetic hci research data: a case study. In *Proceedings of the 2023 CHI conference on human factors in computing systems* (pp. 1-19).

Hoorani B.H., Nair L.B., & Gibbert M. (2019). Designing for impact: The effect of rigor and case study design on citations of qualitative case studies in management. *Scientometrics*, 121(1): 285-306. DOI: 10.1007/s11192-019-03178-w

Hullman J., Brosk D., Sun, H, & Shaw A. (2026). *This human study did not involve human subjects: Validating LLM simulations as behavioral evidence. arXiv preprint arXiv:2602.15785*.

Kellogg K.C., Valentine M.A., & Christin A. (2020). Algorithms at work: The new contested terrain of control. *Academy of management annals*, 14(1): 366-410. DOI: 10.5465/annals.2018.0174

Langley A. (1999). Strategies for theorizing from process data. *Academy of Management review*, 24(4): 691-710. DOI: 10.5465/amr.1999.2553248

Leonardi P.M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS quarterly*, 35(1): 147-167. DOI: 10.2307/23043493

Li C. Y., Fang Y.H., & Chiang Y.H. (2023). Can AI chatbots help retain customers? An integrative perspective using affordance theory and service-domain logic.

Technological Forecasting and Social Change, 197, 122921. DOI: 10.1016/j.techfore.2023.122921
Lin X., Wang T., & Sheng F. (2025). *The relationship between AI-adoption intensity and firm innovation performance: The role of AI affordances.* IEEE Transactions on Engineering Management.
Lindebaum D., & Ashraf M. (2024). The ghost in the machine, or the ghost in organizational theory? A complementary view on the use of machine learning. *Academy of Management Review*, 49(2): 445-448. DOI: 10.5465/amr.2021.0036
Lindebaum D., Moser C., Ashraf M., & Glaser V.L. (2023). Reading the technological society to understand the mechanization of values and its ontological consequences. *Academy of management review*, 48(3): 575-592. DOI: 10.5465/amr.2021.0159
Lindgreen A., Di Benedetto C.A., & Beverland M.B. (2021). How to write up case-study methodology sections. *Industrial Marketing Management*, 96, A7-A10. DOI: 10.1016/j.indmarman.2020.04.012
Naeem M., & Thomas L. (2025). Case study research and artificial intelligence: A step-by-step process to using ChatGPT in the development of case studies in qualitative research. *International Journal of Qualitative Methods*, 24, 16094069251371478. DOI: 10.1177/16094069251371478
Naeem M., Ozuem W., Howell K., & Ranfagni S. (2023). A step-by-step process of thematic analysis to develop a conceptual model in qualitative research. *International journal of qualitative methods*, 22, 16094069231205789. DOI: 10.1177/16094069231205789
Naeem M., Smith T., & Thomas L. (2025). Thematic analysis and artificial intelligence: A step-by-step process for using ChatGPT in thematic analysis. *International Journal of Qualitative Methods*, 24, 16094069251333886. DOI: 10.1177/16094069251333886
Odacioglu E.C., Zhan L. & Allmendinger R. (2022). *Combining topic modeling with grounded theory: Case studies of project collaboration. arXiv preprint arXiv:2207.02212*.
O'Grady C. (2025). AI-generated' participants' can lead social science experiments astray. *Science*, 390(6769). DOI: 10.1126/science.z232cbo
Orlikowski W.J., & Scott S.V. (2008). 10 sociomateriality: challenging the separation of technology, work and organization. *Academy of Management annals*, *2*(1): 433-474. DOI: 10.1080/19416520802211644
Pachidi S., Berends H., Faraj S., & Huysman M. (2021). Make way for the algorithms: Symbolic actions and change in a regime of knowing. *Organization Science*, 32(1): 18-41. DOI: 10.1287/orsc.2020.1377
Page M.J., McKenzie J.E., Bossuyt P.M., Boutron I., Hoffmann T.C., Mulrow C.D., ... & Moher D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *bmj*, *372*. DOI: 10.1136/bmj.n71
Pillai, S.D., Goldfarb, B., & Kirsch, D. (2024). Lovely and likely: Using historical methods to improve inference to the best explanation in strategy. *Strategic Management Journal*, 45(8): 1539-1566. DOI: 10.1002/smj.3593

Raisch S., & Krakowski S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of management review*, 46(1): 192-210. DOI: 10.5465/amr.2018.0072

Sapkota R., Roumeliotis K.I., & Karkee M. (2025). Ai agents vs. agentic ai: A conceptual taxonomy, applications and challenges. *Information Fusion*, 103599. DOI: 10.1016/j.inffus.2025.103599

Snyder H. (2019). "Literature review as a research methodology: An overview and guidelines", *Journal of Business Research*, 104: 333-339. DOI: 10.1016/j.jbusres.2019.07.039

Stake R.E. (1995). *The art of case study research*. Sage.

Welch C., Piekkari R., Plakoyiannaki E., & Paavilainen-Mäntymäki E. (2019). Theorising from case studies: Towards a pluralist future for international business research. In *Research methods in international business* (pp. 171-220). Cham: Springer International Publishing.

Welch C., Paavilainen-Mäntymäki E., Piekkari R., & Plakoyiannaki E. (2022). Reconciling theory and context: How the case study can set a new agenda for international business research. *Journal of International Business Studies*, 53(1): 4-26. DOI: 10.1057/s41267-021-00484-5

Yang J., Amrollahi A., & Marrone M. (2024). Harnessing the potential of artificial intelligence: affordances, constraints, and strategic implications for professional services. *The Journal of Strategic Information Systems,* 33(4): 101864. DOI: 10.1016/j.jsis.2024.101864

Yin R.K. (2018). *Case study research and applications* (Vol. 6). Sage.