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Beyond the GenAI hype: a framework for Generative AI in business

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Abstract
The use of Artificial Intelligence (AI), and more recently the rise of Generative AI (GenAI), is fundamentally transforming businesses. This study explores the emerging role of GenAI in business, identifying and analyzing concrete use cases from business practice. Despite recent growth, research on GenAI in business is still in its infancy and lacks comprehensive foundational studies for understanding the phenomenon. To address this gap, the study's objective is to organize the landscape of GenAI use cases in business, enabling theory building, while also offering practical insights for managers. To achieve this objective, a scoping review was conducted, collecting 680 real-world use cases of GenAI in business from both academic and non-academic sources. This sample was analyzed using an inductive concept development approach. First, a typology was developed, providing an understanding of six main types and 21 subtypes organized along two dimensions: existing business enhancement and new business enablement. Second, a framework was derived, extending the typology by mapping the configuration of human-AI collaboration in each subtype, showing how GenAI is assisting, augmenting, or automating business activities. Overall, this study provides a comprehensive typology and application framework for the growing academic discussion and equips practitioners with guidance on navigating and deploying GenAI within organizations.

Keywords Generative Artificial Intelligence · Generative AI · GenAI · Business applications · Business use cases · Business model innovation · Scoping review

JEL Classification O33 · L25 · M15 · O31

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1 Introduction

While Artificial Intelligence (AI) has been applied in various domains for many years, the emergence of Generative Artificial Intelligence (GenAI) is widely regarded as a breakthrough in AI in business and society due to its powerful capabilities. GenAI excites a broad audience with its ability to autonomously generate text, images, and other content (Davenport and Mittal 2022; Sengar et al. 2024). OpenAI's introduction of ChatGPT, an intuitive user interface for interacting with GenAI in 2022, marked a defining shift in how AI technologies are perceived and accessed by the public. ChatGPT's rapid adoption, reaching one million users within five days and 100 million monthly users in just 2.5 months (OpenAI, 2022; Perez 2025), illustrates GenAI's global scale and impact.

The emergence of GenAI has significantly intensified the discourse around the implementation of AI across business and academia, especially on the impact of GenAI on Business Model Innovation (BMI). The technological advancement of GenAI in business is seen as a driver to transform and create new business models, including new processes, ways of working, and customer interactions and experiences (Kanbach et al. 2024). GenAI can be seen as a catalyst for BMI, changing the way value is created, offered, and captured (Clauss 2017; Kanbach et al. 2024). In line with the broader discourse on technology adoption and business outcomes, Kallmuenzer et al. (2024) argue that an intelligent adoption of new technologies increases a firm's likelihood of securing a competitive advantage within its industry. Similarly, D'Angelo et al. (2026) demonstrate how AI shapes entrepreneurial learning and new venture creation, highlighting the broader transformative potential of AI technologies across different business contexts.

Yet, as GenAI is a very recent phenomenon, businesses currently lack practical guidance for its intelligent adoption, and academic research on GenAI in business remains in its infancy. According to Carlile and Christensen (2005), a novel research field such as GenAI in business requires foundational studies that collect and organize scattered observations about the phenomenon into an understandable structure, thereby making it tangible for scholars and enabling theory development in that field. Accordingly, many case studies have emerged (e.g., Brown et al. 2024; Cognizant, 2023; Microsoft, 2024a), alongside a small number of studies that classify GenAI use cases in business (e.g., Singh et al. 2024; Malik-Kozlowska & Kozlowski, 2025). Yet, existing research remains fragmented and conceptually heterogeneous. Prior classification efforts are predominantly deductive or case-based and typically structure GenAI applications along a single dominant dimension, such as application domain, organizational function, or industry. While these approaches provide useful structure within their respective lenses, they offer limited integrative guidance for organizing GenAI applications across organizational activities.

This study addresses this research gap through two primary contributions: (1) a typology that provides a comprehensive and structured overview of GenAI applications in business, and (2) a framework that characterizes human-AI collaboration across these application types to illustrate the extent to which GenAI disrupts established business processes. The research is guided by the question: *What are the use cases of Generative Artificial Intelligence in business, and how can they be organized* *into a typology?* To answer this question, the study conducts a scoping review following Arksey and O'Malley (2005) and Peters et al. (2021) to identify GenAI use cases across academic and non-academic sources. We analyze and synthesize the identified use cases into an inductively developed typology that provides a structured framework for organizing the landscape of GenAI applications in business. The typology establishes a shared conceptual vocabulary that enables systematic comparison, supports the identification of GenAI adoption patterns, and facilitates cumulative theory building in GenAI research.

2 Literature basis and conceptual background

2.1 Generative Artificial Intelligence in business

Understanding the core technologies behind GenAI provides the foundation for examining its use in business. GenAI refers to complex machine learning models using deep neural networks, called "generative models", that can produce novel human-like content, including but not limited to text, code, images, audio, video, or three-dimensional models (Fui-Hoon Nah et al. 2023). These generative models learn patterns in data and use this knowledge to generate new, synthetic content (Sengar et al. 2024). A wide range of generative models emerged over time, differing in both output modality and architectural design. While unimodal models process and generate the same type of data, such as text-to-text generation, multimodal models can handle and produce outputs across multiple data types, such as text-to-image generation (Feuerriegel et al. 2024). Different architectural designs of generative models exist that differ in their way of working and their capabilities with the most prominent being Generative Adversarial Networks, Variational Autoencoders, Diffusion Models, and Transformer-based Models (Sengar et al. 2024). The introduction of the Transformer architecture by Vaswani et al. (2017) and later Large Language Models (LLMs) marked the breakthrough of GenAI, which initiated a new era of AI development with novel applications (Fui-Hoon Nah et al. 2023; Sengar et al. 2024). While LLMs were originally designed for understanding, generating, and analyzing texts, recent advancements have expanded their scope beyond language. These multimodal LLMs, such as GPT or Gemini, can process and generate output across multiple data modalities, such as images or audio (Google, n.d.; OpenAI, n.d.). The rise of generative models, particularly LLMs, has led to the emergence of an entire ecosystem that encompasses both an infrastructure and an application layer. This infrastructure layer includes companies providing the computational power to train and run generative models, as well as developers of LLMs, such as OpenAI, Anthropic, Google, Amazon, and Meta (Banh and Strobel 2023; Samila and Berrone 2023). The application layer comprises firms creating use-specific applications that make GenAI technology accessible and practical for individuals and professionals across business, education, and healthcare (Fui-Hoon Nah et al. 2023). While 2023 was the year businesses first discovered GenAI and experimented with its capabilities, 2024 marked the start of large-scale implementation and value generation from its use cases (Singla et al. 2024). For instance, Davenport and Bean (2024) describe how a financial service

Table 1 Comparative review of existing literature on the application of Generative AI in business. (Source: Own illustration)

Authors and year	Type and publication body	Research-approach	Sample size	Classification (Yes / No)	Dominant classification dimension	Typology development	Classification results
Sengar et al. (2024)	Journal article in *Multimedia Tools and Applications*	Systematic literature review	< 10	Yes (Deductive)	By application domain	No	Image translation, video synthesis, NLP, and specialized tasks like knowledge graphs and fault detection.
Prahl (2023*)*	Journal article in *FH Wedel*	Systematic literature review	< 25	Yes (Deductive)	By organizational functions	No	Marketing & Sales, Operations Management, HRM, IT & Software, Finance Management, Product R&D, Employee Utilization
Kanbach et al. (2024)	Journal article in *Review of Managerial Science*	Case study analysis (for use cases only; scoping review used for primary objective)	< 10	No (Individual cases)	N/a (Individual cases organized by industry)	No	N/a (But organized by industry: Software engineering, Healthcare, Finance)
Malik-Kozłowska and Kozłowski (2025*)*	Journal article in *Scientific papers of Silesian University of Technology*	Systematic literature review (including grey literature review) & Qualitative content analysis	< 10	No (Individual cases)	N/a (Individual cases organized by industry)	No	N/a (But organized by industry: Insurance, finance, creative industries, retail, and media)

Table 1 (continued)

Authors and year	Type and publication body	Research-approach	Sample size	Classification (Yes / No)	Dominant classification dimension	Typology development	Classification results
Kar et al. (2023)	Journal article in *Glob J Flex Syst Manag*	Systematic literature review (including grey literature review)	<25	No (Individual cases)	N/a (Individual cases organized by organizational functions and industry)	No	N/a (But organized by business unit: financial management, marketing & sales management, operations management, supply chain and logistics management, human resource management, strategic management); and industry: e-commerce, education, healthcare, infrastructure & construction, hospitality
Singh et al. (2024)	Journal article in *Journal of Innovation & Knowledge*	Structural topic modeling (Patent text documents)	2,400	Yes (Inductive)	By application domain	Indirect (structured, but no typology proposed)	Object detection and identification, medical applications, intelligent conversational agents, image generation and processing, financial and information security applications, cyber-physical systems
Krause et al. (2024)	Conference Paper in *DS 133: Proceedings of the 35th Symposium Design for X(DFX2024)*	Scoping review	<25	Yes (Deductive)	By application domain	No	Requirements, Planning, Development, Production, Sales, Operation (in Product Management)

Table 1 (continued)

Authors and year	Type and publication body	Research-approach	Sample size	Classification (Yes / No)	Dominant classification dimension	Typology development	Classification results
This study	Journal article in *Review of Managerial Science*	Scoping review + Inductive concept development approach	680	Yes (Inductive)	By organizational value dimension	Yes	Workforce productivity boost, core process enhancement, support process enhancement, Innovation acceleration, Customer offering innovation, Business decision-making support

company applies GenAI across software engineering, customer service, knowledge management, and employee sentiment analysis, illustrating the breadth of emerging applications in practice and how GenAI can affect different organizational activities. Complementing this perspective, Brynjolfsson et al. (2025) report productivity gains associated with GenAI, for example, in customer service operations. However, beyond the ongoing GenAI hype, several sources indicate that many firms continue to face difficulties in systematically translating GenAI's potential into practice (Li et al. 2025; Rosenbush 2025). Moreover, the integration of GenAI into the workplace raises important questions about its psychological impact on employees, including effects on job satisfaction (Zahs and Schmodde 2026).

The current state of academic literature is scarce when it comes to foundational studies on the application of GenAI in business practice. Table 1 provides a comparative review of seven studies published between 2023 and 2025, indicating a small but growing body of studies on GenAI business use cases (e.g., Crumbly et al. 2024; Kar et al. 2023; Malik-Kozlowska and Kozlowski, 2025). Only a few prior studies attempt to derive an organizing structure for the phenomenon (e.g., Singh et al. 2024; Krause et al. 2024), and explicit typology development remains rare, particularly for organizing GenAI applications from a broader organizational perspective.

This limitation is primarily rooted in methodological and conceptual patterns in prior classification efforts. Methodologically, existing studies often rely on small, context-specific samples and predominantly apply deductive methods or draw on case-based evidence. These approaches can yield useful structure within their respective contexts, but they offer limited leverage for deriving a typology intended to organize GenAI applications across organizational activities and business settings. Although Singh et al. (2024) employ an inductive approach based on a large dataset, their resulting structure primarily organizes GenAI use cases by application domain rather than offering an explicitly articulated typology. Conceptually, prior work typically structures GenAI applications along a single dominant dimension, for example, by application domain (e.g., Sengar et al. 2024), organizational function (e.g., Prahl

2023), or industry (e.g., Kanbach et al. 2024). While such lenses provide a valuable initial structure, they adopt single-dimensional perspectives and lack an integrative organizing logic. As a result, existing classifications often remain partially overlapping and do not form mutually exclusive or collectively exhaustive frameworks (e.g., Prahl 2023; Malik-Kozlowska and Kozlowski, 2025), limiting their usefulness as a shared analytical reference across business contexts.

Addressing this gap, our study develops an integrative, empirically grounded typology that emerged inductively from the systematic analysis of a large set of GenAI use cases. By embedding previously separate classification lenses within a unified, value-oriented organizational framework, the typology establishes a shared conceptual vocabulary that may enable systematic comparison, identification of adoption patterns, and cumulative theory-building in GenAI research.

2.2 Business model innovation and technological progress

Business models are subject to continuous change and are inherently unstable. Environmental disruptions, such as rapid technological advancements, frequently force companies to innovate their business models (Kraus et al. 2022b). BMI is understood among scholars as the design, implementation, and maintenance of a firm's core logic for creating, delivering, and capturing value (Kraus et al. 2020). A variety of conceptual models have been proposed to describe BMI. One of the recent models capturing the latest findings on BMI dimensions was developed by Clauss (2017). This model has been selected as the conceptual basis for this study as it integrates widely accepted concepts of BMI. According to Clauss (2017), BMI consists of three interrelated dimensions: value creation innovation, value proposition innovation, and value capture innovation. This framework allows for a structured analysis of how firms innovate their business models in response to changes in their environments. While the level of innovation may vary across dimensions, effective BMI typically entails changes in all three dimensions (Clauss 2017; Kraus et al. 2022c).

The rapidly changing technological landscape is shrinking the lifespan of any kind of business model and forcing companies to continuously adapt their configuration of activities and components to relevant technological advances to maintain or improve their competitive edge (Kanbach et al. 2024). Scholars see technological advancement as a catalyst for BMI, providing companies with opportunities to adapt their current business models, but may, sooner or later, push companies to adopt the emerging technology to remain competitive (Lee et al. 2019). The impact of technology on BMI is a topic that is gaining popularity in the academic discourse. For example, Kraus et al. (2022c) explore BMI with the introduction of the metaverse. In their study, they highlighted that technology is the main driver for change in the value creation of Meta's business model (Kraus et al. 2022c). Another example is the study by Kanbach et al. (2024) on the impact of GenAI on BMI, projecting how GenAI will transform and create new business models. More recently, Schleth et al. (2026) demonstrate how AI drives BMI specifically in service industries, further substantiating the link between AI adoption and business model transformation.

3 Methodology

3.1 Research design

Following the descriptive theory-building process outlined by Carlile and Christensen (2005), this study adopts an inductive research design to systematically observe and organize the phenomenon of GenAI applications. We employed the scoping review methodology (Peters et al. 2021) for systematic use case collection and an inductive concept development approach following Gioia et al. (2012) for data structuring and pattern identification, enabling the development of a typology for GenAI business use cases. Scoping reviews share the methodological rigor and systematic approach of systematic literature reviews. However, they extend the scope by including diverse non-academic sources, such as grey literature, to provide a comprehensive overview of a novel phenomenon like GenAI in business. This wider coverage is especially important in a nascent research field, where evidence may not yet be captured by peer-reviewed research (Arksey and O'Malley 2005; Kraus et al. 2022a; Peters et al. 2021). Studies such as Brenk et al. (2025) about Metaverse applications in business demonstrate that scoping reviews are well-suited for examining rapidly evolving technologies for which academic literature is limited, and evidence is scattered. Scoping reviews generally allow for flexible adaptation of the process according to the research objective (Peters et al. 2021). Given the expected breadth of data and the target of deriving a typology inductively, the scoping review is augmented with a qualitative content analysis following Gioia et al. (2012), which supports the identification of emerging patterns and the systematic organization of collected evidence into a structured overview of GenAI business use cases. While this approach has been adopted in other novel research fields (e.g., Hoffmann et al. 2024), this study is the first to apply it to the research field of GenAI in business. Kraus et al. (2022a) recommend that high-quality review articles follow a systematic selection and data analysis process that is reproducible, well-evidenced, and transparent, ensuring a sample that includes all relevant and appropriate studies. Therefore, the research was conducted and reported in accordance with the PRISMA-ScR protocol (Arksey and O'Malley 2005).

3.2 Data collection

Following Peters et al. (2017), the scoping review is designed to be as comprehensive as possible, within the constraints of time and resources, to achieve broad coverage of GenAI business use cases. Therefore, a two-pillar data collection approach was implemented, including (1) an academic source pillar to capture peer-reviewed research and (2) a non-academic source pillar to capture evidence that is not yet addressed by academia. The search strategy was designed to yield a broad yet manageable set of studies that align with the research question (Arksey and O'Malley 2005). To maintain a coherent search strategy across sources and considering the individual particularities of each search pillar, the search strategies are designed to always include three key parameters of the research question: "GenAI", "use cases", and "business".

The first search pillar focuses on capturing academic sources. Therefore, two commonly used databases were selected, EBSCOhost and Web of Science, following comparable studies in the field of technology application in business (e.g. Brenk et al. 2025). Both databases were searched for the defined keywords within either title or abstract. Adopting the multi-step search strategy proposed by Peters et al. (2020), the search string was iteratively refined until the preliminary results adequately reflected the research question. Following three iterations of review and refinement, the final search string used for data collection across both databases was: *"GenAI" OR "Generative Artificial Intelligence" AND "use case*" OR "case stud*" OR "application*" AND "business*" OR "compan*" OR "industr*" OR "corporate*" OR "enterprise*"*. The search was limited to the publication stage to "only peer-reviewed articles" since this data collection pillar targets academically rigorous articles. As recommended for scoping reviews, we explicitly considered Languages Other Than English and included studies published in English and German (Wang and Moody 2025). We included English as it is the dominant publication language in leading management journals (PJIP, n.d.). Further, we included German to broaden the scope of the review and capture relevant regional and practitioner-oriented contributions that may not be published in English. The research team's proficiency in both languages ensured accurate comprehension and critical evaluation of the included studies. As a result, 362 records were exported, including 234 records from EBSCOhost and 128 records from Web of Science. Before screening, all records were filtered for duplicates, resulting in the removal of 60 entries. Consequently, 302 peer-reviewed academic records were included for further screening (see Fig. 1).

Public stock indices were consulted to provide a comprehensive overview of the global economy, offering diverse enterprises with a wealth of publicly available information. The NASDAQ-100 was chosen for its representation of the top 100 publicly traded companies across industries and its manageable number of companies to investigate, given the research project's time and resource restraints. The English version of each company's website, preferably the U.S. regional site, for companies listed on the NASDAQ-100 as of May 2, 2025, was examined. The search strategy for company publications followed a structured and consistent three-step approach: (1) employing website search functions where available, (2) examining key sections such as "Newsroom," "Press Releases," "Blogs," "Resources," and "Customer Success Stories" utilizing section-specific search functions when present, and (3) reviewing dedicated GenAI content hubs, such as those maintained by Adobe (e.g., Adobe, n.d.). Company websites were searched from May 15 to May 18, 2025. The search string focused on "GenAI" and its synonyms, with no additional terms applied, as company publications already provide contextual use cases. The search strategy yielded 62,008 records, reflecting the total number of hits on each company's website across publications of 39 companies. Due to time and resource constraints, duplicate removal and screening were conducted on the website results, and only eligible, non-duplicate sources were exported (see Fig. 1).

Prioritizing breadth over depth in the initial search, many irrelevant studies were likely captured, as reflected in the high number of non-academic records. The selection process of studies is transparently documented in the PRISMA-ScR flowchart in Fig. 1 (Elm et al. 2019; Tricco et al. 2018). Applying inclusion and exclusion criteria aligned with the study's research objective (Peters et al. 2020; Tricco et al. 2018), only studies detailing GenAI use cases with sufficient empirical business context and depth were included. In total, 61,941 records were removed. Most non-academic sources were removed for not focusing on specific use cases, such as theoretical explanations of GenAI or overly technical content. Screening title and abstract first, and the full text of the remaining records, resulted in a total of 404 records to be included in the final sample, thereof 49 academic and 355 non-academic sources. Since one source could include multiple use cases, all use cases that were eligible for inclusion were extracted for the final sample. Each entry in the sample represents a unique use case with its respective empirical reference. The final sample included 680 use cases with empirical references (see Fig. 1).

3.3 Data analysis

The sample was analyzed in two ways. First, the sample's descriptive characteristics were examined to contextualize the findings, account for potential biases, and provide an overview of the landscape of GenAI use cases at the time of data collection. Second, a thematic analysis was performed, using an inductive concept development approach to identify emerging patterns that describe GenAI in business in an understandable way (Levac et al. 2010).

3.3.1 Descriptive overview

The share of use cases originating from academic sources versus non-academic sources is 14% to 86%. The split highlights that academia in this field is still in its infancy even though empirical evidence exists, supporting our study's purpose. Use cases, originating from academic sources, are all journal articles. The phenomenon at hand is most represented in journals that deal with General & Strategic Management, and Innovation, Technology, and Entrepreneurship. Use cases, originating from a non-academic source, are from web publications of companies. The top ten publishing companies are from the information technology sector and contribute 85% of all the non-academic use cases. The top three companies, contributing the most use cases to this study's sample, are Microsoft, Google, and Amazon. The use cases included in the sample were published between 2021 and 2025, while the majority of use cases were published in 2024. Following the Morgan Stanley Capital International's (MSCI, n.d.) standard sector- and industry classification framework, GICS, a large share of the use cases (45%) come from the Information Technology sector, with industries like Software & Services, followed by Consumer Discretionary (24%), referring to industries like Retail, and Communication Services, such as Media and Entertainment industries (16%). 84% of all use cases originate from enterprises, while 12% are from start-ups & SMEs. Use cases are distributed among 15 business areas. However, many use cases are not department-specific (16%). Business areas that are strongly represented in this study's sample are product (design), marketing, e-commerce, and customer service.

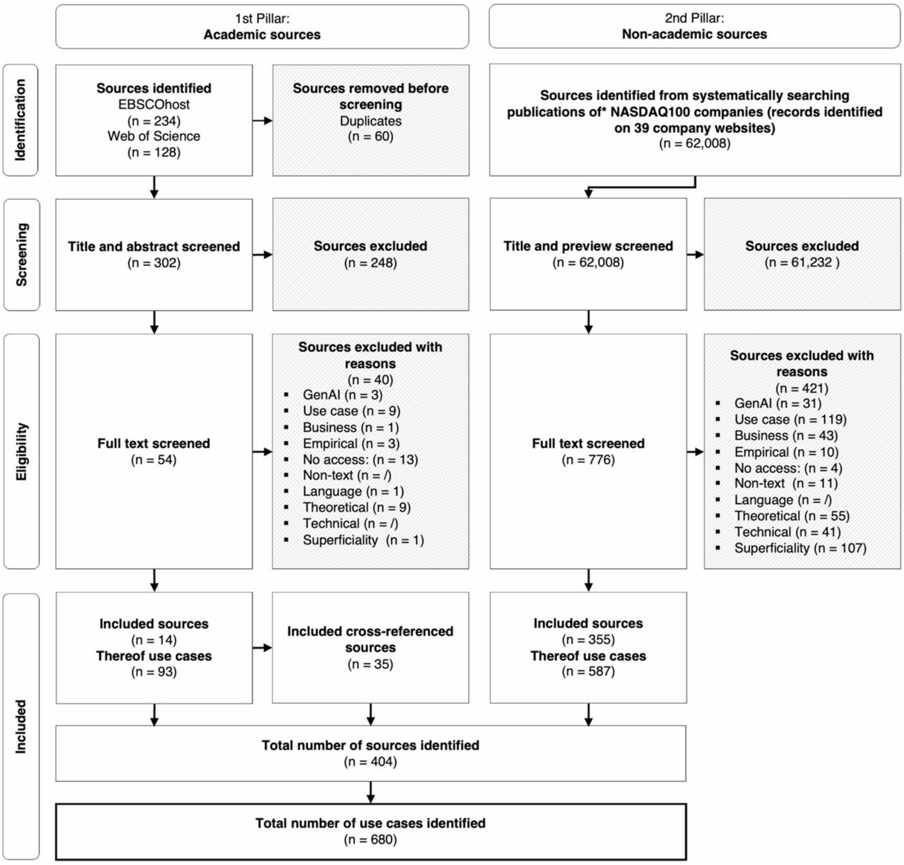

Fig. 1 PRISMA-ScR Diagram Reflecting Data Selection Stages. (Source: Own illustration, following Tricco et al. (2018)

3.3.2 Thematic overview

Following an inductive concept development approach, this study employed Gioia et al.'s (2012) pattern-inducing technique. Using this method, the data sample was organized into a data structure consisting of 1st order concepts, 2nd order themes, and aggregated dimensions. This structure not only facilitates clear communication of the study's findings but also demonstrates methodological rigor in line with qualitative research standards (Gioia et al. 2012). The 1st order concepts remain closely aligned with the "informant terms," reflecting the language and context of the original use cases (e.g., "Customer case resolution advisory"). We derived the concepts from the use case descriptions and iteratively refined them during the coding process. Initially, this resulted in a relatively large number of concepts, which were further refined and abstracted as the analysis progressed (Gioia et al. 2012). The construction of the 2nd order themes was guided by the objective of identifying patterns that explain GenAI use cases in business in an understandable way. We generated themes iteratively by moving back and forth between 1st order concepts and a more abstract analytical perspective (Charmaz 2014). The formation of 2nd order themes was guided by two analytical questions: (1) Which business area (e.g., "Customer Service") or activity (e.g., "Business Communication") is affected by GenAI across organizational contexts? (2) What novel capability (e.g., "Conversational Products") or form of value creation (e.g., "Marketing acceleration") does GenAI enable within this area? The 2nd order themes were subsequently consolidated into overarching types, analytically grounded in a BMI perspective, thereby forming a comprehensive typology of GenAI use cases in business. To enhance methodological rigor, the lead researcher conducted the primary coding. At each stage of the analysis, at least one additional member of the research team independently reviewed and critically challenged the emerging codes and category structure. We discussed all coding decisions and interpretations in iterative meetings and refined them jointly until the research team reached consensus. This procedure strengthened the intersubjective reliability of the coding process, reduced individual interpretive bias, and ensured a shared understanding of the resulting data structure.

Figure 2 shows the final data structure, which organizes the use cases of the study's sample into 91 1st order concepts, which are consolidated into 21 2nd order themes and grouped into six aggregated dimensions. The aggregated dimensions reflect the types, and the 2nd order themes represent the subtypes, of a comprehensive GenAI business use case typology.

4 Results

4.1 GenAI business use case typology

This study organizes 680 use cases into six main types and 21 subtypes with guiding questions clarifying boundary conditions and supporting consistent classification (see Fig. 3). There are six main types structured along two dimensions. One dimension comprises three types focused on enhancing existing business operations (inward-looking), whereas the other comprises three types focused on enabling new business opportunities (forward-looking). Each main type comprises several subtypes that cluster related use cases. The following sections describe each type and its subtypes in detail.

4.1.1 Type 1: workforce productivity boost

Workforce Productivity Boost is the second most represented type in the sample based on its share of use cases. It focuses on improving overall employee productivity by addressing essential, organization-wide activities, such as collaboration and skill development, which apply to all employees regardless of their role. GenAI boosts productivity by automating routine tasks and freeing up time for higher-value activities, thereby enhancing value creation and strengthening value propositions that drive growth and competitiveness.

Workforce Productivity Boost comprises four subtypes: two enhance workforce collaboration and two strengthen employees' capabilities. *Business Communication*

Management addresses use cases in which GenAI enhances collaboration by facilitating business communication. GenAI can support tasks such as transcribing meetings, translating messages, and sorting communication. Apple's Mailbox feature, for example, is designed to prioritize time-sensitive emails in the inbox, helping users manage their work tasks efficiently (Apple, 2025). GenAI also facilitates business communication by summarizing key points and suggesting responses. For instance, Localiza & Co. uses GenAI to support crisis management by summarizing and generating reports from meeting discussions (Microsoft, 2024h). Atlassian (2024), on the other hand, leverages GenAI to suggest comments for employees to add to the communication history in software or service tickets. *Business Content Management* includes use cases where GenAI eases collaboration through simple interactions with any type of business content. GenAI adds value by extracting insights from workplace documents and generating new content. For example, Workday's software uses GenAI to support employees in drafting internal news articles based on insights from new company policies (Workday, 2023). Additionally, an example from Softchoice illustrates how GenAI can reduce the time required to create training content for their sales department (Microsoft, 2024k). *Knowledge Discovery & Management* covers use cases where GenAI enhances employees' capabilities by streamlining access to relevant information and expertise. GenAI enables organizations to process vast amounts of information and to make it easily accessible for their employees. For example, Box uses GenAI to automatically label content, enabling easier knowledge discovery (Google, 2023b). Also, GenAI facilitates context-specific knowledge delivery through conversational interfaces. For example, E.ON uses a copilot that provides employees with relevant facts and figures needed for creat-

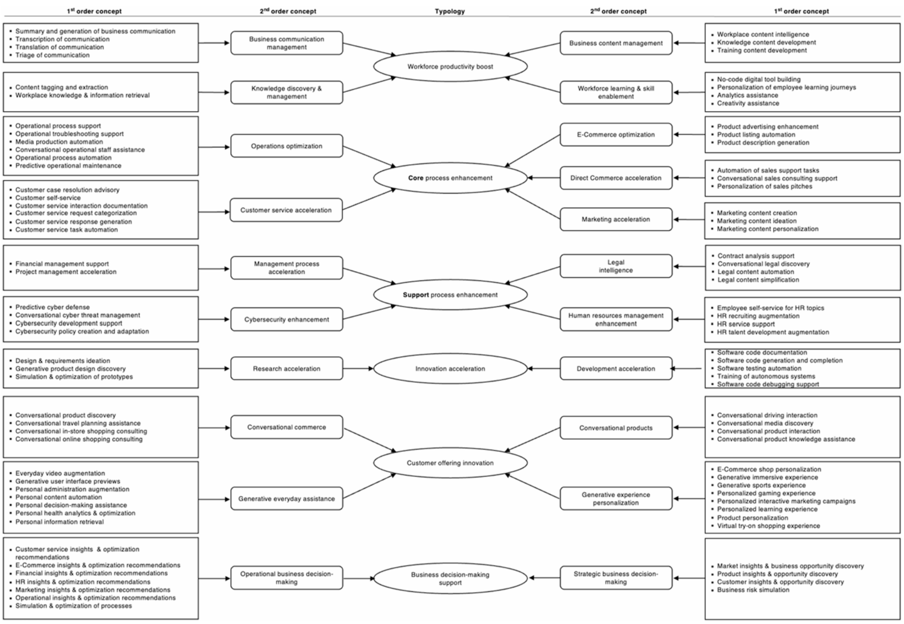

Fig. 2 Data Structure of the Sample. (Source: Own illustration following Gioia et al. (2012)

ing presentations (Microsoft, 2024g). *Workforce Learning & Skill Enablement* comprises use cases in which GenAI supports personalized learning through adaptive learning journeys tailored to individual needs. Beyond learning, GenAI augments employees' cognitive abilities by assisting with creativity and analytical thinking. La Poste, for instance, uses AI to support the brainstorming process of their employees, while intelligent captioning features in Adobe tools help employees quickly interpret data visualizations in reports (Adobe, 2023; Microsoft, 2025e). Moreover, GenAI empowers employees to build digital tools without prior coding experience. Atlassian, for example, allows employees to create their own service desks, while Amazon Q Business enables employees to build GenAI-powered apps by simply describing their intended functionality in natural language (Amazon, 2024a; Atlassian, 2025).

4.1.2 Type 2: core process enhancement

Core Process Enhancement is the most represented type of use cases. This type captures use cases that address primary activities within a firm's value chain, such as logistics, marketing, commerce, and customer service, which are central to the firm's business model. Here, GenAI strengthens existing core processes, improving how businesses create, deliver, and capture value.

Core Process Enhancement includes five subtypes, each of which targets a specific area of the value chain. They can be grouped into subtypes that either improve process efficiency or enhance the quality of process outcomes. *Operations Optimization* incorporates GenAI use cases that support or automate various operational processes to improve process efficiency. For example, Air India uses GenAI to automate pilot briefings, and DHL augments computer vision with GenAI to count inventory and parcels for improving logistics operations (Cognizant, 2023; Brown et al. 2024). In addition, operational staff benefit from conversational copilots that support a wide

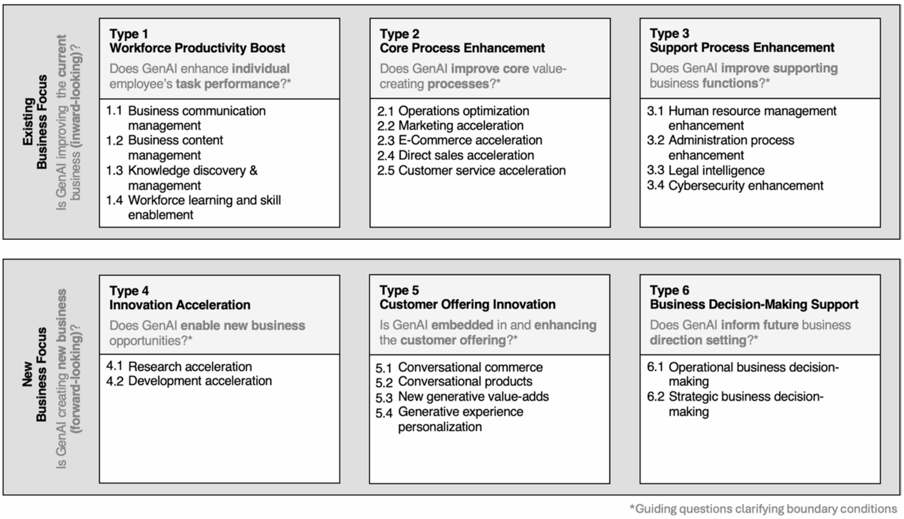

Fig. 3 GenAI Business Use Case Typology. (Source: Own illustration)

range of tasks and queries. At Schaeffler, operational staff use a conversational agent to access key performance metrics, such as yields and scrap rates, or to generate reports detailing the impact and root causes of downtime (Microsoft, 2024j). Additionally, this subtype includes use cases related to production processes. Media production was the most common example in this sample. For example, Amper Music produces music with GenAI (Kar et al. 2023). Moreover, this subtype covers use cases in which GenAI supports predictive maintenance and operational troubleshooting. In the context of operational troubleshooting, Siemens, for example, uses GenAI to provide staff with repair instructions to streamline the troubleshooting process (Microsoft, 2023b). For *Customer Service Acceleration* use cases, most applications focus on improving process efficiency through automated categorization of service requests, task automation, interaction documentation, and customer self-service solutions. One example of customer self-service is TOBi, Vodafone's virtual agent, which assists customers with tasks such as bill payments or resolving network-related issues (Microsoft, 2025c). However, other use cases focus primarily on improving service quality. These include tools that help agents resolve customer issues or generate responses, as seen in customer relationship management products from Salesforce (2023) and Microsoft (2024e). *E-Commerce Optimization* focuses primarily on use cases in digital sales channels that optimize process efficiency. These use cases involve automating product listing processes, generating engaging product descriptions, and creating advertising content using GenAI. For example, Amazon has introduced several GenAI-powered tools in recent years to support merchants. These tools include features like "Enhance My Listings" and "A+," which streamline e-commerce tasks. Complementary to this, another group of use cases emerges in the context of direct commerce, which is characterized by offline sales conducted through interpersonal engagement rather than digital channels. *Direct Commerce Acceleration* use cases aim to improve the quality of sales team activities by enabling personalized sales pitches and enhancing sales consulting capabilities with a conversational sales assistant. For instance, at AlpiTour, in-store travel consultants are assisted by a copilot that helps them extract and organize information to consult customers with travel planning (Microsoft, 2024d). This subtype also includes use cases where sales support tasks, such as creating quotations, are automated. *Marketing Acceleration* use cases employ GenAI primarily to improve outcome quality. This category includes use cases in which GenAI supports marketing teams by helping them generate ideas, create content, and personalize it. For example, The Coca-Cola Company uses GenAI to personalize and scale advertising copy, images, and messages across channels while maintaining brand consistency (Brown et al. 2024).

4.1.3 Type 3: support process enhancement

Unlike the second type, *Support Process Enhancement* focuses on support processes rather than core processes. This type includes use cases that address secondary activities within a firm's value chain. These activities encompass human resources, legal services, cybersecurity, and other administrative functions. For this type, GenAI augments support processes, improving both the quality of outcomes and operational efficiency. Here, GenAI strengthens support functions within the existing business, indirectly enabling value creation while directly improving value capture through the restructuring of costs.

Support Process Enhancement consists of four subtypes, each addressing a different support function. It is important to note that these subtypes reflect the use cases found in this study's sample and are not intended to be collectively exhaustive for all support functions in typical value chains, as described in Porter's (1985) model. This reflects the inductive nature of this study. *Human Resources Management Enhancement* includes use cases where GenAI supports human resources (HR) managers in areas such as recruiting, talent development, and employee services. For instance, the startup Careeryze predicts career development paths and suggests proactive actions to help keep employees engaged (Careeryze, n.d.). GenAI also enables employee self-service for HR-related inquiries, reducing the cost for HR service managers of handling repetitive requests. Ernst and Young, for example, introduced a GenAI chatbot that answers payroll questions for employees across global offices (Microsoft, 2023a). *Legal Intelligence* encompasses use cases where GenAI supports legal professionals by analyzing legal documents and simplifying complex content. For example, the AI startup Harvey assists legal experts in summarizing, comparing, and reviewing documents for completeness and inconsistencies (Microsoft, 2024a). Similarly, Legal Robot translates complex legal language into plain, understandable text (Kar et al. 2023). GenAI also supports legal research and case discovery, along with the drafting of legal documents such as patents (Bui 2025). Moreover, Cybersecurity *Enhancement* includes use cases in which GenAI improves the efficiency of cybersecurity tasks. These use cases include supporting the creation of policies, developing cybersecurity mechanisms, and managing threats with the help of conversational assistants, as seen in offerings from companies like Fortinet (2024). In addition to increasing efficiency, GenAI enhances cybersecurity effectiveness by enabling predictive cyber defense. For instance, CrowdStrike (2023) uses GenAI to automatically prioritize and enrich incident data, enabling employees to focus on the most critical threats. Lastly, *Administration Process Enhancement* comprises use cases where GenAI supports administrative tasks such as improving financial management or accelerating project planning. For example, Adobe (2024) helps companies turn campaign briefs into project plans using GenAI.

4.1.4 Type 4: innovation acceleration

The fourth type, *Innovation Acceleration*, captures use cases where GenAI strengthens a firm's ability to innovate beyond existing business practices and offerings, which is a critical capability for adapting to rapidly evolving markets and securing future growth. While innovation can be seen as part of a firm's core processes, it is distinct in its forward-looking nature and focus on creating new value. Due to its strategic role in enabling long-term growth, it is treated as a separate category in this study's typology.

Innovation Acceleration consists of two subtypes, each demonstrating how GenAI improves the quality and speed of different stages in the innovation process. *Research Acceleration* includes use cases where GenAI accelerates the early stages of the innovation process. This involves supporting design and requirement definition, as well as enabling the simulation of prototypes to refine ideas before full development. For instance, KIA uses GenAI to assist industrial designers in creating new automotive designs, leveraging keyword prompts, reference materials, or hand-drawn sketches (Autodesk, 2024). GenAI also supports the discovery of innovative product concepts. PepsiCo, for example, uses it to experiment with new combinations of product characteristics. The development of a new Cheetos flavor was completed in just six weeks, which is significantly faster than the typical product development cycle of six to nine months (PepsiCo, 2024). *Development Acceleration* addresses use cases where GenAI speeds up and improves the quality of innovation development processes. In this study, these use cases primarily involve the generation and optimization of software. For example, Siemens uses GenAI to support engineers in programming industrial automation and robotic systems (Microsoft, 2023b). This subtype also includes use cases where GenAI powers the training of autonomous systems. For instance, the startup Wayve uses GenAI to generate synthetic training data that reflects realistic driving scenarios, which is used to train its autonomous driving software (NVIDIA, 2024a).

4.1.5 Type 5: customer offering innovation

The fifth type, *Customer Offering Innovation*, is the third most represented type in this study's sample. It includes use cases where GenAI empowers firms to rethink and expand what they offer to customers, from entirely new products and services to generative features that enhance existing offerings with added value. By enabling new customer offerings, GenAI enhances firms' value propositions and competitive advantages, positioning them to meet future market expectations as its adoption grows.

Customer Offering Innovation consists of four subtypes, three focused on enhancing existing offerings and one capturing use cases where GenAI enables entirely new added value. *Conversational Commerce* is composed of use cases in which GenAI introduces entirely new ways for customers to purchase products. It is particularly impactful in e-commerce, where it supports conversational product discovery and consultation. For example, Marriott allows customers to search for vacation accommodations using natural language (Marriott, 2024). Similarly, the startup Virbe uses GenAI to create digital avatars that help customers explore products and answer detailed questions while shopping online (Microsoft, 2024l). In consulting-intensive industries such as travel, GenAI enables a conversational travel planning experience. For instance, Booking offers an AI trip planner that helps customers plan their journeys (Booking, 2023). GenAI also enhances the in-store experience by guiding and assisting customers directly at the point of sale. For example, GoTrust uses GenAI in pharmacies to help customers locate products more easily (Qualcomm, 2025). *Conversational Products* includes use cases where GenAI enables new forms of interaction with a firm's products. This study's sample includes use cases where GenAI is enhancing product experiences in areas such as driving, media, and software. For example, Audi uses a GenAI-powered voice assistant that allows customers to control infotainment features and vehicle functions (Microsoft, 2024i). Similarly, GE Appliances uses GenAI to power its SmartHQ assistant, which guides customers regarding the use and maintenance of their home appliances through natural language interactions (Google, 2023a). *Generative Experience Personalization* covers use cases in which GenAI personalizes the customer experience for the user across areas such as online shopping, immersive attractions, sports, gaming, branding, learning, and consumer products. For example, Mattel allows fans to create personalized Barbie posters by uploading their own images, offering a new and engaging way to interact with the brand (Chan and Choi 2025). Other innovative examples include Xbox, which uses GenAI to dynamically generate game narratives based on player actions (Microsoft, 2023c), and Hypercinema, which creates immersive exhibition experiences tailored to each customer's interests (Microsoft, 2025d). *New Generative Value Adds* encompasses use cases where GenAI creates entirely new forms of value for consumers. These range from everyday camera augmentation and generative previews in consumer applications to personal health insights and optimizations. For example, Snap uses GenAI to translate content captured by the camera or provide directional instructions overlaid onto the camera view (Google, 2024a). GenAI also supports personal productivity by assisting with administrative tasks, enabling new forms of content creation, and helping consumers retrieve information or make decisions more easily. One example is Apple, which uses GenAI to let users extract personal information using natural language (Apple, 2025).

4.1.6 Type 6: business decision-making support

The sixth type, *Business Decision-Making Support*, encompasses use cases where GenAI assists employees in both operational and strategic decision-making. It does so by generating business insights, offering optimization recommendations, simulating scenarios, and identifying potential growth opportunities. Here, GenAI supports decisions that create value, strengthen the value proposition, and enhance value capture for future business growth.

Business Decision-Making Support consists of two subtypes, both aimed at supporting business decision-making, but each focused on a different time horizon and level of granularity. *Operational Business Decision-Making* includes use cases where GenAI provides insights and optimization recommendations across various core and support business functions to run the current business. These decisions are typically short-term to mid-term in focus and lead to operational adjustments. For example, Amazon uses GenAI to analyze customer feedback on post-purchase experiences, identify root causes of negative customer sentiment, and recommend improvements to address them (Amazon, 2024b). This subtype also contains use cases where GenAI simulates business processes to identify short to mid-term optimization potential. For example, SyncTwin creates digital factory twins to support scenario-based decision-making (NVIDIA, 2024b). *Strategic Business Decision-Making* covers use cases where GenAI supports the discovery of new business opportunities and the simulation of strategic risks. These decisions are mid- to long-term in focus and help define the future direction of the business. GenAI generates insights about markets, customers, and products, uncovering growth opportunities and informing strategic planning. For example, Google (2024b) uses GenAI in its products to provide geographic insights that support decisions such as selecting business locations. GenAI also helps simulate business risks under different scenarios, enabling firms to make proactive adjustments. For instance, Virgin Media O2 uses GenAI to produce risk reports related to new laws and compliance regulations, supporting timely business responses (Strategy Software, 2025).

4.1.7 Triangulation

To enhance the validity of the typology, Arksey and O'Malley (2005) recommend consulting external experts for triangulation. Accordingly, independent researchers without prior exposure to the study results tested the typology against randomly identified use cases beyond the study sample. First, Wirminghaus et al. (2025), writing in Capital magazine, reported two use cases: Commerzbank's customer self-service agent and Frankfurt Airport's flight preparation assistant. Researchers mapped the former to *Core Process Enhancement* with the subtype *Customer Service Acceleration* and the latter to *Core Process Enhancement* with the subtype *Operations Optimization*. Second, two randomly selected use cases from company websites were assessed. Skyscanner's (2023) AI route planner was mapped to *Customer Offering Innovation* with the subtype *Conversational Commerce*, while ParcelLab's (n.d.) AI-powered post-purchase personalization aligned with *Customer Offering Innovation* with the subtype *Generative Experience Personalization*. In all instances, the researchers assigned the use cases to the intended categories, confirming that the typology is mutually exclusive and collectively exhaustive.

4.2 GenAI business use case configuration framework

Whereas the *GenAI Business Use Case Typology* provides a structured overview of how GenAI is applied in business contexts, a complementary second dimension systematically categorizes the typology's 21 subtypes based on the configurations of human-GenAI collaboration. This second dimension highlights how the application of GenAI is reconfiguring business activities by capturing the level of human involvement versus the functional role of GenAI. Three configurations of human-GenAI collaboration are identified among the 21 subtypes: (1) GenAI assists humans in completing tasks, (2) GenAI augments human work, and (3) GenAI fully automates activities that were previously performed by humans.

The resulting *GenAI Business Use Case Configuration Framework* in Fig. 4 expands the typology by categorizing the subtypes according to these three configurations. This framework provides insight into how GenAI's role is realized across different use case types, thereby deepening the understanding of how GenAI creates value.

4.2.1 Configuration 1: assistance

The configuration *Assistance* refers to use cases that are predominantly driven by human actors, with GenAI playing a supportive role. It assists individuals by providing knowledge or insights that help them better execute their tasks. In this configuration, human involvement remains high, while the contribution of GenAI is relatively limited. For a limited number of subtypes, GenAI serves an assistive role. The use case subtypes share a common characteristic: They provide general or domain-specific insights and knowledge that enable humans in business to take action. GenAI is primarily assisting humans in contexts where decisions or actions may have significant consequences, such as in business decision-making or in the legal domain. For example, at Swisscom, GenAI is powering e.foresight, a tool that allows Swisscom employees to explore market trends in banking, which helps them to consider new strategies (MongoDB, n.d.). Another example is a study of legal professionals, which has shown that GenAI assists them in researching legal cases to prepare their litigation strategies (Chien and Kim 2024).

4.2.2 Configuration 2: augmentation

The *Augmentation* configuration covers use cases in which GenAI complements the work of humans to increase their efficiency, creativity, or other capabilities. This configuration reflects a balanced involvement of GenAI and human actors, emphasizing their shared contribution to business functions. The configuration *Augmentation* is the largest represented in this study's typology. It should be noted that in almost all use cases that focus on enhancing existing business operations (e.g., *Workforce Productivity Boost*, *Core and Support Process Enhancement*), GenAI is augmenting the work of human employees. In this context, GenAI is a team member, often referred to as Copilot, working in collaboration with human employees, partially taking over the execution of subtasks. For example, firms such as Amadeus and Raiffeisen Bank employ GenAI to draft emails, while retaining human oversight for the final decision to send them (Microsoft, 2024b, 2025b). Additionally, at Axa and La Poste, GenAI facilitates sub-tasks in the HR recruitment process, such as drafting job descriptions, evaluating resumes against predetermined criteria, and generating interview questions (Microsoft, 2024c, 2025e). Additionally, GenAI is accelerating the innovation process by augmenting the work of key research and development roles with extra creativity, analytical skill, and faster prototyping and delivery of ideas. Unilever exemplifies innovation augmentation. GenAI augments the research process for new hair products. This augmentation is taking place in two ways: first, through conversational search for new product components, and second, through the simulation of new product compositions (Microsoft, 2024f).

4.2.3 Configuration 3: automation

The configuration *Automation* covers use cases that are largely executed by GenAI with minimal human input. In this scenario, GenAI assumes the lead role, while human involvement is typically limited to oversight or control functions. This setup represents a high degree of automation with correspondingly low human participation. This study's sample demonstrates a limited number of use cases that are fully automated by GenAI. GenAI has the capacity to automate individual use cases within certain subtypes, such as operations, customer service & support, business functions, HR, and cybersecurity. However, it is important to note that this capability does not extend to all use cases within these subtypes. This suggests that GenAI

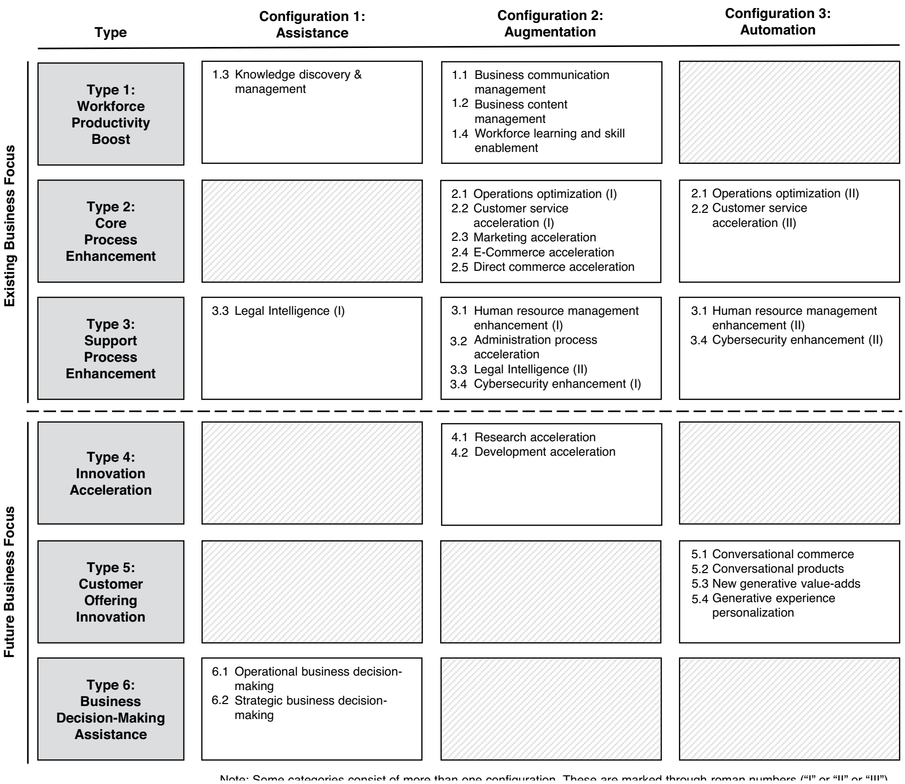

Fig. 4 GenAI Business Use Case Configuration Framework. (Source: Own illustration)

is currently unable to fully automate entire job profiles, although it holds potential for broader automation as the technology evolves. There are a few examples where GenAI automates individual use cases. For example, for Air India's customer service, GenAI is replacing the first-level customer service, automating the resolution of low-complexity customer requests. This covers 97% of their customer queries, while the remainder is referred to their customer service teams for resolution (Cognizant, 2023; Microsoft, 2025a). Workday's HR example demonstrates how GenAI facilitates the automated resolution of employee service requests, such as inquiries regarding policies or benefits (Workday, 2023).

5 Discussion

5.1 Contextualizing the results

Technological advancements in GenAI have led to the development of a broader ecosystem. Management research primarily focuses on the application layer of this ecosystem, where the technology is contextualized for specific use cases and made accessible to businesses and their customers. A review of prior studies reveals the breadth of GenAI business use cases but also the absence of a shared framework for understanding how GenAI is applied in business. By comprehensively collecting and organizing business use cases into the GenAI Business Use Case Typology, this study provides a structured perspective on the application of GenAI in business. The main types of the typology capture all use case patterns found in existing literature and extend beyond them, underscoring the comprehensiveness of the typology.

Technological advancements such as GenAI often serve as catalysts for BMI. Building on the typology, the *GenAI Business Use Case Configuration Framework* maps the configurations of human-GenAI collaboration and highlights how existing business model activities are reconfigured through GenAI. By assisting, augmenting, or automating activities in a business model, GenAI innovates value creation, value proposition, and value capture. This study advances research at the intersection of GenAI and BMI through the *GenAI Business Use Case Configuration Framework*. The framework structures GenAI business use cases and demonstrates how the application of GenAI leads to BMI. Its integration into the broader research landscape is illustrated in Fig. 5.

5.2 Contributions

Overall, this study contributes to both academia and business practice. From an academic perspective, the study makes two contributions to the emerging literature on GenAI in business. Specifically, it addresses a key limitation in the current literature: the absence of a shared, empirically grounded organizing structure that enables consistent cross-context comparison of GenAI applications.

First, the *GenAI Business Use Case Typology* provides a structured empirical basis for organizing GenAI applications in business. Building on a scoping review of 680 use cases, it synthesizes the identified GenAI applications into six main types and 21 subtypes. While prior classification efforts often rely on smaller, context-specific samples or single-lens schemes, our proposed typology provides a broader basis for cross-context comparison across business models and cumulative knowledge development. This also complements adjacent work developing systematic frameworks for AI applications in related domains, such as new product development (Vallé et al. 2026). Aligned with the inductive theory-building process outlined by Carlile and Christensen (2005), the typology represents a critical step from empirical observation to conceptual understanding. The typology provides a shared conceptual vocabulary that future research can use to systematically compare GenAI applications across organizations, identify recurring adoption patterns across business model activities, and examine boundary conditions and outcomes across industries and business model dimensions.

Second, this study contributes to the broader research on technological innovation and business transformation. The *GenAI Business Use Case Configuration Framework* illustrates how GenAI reconfigures business model activities by distinguishing between Assistance, Augmentation, and Automation as systematically different forms of human-technology collaboration. This lens complements the typology by providing an additional organizing logic for analyzing how AI-enabled work is configured across organizational activities. The configuration framework links two streams that

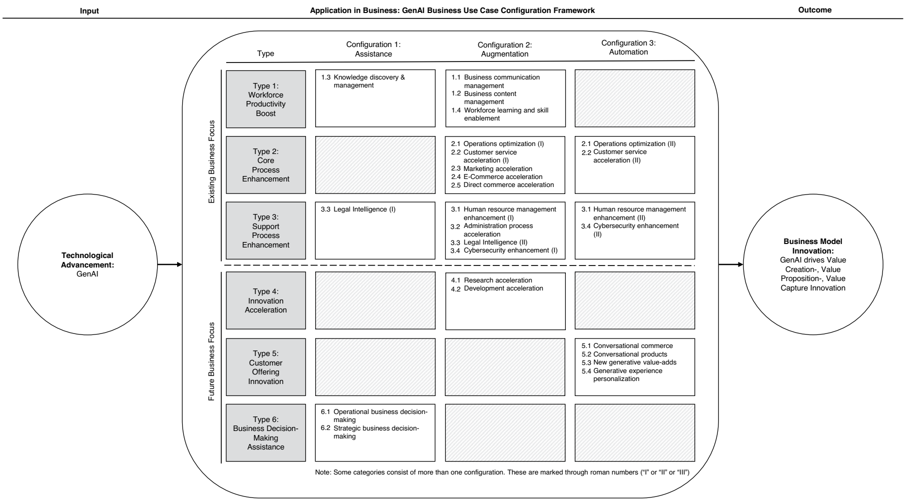

Fig. 5 Contextualizing the Results into the Research Landscape. (Source: Own illustration)

are often discussed in parallel, classifications of AI application domains and theorizing on how AI reshapes the human role in organizational activities through a common configuration lens. This enables future research to analyze collaboration configurations as a cross-cutting dimension within and across application types, identify systematic patterns of variation, and examine boundary conditions and outcomes across organizational contexts.

In summary, this study offers two key theoretical contributions: the *GenAI Business Use Case Typology* that structures the landscape of GenAI business use cases to support future theory development, and the *GenAI Business Use Case Configuration Framework* that conceptualizes how technological advancements reshape business activities. Together, these contributions support future research at the intersection of GenAI, BMI, and technological change.

From a practitioner perspective, this study offers five managerial implications to support managers in evaluating GenAI's potential and guiding its implementation. First, the *GenAI Business Use Case Typology*, consisting of six clearly defined use case types and 21 subtypes, provides managers with a structured and accessible overview of how the technology is being applied in practice. These six types span all key dimensions of a business model, including value creation, value proposition, and value capture. This illustrates how GenAI can both optimize existing operations and unlock new business growth. Second, complementing the typology, the *GenAI Business Use Case Configuration Framework* provides deeper insight into how humans interact with GenAI capabilities, emphasizing both the role of the technology and the configuration of human-GenAI collaboration in real business applications. It distinguishes between three configurations: *Assistance*, *Augmentation*, and *Automation*, which demonstrate how the role of GenAI is evolving. This classification can support managers in comparing implementation requirements and governance needs across domains and in using the typology as a diagnostic tool when discussing adoption and implementation. Third, three use case types demonstrate how GenAI can optimize the efficiency and quality of a firm's existing business model. Across these areas, GenAI can enhance human capabilities and, in some cases, automate specific tasks across core and support processes. In many observed use cases, these applications are described as targeting efficiency gains and improvements in work quality across existing workflows. In this sense, the typology helps locate where GenAI is applied across value-creation, value-proposition, and value-capture activities. Fourth, the remaining three use case types illustrate how GenAI can enable new business opportunities beyond the existing business model. GenAI accelerates research and development by augmenting human capabilities, enabling new customer offerings that are automated through GenAI, and supporting decision-making that helps steer the strategic direction of the business. These types of use cases enhance a company's ability to respond to market changes, identify new opportunities for value creation and capture, and strengthen long-term competitiveness. Fifth, at its current stage of technological maturity, GenAI primarily serves to augment human capabilities, enhancing both efficiency and work quality. However, early efforts in areas such as customer service indicate a trajectory toward more extensive task and process automation, although the extent and pace of such developments are likely to vary across contexts. As the technology advances, broader automation may become feasible. For managers, this underscores the importance of monitoring how collaboration configurations evolve and of approaching implementation as a staged, learning-oriented process. In summary, this study provides empirically grounded insights that managers can use to better understand, assess, and reflect on potential GenAI applications within their organizations. The *GenAI Business Use Case Typology* and *GenAI Business Use Case Configuration Framework* serve as valuable tools for evaluating adoption potential, planning implementation, and tracking progress. Additionally, they provide a straightforward and easily understandable method for communicating GenAI initiatives within the organization and facilitating the overall change process.

By offering a shared conceptual language, the typology and configuration framework support managerial decision-making and facilitate dialogue between practitioners and researchers studying the organizational implications of GenAI.

5.3 Limitations and future research

While this study contributes to a comprehensive understanding of how GenAI is applied in business, five limitations should be acknowledged that may affect the interpretation and generalizability of the results.

A first limitation is the sample's bias toward large enterprises, technology companies, and US-based firms. This is a consequence of the chosen data collection approach, which focused on company publications from NASDAQ-100 firms. Notably, over half of the use cases were published by three major U.S.-based technology providers: Microsoft, Google, and Amazon. These companies play a central role in enabling the adoption of GenAI and frequently publish case studies, which explains why they dominate this area. This concentration may shape which types and subtypes are most visible in the dataset and potentially reflect vendor narratives instead of organization-level practices in all cases. However, it is noteworthy that 55% of the included use cases are from other industries, and 12% represent small and medium-sized enterprises and start-ups. To mitigate potential bias, the research team actively discussed the technology firm concentration in the data and iteratively reviewed coding and categorization decisions with this limitation in mind. Furthermore, triangulation with use case examples from non-US companies (e.g., Commerzbank, Frankfurt Airport, ParcelLab) supported the applicability of the typology across diverse organizational contexts. At the same time, this bias cannot be fully eliminated. Second, a limitation of this study is its reliance on secondary data, due to the limited availability of empirical academic research on the application of GenAI in business. Most use cases were sourced from company-generated materials, such as case studies, customer success stories, and product presentations. While these sources are valuable for identifying emerging trends, they may offer idealized or marketing-oriented narratives rather than objective information. Importantly, the objective of this study is not to evaluate the maturity or performance outcomes, but to descriptively map and categorize the landscape of GenAI applications. To mitigate potential bias, peer-reviewed sources complemented grey literature by providing independent perspectives, thereby reducing the risk of one-sided vendor framing and supporting a more balanced interpretation of the use case evidence. Moreover, the final typology reflects a higher level of abstraction and was iteratively refined to support robust categorization despite the nature of the source material. Third, the integration of peer-reviewed academic literature in this study is limited. Due to the nascent state of the research field, few studies met the inclusion criteria of this study. This further highlights the need for foundational work in this area, justifying the use of a scoping review methodology to incorporate insights from grey literature. Fourth, the qualitative content analysis was conducted by a lead researcher, rather than the collaborative coding approach recommended by Gioia et al. (2012) to enhance analytical rigor. However, we took several steps to enhance the validity of the findings: (1) at each stage, at least one additional researcher independently reviewed and critically evaluated the emerging codes and category structure; (2) coding decisions and interpretations were discussed and refined iteratively until consensus was reached; and (3) fellow researchers verified the final typology by correctly classifying randomly selected use cases outside the study sample. Fifth, the rapid pace of GenAI development raises questions about the long-term relevance of the study's findings. However, by focusing on generalizable patterns of technology application and interpreting them through broader conceptual lenses such as BMI, this study provides a conceptual foundation that is likely to remain relevant and to inform future research in the field of GenAI in business and, more broadly, in the application of emerging technologies in business. Additionally, comparing the study results with existing literature and triangulation supported the robustness of the typology as a conceptual foundation.

While this study focuses on GenAI as a specific technological manifestation, the findings are likely not exclusive to this technology. The typology and configuration framework developed here reflect broader patterns of how AI-based technologies are integrated into business activities, and we expect them to transfer, at least in part, to future developments in AI more broadly. As AI technology continues to evolve rapidly, new capabilities and paradigms will emerge that further transform how businesses operate and innovate. The recent rise of agentic AI, characterized by systems capable of autonomously planning and executing multi-step tasks, serves as an illustrative example of this ongoing development. Future research could explore the extent to which the typology and framework remain applicable across such emerging AI paradigms, and whether new use case types or collaboration configurations arise that call for an extension of the framework.

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