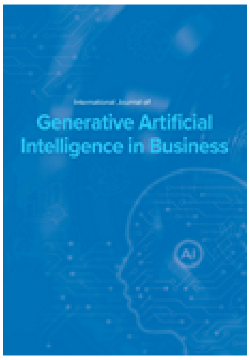

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Business transformation in the age of generative AI: from strategy to societal impact

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Business transformation in the age of generative AI: from strategy to societal impact

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Abstract: Generative artificial intelligence (GenAI) is transforming the foundations of business innovation, operations, and strategy. Moving beyond traditional AI's focus on prediction, GenAI enables the autonomous creation of novel content, designs, and processes across diverse business domains. This paper synthesises the state of research on GenAI's transformative impact, covering strategic innovation, operational excellence, customer engagement, and organisational development. It explores key technical architectures, transformers, GANs, VAEs, diffusion, and multimodal systems, and examines emerging challenges related to ethics, fairness, privacy, and regulation. Drawing from recent literature and practical deployments, the study identifies critical gaps and proposes a future research agenda at the intersection of AI and business. The analysis highlights GenAI's dual role as a catalyst for business model innovation and a driver of systemic change in organisational learning and decision-making. The paper invites scholars and practitioners to engage in shaping this rapidly evolving field with responsibility and foresight.

Keywords: generative artificial intelligence; GenAI; business model innovation; BMI; strategic transformation; operational excellence; customer experience; AI architectures; ethical AI; supply chain optimisation.

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1 Introduction

The release of ChatGPT by OpenAI in November 2022 marked a significant inflection point in the trajectory of artificial intelligence (AI), placing GenAI into the centre of academic, corporate, and public discourse. While AI technologies have been integrated into business processes for decades, the advent of GenAI systems such as ChatGPT, Bard, Jasper, Midjourney, and DALL-E has signaled a shift in both scale and scope. These systems outperform earlier models in terms of output quality and flexibility and democratise AI capabilities through intuitive interfaces and prompt-based interaction.

GenAI enables the autonomous generation of content, ranging from natural language text to images, videos, code, and synthetic data, expanding its utility far beyond traditional decision-support tools (De Santis, 2024). As a result, it presents vast potential to redefine entire sectors and value chains. This transformative potential urges companies to revisit and reinvent their business models, operational strategies, and knowledge systems. Recent literature suggests that GenAI is not simply another efficiency enabler; it is a foundational technology that can reshape how businesses generate, deliver, and capture value.

The implications for business model innovation (BMI) are particularly profound. GenAI functions as both an internal and external force in organisational transformation, disrupting processes, empowering augmentation, and introducing new capabilities that challenge traditional organisational learning, strategy, and design boundaries. Furthermore, GenAI's integration into business analytics and knowledge work processes introduces new questions about augmentation versus automation, ethical risk, and the sustainability of human-AI collaboration over time.

The implications of GenAI adoption span multiple levels of business operations and strategy. It alters decision-making structures, augments workforce productivity, and challenges the resilience of organisational capabilities. On the societal level, GenAI raises essential questions about digital inclusion, fairness, explainability, and long-term impacts on employment and education. For policymakers and regulators, the rise of generative technologies demands a new paradigm in oversight and governance frameworks.

These far-reaching implications demand a comprehensive understanding of how GenAI reconfigures business model dynamics, reshapes organisational capabilities, and interacts with evolving societal norms. In this context, the study is guided by the following overarching research question: *How is GenAI transforming business models, strategic decision-making, and organisational practices across industries?*

To address this central inquiry, the study explores the following subquestions:

- In what ways does GenAI act as a catalyst for BMI by reconfiguring value creation, delivery, and capture mechanisms?
- How does GenAI affect the balance between human augmentation and automation in business analytics and operational decision-making?
- What are the strategic and ethical implications of GenAI integration for workforce capabilities, resilience, and long-term competitiveness?
- How can organisations and policymakers develop governance frameworks that ensure responsible, inclusive, and sustainable adoption of GenAI technologies?

These questions frame the structure of the paper and provide a foundation for synthesising insights from both academic literature and emerging business practices.

The structure of this paper is as follows: Section 2 presents the theoretical and conceptual foundations of GenAI, tracing its historical development and delineating its distinction from traditional AI models. Section 3 explores its applications across core business functions, including innovation management, marketing, operations, finance, human resources, and supply chain. Section 4 discusses emerging challenges such as algorithmic bias, data privacy, and regulatory uncertainty. Section 5 proposes a forward-looking research agenda, and Section 6 concludes with reflections on the strategic and societal transformation driven by GenAI.

2 Theoretical and conceptual foundations

As organisations across industries adopt GenAI, understanding its conceptual and technological foundations becomes critical. GenAI is more than just a technical enhancement; it represents a paradigm shift in how businesses generate value, engage customers, manage knowledge, and execute decisions. This section provides a comprehensive grounding by defining GenAI and its core capabilities, distinguishing it from traditional AI systems, analysing the architectural innovations that drive it, and identifying the mechanisms through which it transforms business performance. These insights form the basis for assessing GenAI's practical applications in the following sections.

2.1 Definitions and core capabilities of GenAI

GenAI represents a foundational breakthrough in the field of AI, redefining how machines learn, interpret, and produce content. Unlike traditional AI systems that rely on discriminative models, used primarily for classification, regression, or prediction based on existing patterns, GenAI systems are generative in nature. They learn the underlying probability distributions of large-scale datasets and use this knowledge to synthesise entirely new, coherent outputs in the form of text, images, audio, video, or code (Martineau, 2023; Feuerriegel et al., 2024). This distinction has profound implications: rather than simply optimising existing processes, GenAI unlocks the ability to create novel solutions, narratives, and artifacts, which is central to innovation and transformation in business contexts.

At the heart of GenAI's appeal is its unique set of core capabilities. These include prompt-based generation, enabling systems like ChatGPT and Bard to generate contextually relevant text in real time; multimodal synthesis, where tools such as Midjourney and DALL·E generate images or videos from textual prompts; and semantic reasoning, which allows GenAI to produce logically consistent outputs even in complex domains. Moreover, GenAI systems demonstrate adaptive learning and interactive feedback mechanisms that empower organisations to automate content generation, design intelligent systems, prototype faster, and engage customers through personalised and dynamic interfaces (Sedkaoui and Benaichouba, 2024). These technologies serve as co-creators in product design, content development, training simulations, and decision support.

An important contribution to the current understanding of the field is the bibliometric and thematic mapping of GenAI research. Pathak and Pallasena (2024) conducted a large-scale review of 5,346 scholarly articles published between 2015 and 2024. Their study identified four thematic pillars in GenAI research: architectural innovations (such as diffusion models and multimodal transformers), applied business use cases, model validation and benchmarking, and broader systemic and societal considerations. By employing citation, co-citation, and centrality analyses, the authors highlighted the field's intellectual structure, its evolving maturity, and key research frontiers. This mapping reveals not only the breadth of GenAI applications but also the need for more rigorous and interdisciplinary frameworks to guide future research.

Beyond technological capabilities, GenAI also signifies a paradigmatic shift from automation to augmentation. Traditional automation focuses on replacing human input in repetitive, rule-based tasks. In contrast, GenAI augments human decision-making and creative processes by providing dynamic, explainable outputs through conversational interfaces, simulation environments, and semantic search (Robertson et al., 2024). Its interaction design promotes iterative problem-solving, human-AI co-creation, and continuous learning. Storey et al. (2025) underscore this dual nature by describing GenAI as both a symbolic and connectionist system, capable of combining rule-based logic with deep learning representations. This hybridisation is what enables GenAI to function not just as a computational tool, but as a reasoning entity that supports context-aware content generation, making it instrumental in complex business environments characterised by uncertainty and rapid change.

Taken together, these capabilities position GenAI as a transformative digital general-purpose technology. It is not only a tool for automating tasks, but also a cognitive partner that redefines how knowledge is created, decisions are made, and organisations interact with their stakeholders. From enhancing productivity to enabling breakthrough innovation, GenAI's conceptual and technical foundations set the stage for its pervasive influence across sectors and disciplines.

2.2 GenAI vs traditional AI in business contexts

The distinction between generative and traditional AI is not merely technical, it fundamentally reshapes the scope, depth, and philosophy of AI-enabled business practices. Traditional AI, typically categorised as discriminative, operates on the principle of learning mappings between inputs and outputs using labelled datasets. It excels at classification, clustering, regression, and anomaly detection tasks, relying on large volumes of structured or semi-structured historical data to make predictions or optimise decisions. In business contexts, such systems are widely deployed in fraud detection, demand forecasting, credit scoring, predictive maintenance, and customer segmentation, domains where data patterns are relatively stable and accuracy-driven models can yield significant efficiency gains (Salazar and Kunc, 2025).

GenAI, in contrast, leverages unsupervised or self-supervised learning approaches to understand and reproduce the underlying data distribution, enabling it to create novel and coherent outputs. Instead of merely identifying a likely label or category, GenAI systems produce synthetic yet plausible artifacts, such as marketing copy, customer service dialogues, software code, product mockups, or even financial narratives, based on high-level prompts. These capabilities have been operationalised in tools like DALL·E for visual generation, Synthesia for AI-driven video content, and GitHub Copilot for real-time code assistance. These tools not only broaden the spectrum of tasks AI can perform but also infuse AI with capabilities previously associated with human creativity and design (Hsu and Ching, 2023; Gupta et al., 2024).

From an analytical perspective, the shift from traditional to GenAI enables a more exploratory approach to business intelligence. Traditional AI aims to improve decision-making through retrospective insights, predicting what might happen next based on what has already occurred. GenAI extends this by allowing organisations to simulate future possibilities, generate alternative business scenarios, and test hypotheses through synthetic experimentation. For instance, generative models can simulate consumer responses to a new pricing strategy, generate market commentary for unanticipated economic events, or produce training data in domains where real data are scarce or ethically constrained (Feuerriegel et al., 2024). This transition from predictive accuracy to creative reasoning expands the decision-making toolkit available to business leaders operating under uncertainty and time pressure.

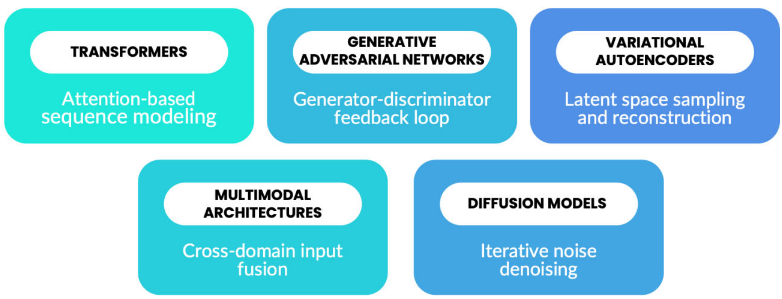
Perhaps most importantly, GenAI also transforms the relationship between humans and machines in the workplace. Traditional AI often emphasises automation, replacing repetitive and manual tasks to improve efficiency. GenAI, on the other hand, emphasises augmentation. It supports human professionals by generating content, providing suggestions, and enabling iterative refinement, creating a collaborative loop between human judgment and machine creativity. This has direct implications for workforce capabilities. New skill sets are now essential, including prompt engineering (the ability to effectively design prompts to steer GenAI output), critical evaluation of machine-generated content, and ethical governance of generative processes. As Schmitt (2023) and Kasneci et al. (2023) argue, the rise of GenAI necessitates a rethinking of organisational learning, with a focus on hybrid intelligence, algorithmic accountability, and the social dimensions of AI deployment.

In sum, while traditional AI continues to provide value through data-driven prediction and optimisation, GenAI introduces a new paradigm, one that embraces ambiguity, supports ideation, and facilitates co-creation across multiple levels of the enterprise. Its integration into business contexts marks not just a technological upgrade, but a shift in how organisations innovate, learn, and make decisions in the age of intelligent machines.

2.3 Architectures and techniques

The technological evolution of GenAI has been driven by major architectural innovations that enable models to generate coherent, diverse, and contextually relevant outputs. These architectures are the computational engines behind the wave of GenAI tools transforming industries today. This section provides a structured analysis of five foundational architectures that have enabled GenAI's rise: transformers, generative adversarial networks (GANs), variational autoencoders (VAEs), diffusion models, and multimodal architectures. Each embodies distinct design principles, learning mechanisms, and use cases, shaping how GenAI is adopted across business functions (see Figure 1).

Figure 1 Modern GenAI architectures (see online version for colours)



Transformers form the core of most state-of-the-art GenAI models. Introduced by Vaswani et al. (2017), this architecture revolutionised machine learning by replacing recurrent computations with self-attention mechanisms that capture long-range dependencies in sequences. Unlike traditional models that process inputs linearly, transformers analyse all input positions simultaneously, enabling them to model contextual relationships with unprecedented accuracy and efficiency. Their scalability and flexibility have made them the foundation of powerful generative models such as OpenAI's GPT series, Google's LaMDA, and Meta's LLaMA. These models now power a wide range of applications, from natural language processing (e.g., chatbots, translation, summarisation) to code generation and multimodal interaction, significantly expanding the interface between humans and machines (Veeramachaneni, 2025; Asselborn et al., 2025).

GANs, proposed by Goodfellow et al. (2014), introduced a competitive learning paradigm in which two neural networks, the generator and the discriminator, compete in a zero-sum game. The generator produces synthetic outputs while the discriminator attempts to distinguish between real and fake data, driving the generator to improve iteratively. This adversarial setup enables GANs to generate high-resolution, photorealistic images, making them particularly valuable in creative industries. In business, GANs have been applied in marketing for image generation and brand visualisation, in fashion for automated clothing design, and in entertainment for game asset creation and face synthesis (Dwivedi et al., 2023). GANs also support data augmentation in scenarios where real data are scarce or sensitive.

VAEs are another key architecture for generative modelling. Unlike GANs, which focus on realism, VAEs prioritise controllability and variation. They encode inputs into a probabilistic latent space and reconstruct outputs by sampling from this space. This allows users to explore variations in the data generation process, making VAEs especially useful in applications requiring customisation, novelty, and anomaly detection. In business settings, VAEs have been employed for product configuration tools, sensor data diagnostics, and pharmaceutical research where structural diversity is crucial (Kingma and Welling, 2019; Wu et al., 2021; Akkem et al., 2024). The mathematical tractability of VAEs also facilitates interpretability and robustness, qualities increasingly valued in regulatory or mission-critical environments.

Diffusion Models represent the latest frontier in generative architecture. These models work by gradually adding noise to data and then learning to reverse this process to recover or generate clean data. This denoising approach allows them to generate highly detailed, realistic content from pure randomness. Diffusion models such as Stable Diffusion have achieved state-of-the-art results in artistic rendering, design ideation, and high-resolution video generation. Their ability to control the generation process with fine granularity makes them particularly appealing in digital content industries and simulation-heavy environments like architecture, automotive design, and media production (Croitoru et al., 2023; Hastings Blow et al., 2025).

Table 1 Key GenAI architectures and their applications

Architecture type	*Key features*	*Applications*	*References*
Transformers	Attention-based sequence modelling	NLP, chatbots, summarisation, code gen	Vaswani et al. (2017), Veeramachaneni (2025). Asselborn et al. (2025)
GANs	Generator-discriminator feedback loop	Image/video generation, style transfer	Goodfellow et al. (2014), Dwivedi et al. (2023)
VAEs	Latent space sampling and reconstruction	Anomaly detection, design variation	Kingma and Welling (2019), Wu et al. (2021), Akkem et al. (2024)
Diffusion models	Iterative noise denoising	High-res images, artistic rendering	Croitoru et al. (2023), Hastings Blow et al. (2025)
Multimodal architectures	Cross-domain input fusion	Text-to-image, interactive agents	Martineau (2023), Lakatos et al. (2024), Li et al. (2025)

Together, these architectures define the technological foundation of the generative revolution. Each contributes uniquely to the expanding application space of GenAI, and their continued evolution will shape the trajectory of future innovations. Table 1 provides a comparative summary of these architectures, highlighting their distinctive features and key business applications.

2.4 Value creation mechanisms enabled by GenAI

GenAI is redefining the foundations of business value creation through a convergence of capabilities that enhance productivity, innovation, decision-making, and organisational agility. Unlike traditional IT tools that focus on automation or efficiency, GenAI operates as a co-creative and predictive system that supports human cognition, reduces the cost of experimentation, and amplifies the strategic range of action across business functions. This section identifies four interdependent value creation mechanisms through which GenAI delivers tangible and strategic advantages: mass personalisation, accelerated innovation, strategic simulation, and democratisation of expertise.

One of the most impactful areas where GenAI delivers business value is mass personalisation. By leveraging vast amounts of structured and unstructured data, GenAI systems can dynamically tailor product recommendations, onboarding workflows, and marketing messages at an individual level. This hyper-personalisation capability enhances user engagement, customer satisfaction, and ultimately conversion rates, particularly in digital commerce, media streaming, and mobile applications. As Brynjolfsson et al. (2025) note, personalisation not only improves targeting precision but also opens new models of customer experience design, enabling real-time adaptation to behavioural signals and contextual factors. Through natural language generation and multimodal customisation, GenAI facilitates scalable yet individualised customer journeys, a long-sought objective in marketing and CRM ecosystems.

Accelerated innovation is another major pathway through which GenAI creates value. The ability to quickly generate text, code, visuals, and structured content enables faster ideation, prototyping, and iteration. For example, GitHub Copilot automates portions of code development, reducing debugging time and supporting collaborative software engineering. Similarly, tools like DALL·E and Midjourney allow creative teams to produce visual prototypes, advertisements, or UI mockups without involving multiple design cycles. Wang and Zhang (2025) emphasise how these capabilities shorten time-to-market and reduce the marginal cost of product development. In design-intensive industries such as fashion, architecture, or digital services, this reduction in creative latency translates into greater responsiveness and innovation throughput.

In terms of foresight and planning, GenAI enables strategic simulation, offering organisations the ability to test hypotheses, model scenarios, and generate synthetic datasets when real-world data are scarce, confidential, or too costly to collect. Whether in financial forecasting, supply chain resilience, or talent planning, GenAI-based simulations empower organisations to better understand complex, nonlinear dynamics. As De Santis (2024) and Salazar and Kunc (2025) observe, these simulation capabilities are particularly valuable under conditions of uncertainty, enabling organisations to perform stress tests, estimate opportunity costs, and evaluate strategic contingencies across multiple time horizons. This represents a critical evolution from reactive analytics to anticipatory and exploratory intelligence.

Finally, GenAI fosters the democratisation of expertise, allowing employees without deep technical backgrounds to engage in complex tasks via intuitive, prompt-based interfaces. This includes generating financial reports, analysing customer feedback, preparing business presentations, or designing campaign content with minimal instruction. Robertson et al. (2024) and Gupta et al. (2024) highlight how these affordances lower the barrier to participation in knowledge-intensive processes and promote broader innovation from within the organisation. The shift from tool-centric to conversational interfaces expands the circle of innovation, empowering domain experts, marketers, analysts, and managers to co-create with AI rather than depending on intermediary specialists.

These four mechanisms, personalisation, innovation acceleration, strategic simulation, and skill democratisation, do not operate in isolation. Rather, they reinforce one another, forming a synergistic value loop where increased experimentation informs better personalisation, which feeds more accurate simulations, which in turn expand access to expertise and design possibilities. Table 2 synthesises these mechanisms, their business applications, and key literature sources.

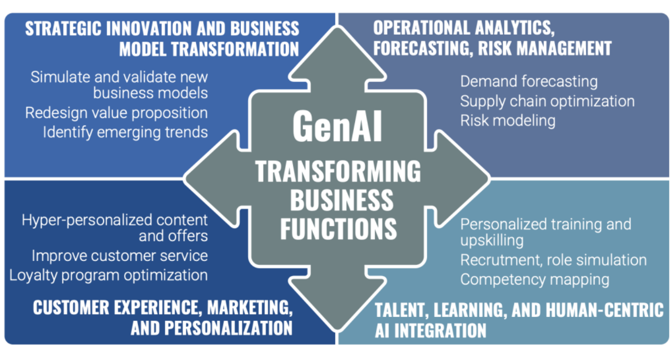
Table 2 Value creation mechanisms of GenAI in business

Mechanism	*Description*	*Example applications*	*References*
Mass personalisation	Automated tailoring of content for individuals	E-commerce, learning, CRM	Brynjolfsson et al. (2025)
Accelerated innovation	Rapid prototyping and testing of new ideas	Software, manufacturing, R&D	Wang and Zhang (2025)
Strategic simulation	Scenario generation and decision support	Finance, HR, logistics	De Santis (2024), Salazar and Kunc (2025)
Democratisation of expertise	Making advanced tools accessible to non-experts	Internal analytics, reporting, content	Robertson et al. (2024), Gupta et al. (2024)

3 Transformative applications in business functions

GenAI is rapidly reshaping the ways in which businesses operate, innovate, and sustain competitive advantage. Its integration into core business functions has moved beyond experimentation to become a key driver of enterprise transformation across industries. Drawing from recent literature and documented use cases, this section synthesises insights across four major domains where GenAI is demonstrating the most profound impact: strategic innovation and business model transformation, operational analytics and decision-making, customer engagement and personalised marketing, and organisational development and workforce enablement (Sedkaoui and Benaichouba, 2024).

Figure 2 Transformative applications of GenAI across business functions (see online version for colours)



Together, these functional applications reveal the systemic influence of GenAI on both the front end (customer-facing and revenue-generating processes) and the back end (internal operations and talent management) of modern enterprises. From enhancing ideation cycles and augmenting financial analysis to transforming human resource development and hyper-personalising customer interactions, GenAI's role is no longer peripheral, it is becoming a strategic infrastructure for intelligent business. Figure 1 below provides a visual synthesis of these application domains, illustrating their interconnections and cumulative business impact.

3.1 Strategic innovation and business model transformation

GenAI is increasingly recognised as a transformative engine for BMI, reshaping how firms conceptualise value creation, delivery, and capture mechanisms. Unlike incremental digital tools that optimise isolated processes, GenAI enables fundamental reconfiguration of entire business architectures. At its core, GenAI introduces a dynamic capability for organisations to simulate, iterate, and refine business models with significantly reduced risk and cost (Sedkaoui and Benaichouba, 2024). Its prompt-based interfaces and large language model capabilities allow companies to experiment with new service designs, revenue models, and operational flows in real time. For example, in healthcare, generative systems are used to synthetically generate patient profiles and simulate demand patterns, which facilitates the development of personalised, preventive care services that are both scalable and cost-efficient (Gupta et al., 2024).

From a strategic lens, GenAI supports both static BMI, which focuses on optimising current value chains, and dynamic BMI, which explores new market positions and configurations. Jorzik et al. (2024) emphasise that generative systems enhance agility in configuring value propositions and revenue streams by interpreting emerging market signals, synthesising scenarios, and visualising potential outcomes. This is particularly evident in the financial sector, where firms use GenAI to develop customised investment portfolios, algorithmic insurance products, and adaptive pricing models that evolve with real-time client behaviour and market fluctuations.

Importantly, GenAI contributes not just to the optimisation of existing strategies but to strategic renewal. As Mariani and Dwivedi (2024) point out, GenAI's capability to analyse vast and unstructured datasets (e.g., social media, open innovation platforms, customer feedback) allows companies to detect weak signals, identify nascent trends, and even generate speculative strategic alternatives. This exploratory function moves innovation beyond conventional R&D boundaries by integrating real-time market intelligence into the business model lifecycle. Moreover, GenAI breaks down the traditional dichotomy between R&D and market execution. By enabling exploratory innovation, firms can prototype and test business models in simulated environments, such as testing customer responses to new service bundling or pricing scenarios, before launching them into volatile markets. This capacity for real-time business modelling under uncertainty positions GenAI as a strategic lever for firms seeking to operate in increasingly dynamic, complex, and competitive environments.

In summary, GenAI is not merely a support tool for business strategy but a catalyst for strategic transformation, equipping organisations with the cognitive and computational tools to reinvent their business logic. It fosters adaptive advantage, reduces experimentation costs, and accelerates strategic learning cycles, core tenets of sustainable competitive advantage in the digital era.

3.2 Operational analytics, forecasting, and risk management

GenAI is redefining how firms engage with operations, risk, and planning by offering data-rich simulations, intelligent forecasting, and automated analytics that go beyond the static modeling capabilities of traditional systems. Through its capacity to generate synthetic yet statistically coherent data, GenAI enables organisations to simulate operational realities under diverse scenarios, strengthening both agility and resilience in decision-making. In the realm of supply chain management, GenAI has emerged as a key enabler for predictive and prescriptive analytics. Organisations now deploy generative models to forecast demand under fluctuating market conditions, simulate supplier disruptions, and explore inventory allocation strategies in advance of actual events. For example, Feuerriegel et al. (2024) highlight how firms use GenAI to model complex supply chain dependencies, generate realistic delay scenarios, and test adaptive sourcing or safety stock policies before disruptions occur. This proactive approach shifts operational planning from reactive to anticipatory, reducing both costs and vulnerabilities.

In financial forecasting and risk modelling, GenAI's power lies in its ability to ingest multimodal inputs, macroeconomic indicators, social sentiment, transactional history, and produce high-fidelity simulations of market behaviours. Salazar and Kunc (2025) underscore the use of generative systems in dynamic credit scoring, where AI generates borrower profiles under shifting interest rates and economic shocks. In fraud detection, GenAI can simulate fraudulent behaviour patterns that are rare in historical datasets, enhancing detection sensitivity and model robustness.

Another practical frontier is automated report generation and regulatory compliance. Tools like GitHub Copilot and Bard are now being adopted not just by developers, but by finance and compliance teams to automate the generation of financial statements, simulate future cash flow positions, and pre-fill compliance forms with high accuracy (Wang and Zhang, 2025). This automation reduces reporting latency, increases precision, and frees human analysts for higher-value interpretive tasks. A particularly important contribution of GenAI lies in enhancing explainability and transparency, two qualities often missing in opaque algorithmic systems. Generative models can translate complex statistical results into coherent narratives, interactive dashboards, or scenario-based visualisations. For instance, in sectors like energy and banking where decisions must be justified to regulators, GenAI supports the creation of understandable risk assessments and trade-off explanations. Kasneci et al. (2023), Kovač (2024), and Storey et al. (2025) collectively argue that narrative generation and visualisation help bridge the gap between data science and executive decision-making, fostering greater trust and inclusiveness.

In sum, GenAI equips organisations with the tools to model uncertainty, test hypotheses, and build operational resilience in increasingly volatile environments. By combining data synthesis, intelligent automation, and human-centred explainability, it transforms operations from static optimisation to dynamic strategic foresight.

3.3 Customer experience, marketing, and personalisation

GenAI is transforming customer engagement strategies by enabling organisations to move beyond segmentation toward true hyper-personalisation. At the core of this shift is GenAI's ability to dynamically create content, text, images, video, and even voice, that adapts in real time to individual customer preferences, behaviours, and context. Brynjolfsson et al. (2025) argue that this level of personalisation significantly enhances customer satisfaction and retention, as interactions become more context-aware and emotionally resonant. Modern marketing platforms now deploy GenAI to develop multilingual, multi-format, and multi-channel campaigns at unprecedented speed and scale. For example, generative models automatically produce tailored product descriptions, marketing e-mails, and promotional visuals based on real-time customer data, purchase history, and engagement metrics. This capability drastically reduces the time and cost of content production while increasing its relevance and impact.

Conversational AI, empowered by GenAI, further refines the customer experience by enabling context-sensitive interactions across service channels. Chatbots and virtual assistants can now interpret user sentiment and intent, adjusting tone, vocabulary, and even emotional resonance on the fly (Robertson et al., 2024). Tools such as Jasper, Midjourney, and DALL·E facilitate rapid generation of creative assets, from product illustrations to brand mood boards, enabling marketers to iterate and launch campaigns with minimal lead time and reduced reliance on external design agencies. Empirical evidence supports these shifts. Soini and Jaakkola (2025) report that organisations deploying GenAI for customer-facing applications saw a measurable increase in engagement rates, click-throughs, and overall campaign effectiveness. Moreover, GenAI enhances customer retention strategies by supporting scenario-based churn prediction and loyalty program design. Marketers can simulate diverse customer journeys, forecast churn risks, and tailor retention actions to specific segments with high precision.

Perhaps most critically, GenAI enables businesses to test new ideas before they go to market. Firms can simulate how consumers might respond to a new pricing strategy, product interface, or marketing message, thus transforming personalisation into a tool for customer-driven innovation. These simulations provide valuable input for agile decision-making, allowing for iterative refinement of value propositions before launch. In essence, GenAI shifts the customer engagement paradigm from one-size-fits-many to dynamic one-to-one experiences, grounded in real-time data and generative creativity. It strengthens the brand-customer relationship, not only by optimising content and interactions but also by enabling co-creation, trust-building, and lasting emotional connection in a digitally saturated environment.

3.4 Talent, learning, and human-centric AI integration

GenAI is redefining the human capital agenda by introducing intelligent, adaptive, and personalised solutions across the entire employee lifecycle. In the realm of human resource management (HRM), GenAI enables a data-driven, proactive approach to recruitment, training, development, and internal communication. As Robertson et al. (2024) and Wang and Zhang (2025) note, this shift is particularly transformative in complex organisations navigating rapid technological change and talent shortages. In recruitment, GenAI systems now assist in resume screening, candidate profiling, and interview design, enhancing both the efficiency and fairness of selection processes. These tools go beyond keyword matching to simulate potential role fit based on behavioural cues, skills clusters, and organisational needs. When implemented with proper oversight, these models can help reduce human bias and increase the diversity of shortlisted candidates. For example, GenAI can generate optimised interview sequences tailored to different candidate archetypes, improving both candidate experience and hiring precision.

Once onboarded, employees benefit from personalised learning journeys, powered by generative systems that adapt to individual performance metrics, learning styles, and career aspirations. This enables organisations to scale competency development and upskilling in real time, especially valuable in fast-evolving industries like digital services, manufacturing automation, logistics, and AI engineering (Salazar and Kunc, 2025).

GenAI tools produce adaptive onboarding materials, job-specific simulations, and role-play scenarios, making the integration of new hires more efficient and culturally aligned. A key advancement is the use of GenAI for talent analytics. Generative models construct competency maps, skills gap assessments, and internal mobility paths, facilitating strategic workforce planning. This allows HR teams to align employee capabilities with future business needs, optimise learning investments, and proactively manage succession pipelines.

Table 3 Applications of GenAI across core business functions

Application area	*Key contributions of GenAI*	*Example use cases*	*Key references*
Strategic innovation and business models	Simulate new business models	Algorithmic financial services	Gupta et al. (2024), Mariani and Dwivedi (2024), Jorzik et al. (2024)
	Enable dynamic value proposition design	Healthcare service design	
	Support exploratory innovation	Strategic scenario modelling	
Operational analytics and forecasting	Synthetic data generation Real-time risk modelling	Supply chain disruption simulation	Kasneci et al. (2023), Kovač (2024), Feuerriegel et al. (2024), Salazar and Kunc (2025)
	Enhanced explainability and scenario planning	Fraud detection	
		Stress testing in finance	
Customer experience and personalisation	Mass customisation at scale	Multilingual ads	Robertson et al. (2024), Brynjolfsson et al. (2025), Soini and Jaakkola (2025)
	Content generation	Chatbot interaction	
	Predictive engagement optimisation	Personalised recommendations	
Talent and human-centric integration	Adaptive learning systems	Skill-gap analysis	Robertson et al. (2024), Salazar and Kunc (2025), Wang and Zhang (2025)
	GenAI-assisted recruitment	Dynamic training	
	Decision augmentation in HR	Interview simulation	

In organisational learning, GenAI-driven platforms enhance knowledge sharing and collaborative decision-making. Natural language interfaces and summarisation tools transform dense documentation into accessible insights, enabling staff at all levels to engage with strategic content. Furthermore, prompt-driven assistants support leadership and project teams by synthesising diverse datasets into scenario visualisations, impact briefs, or policy alternatives, thus enabling faster and more inclusive decision-making processes (Kasneci et al., 2023; Robertson et al., 2024). Importantly, GenAI also contributes to human-centric AI integration, where the goal is not to replace employees but to augment their intelligence and creativity. This aligns with emerging models of augmented leadership, where decision augmentation, ethical reasoning, and emotional intelligence are supported, not supplanted, by generative technologies.

In sum, GenAI empowers organisations to evolve from static HR practices to dynamic, individualised, and forward-looking talent systems. As workforce expectations shift toward continuous learning, transparency, and empowerment, GenAI offers the tools to meet these demands while also enhancing organisational agility and resilience.

4 Emerging challenges and considerations

Despite the vast transformative promise of GenAI, its widespread deployment introduces a constellation of ethical, legal, and societal challenges that demand urgent and sustained attention. These concerns do not merely arise from the scale and speed at which GenAI systems can generate synthetic content, but from deeper issues related to opacity, unpredictability, and adaptability of their outputs across different contexts. The generative nature of these systems, while powerful, often eludes traditional verification methods, creating new dilemmas for governance, trust, and accountability.

This section critically examines four interrelated areas of concern that are central to the debate on responsible GenAI adoption:

- fairness, bias, and explainability, especially in high-stakes decisions
- data privacy and security, given the reliance on vast and often unverified datasets
- regulatory gaps and legal ambiguity, particularly around intellectual property and liability
- and the broader organisational and societal implications, such as workforce disruption, misinformation, and ethical erosion.

Understanding and proactively addressing these issues is vital to ensure that the integration of GenAI into businesses and society remains inclusive, secure, and aligned with democratic and human-centric values. Responsible innovation frameworks must therefore accompany technical progress, fostering trust and ensuring that GenAI serves as a force for good across economic and social systems.

4.1 Ethics, fairness, and bias in GenAI

One of the most critical ethical issues surrounding GenAI lies in its tendency to inherit and magnify existing societal biases. Since these models are typically trained on massive, unfiltered datasets sourced from the internet, they inevitably reflect the historical and cultural prejudices embedded within that data, whether related to race, gender, age, class, or geopolitical identity (Kasneci et al., 2023; Storey et al., 2025). These biases can manifest subtly in language generation tasks, through stereotypical phrasing or cultural erasure, or more explicitly in automated outputs that systematically disadvantage certain groups. When deployed in sensitive domains such as recruitment, credit scoring, or legal prediction, such bias propagation can lead to discriminatory outcomes with real-world consequences. For example, a generative model used to draft hiring summaries may inadvertently favour male-oriented language for technical roles, reproducing systemic exclusion in hiring pipelines.

Furthermore, the generative nature of these models complicates issues of authorship and ownership. Unlike predictive AI that classifies or recommends, GenAI produces novel content, text, code, images, or even voices, often in a way indistinguishable from human creations. This opens up difficult questions regarding intellectual property rights, especially when GenAI systems mimic existing artistic styles or extract from copyrighted material without explicit consent (Islam and Greenwood, 2024). Without formal disclosure of AI involvement, consumers may be unaware that the content they are reading, viewing, or interacting with was generated algorithmically, raising concerns about deception, accountability, and the erosion of trust in digital media.

Equally troubling is the lack of explainability in GenAI outputs. While advances such as attention visualisation offer partial insight, models like GPT, LaMDA, or Gemini remain largely opaque in how they generate specific answers or creative constructs. These systems operate through complex layers of statistical pattern recognition that defy intuitive human understanding. In contexts such as medical diagnostics, financial advising, or legal drafting, this opacity can be dangerous, as stakeholders may be unable to verify how a conclusion was reached or whether critical information was omitted (Gupta et al., 2024). The inability to explain or justify AI-generated outputs limits human oversight and challenges compliance with transparency regulations, particularly under frameworks such as the EU AI Act or GDPR.

In light of these challenges, fostering ethical GenAI requires more than technical fixes; it demands the integration of fairness audits, dataset curation protocols, attribution standards, and human-in-the-loop governance systems. Only then can GenAI systems be aligned with ethical norms and organisational values, ensuring that innovation does not come at the cost of equity, transparency, or human dignity.

4.2 Privacy and security concerns

The deployment of GenAI at scale introduces profound challenges to data privacy and information security. At the heart of these challenges lies the inherently data-intensive training process of GenAI systems, which often relies on vast corpora harvested from online platforms, internal organisational repositories, or open datasets that may not always adhere to stringent consent protocols (Şahin and Karayel, 2024). In many cases, the data used to train large language models (LLMs) or multimodal systems is scraped without adequate filtration or legal scrutiny, raising significant concerns regarding compliance with privacy regulations such as the General Data Protection Regulation (GDPR), the Health Insurance Portability and Accountability Act (HIPAA), and the California Consumer Privacy Act (CCPA). These frameworks mandate transparency, purpose limitation, and data subject rights, conditions that are not always satisfied by current GenAI pipelines.

A particularly concerning vulnerability lies in the models' ability to memorise and regenerate fragments of sensitive training data. Even in non-malicious use cases, such as customer support chatbots or code generators, GenAI systems may inadvertently expose personally identifiable information (PII), trade secrets, or proprietary corporate data embedded in their latent memory (Feuerriegel et al., 2024). This phenomenon becomes more pronounced when attackers prompt models using carefully crafted queries designed to extract memorised content, a risk well-documented in adversarial testing and 'prompt injection' attacks. The lack of formal boundaries between public, private, and confidential knowledge in these models blurs ethical lines and exacerbates compliance vulnerabilities for businesses deploying them in production.

Moreover, GenAI creates new vectors for security exploitation. Its capabilities can be misappropriated to automate the generation of highly targeted phishing messages, ransomware scripts, or even synthetic identities using deepfake voice and video technology. These tools lower the technical barrier for cybercriminals and disinformation agents, dramatically expanding the scale and sophistication of digital threats (Soini and Jaakkola, 2025). For instance, generative models trained on voice data can be used to mimic executives in 'CEO fraud' scams, while synthetic avatars may be deployed in phishing or social engineering campaigns with unprecedented believability.

To mitigate these threats, organisations must go beyond traditional cybersecurity frameworks. Robust governance mechanisms should include continuous red-teaming of GenAI applications, the use of privacy-preserving machine learning techniques (e.g., differential privacy, federated learning), and real-time anomaly detection to monitor for hallucinations or information leakage. Furthermore, watermarking synthetic content and establishing secure model boundaries (e.g., through fine-tuning constraints and domain-specific knowledge firewalls) are critical steps toward responsible deployment. Only through this layered approach can organisations safeguard against both inadvertent breaches and deliberate misuse while preserving the immense value GenAI brings to innovation and productivity.

4.3 Regulatory landscape

The regulatory framework governing GenAI remains in a state of flux, shaped by a rapidly evolving technological landscape and varying policy approaches across jurisdictions. Despite global recognition of the need for oversight, existing regulations often lag behind the pace of innovation, leading to a fragmented and ambiguous compliance environment. The European Union's Artificial Intelligence Act represents one of the most comprehensive efforts to establish a risk-based classification system for AI, assigning different compliance requirements based on the potential harm posed by an application (Helberger and Diakopoulos, 2023). However, the inherent versatility of GenAI models complicates this schema. A single foundation model can simultaneously power low-risk applications, such as text summarisation or image creation, and high-risk scenarios, including clinical diagnosis support or legal document drafting, making it difficult to categorise and govern under a unified regulatory label.

This multifunctionality challenges not only classification but also liability assignment. When harm occurs, such as discriminatory hiring outcomes, financial misadvice, or the spread of medical misinformation, it is rarely clear who bears legal responsibility. The attribution problem is exacerbated by the collaborative nature of GenAI systems, where responsibilities are distributed across model developers (e.g., OpenAI, Anthropic), platform integrators (e.g., Microsoft, Adobe), enterprise users, and in some cases, third-party fine-tuners (Dwivedi et al., 2023). The traditional legal constructs of product liability and negligence are insufficient to address the emergent and probabilistic behaviour of GenAI systems, requiring a rethink of accountability frameworks that incorporate notions of shared and conditional liability.

Moreover, regulatory gaps persist in critical areas such as algorithmic transparency, model auditing, and data provenance. Many GenAI models are considered 'black boxes', lacking interpretability even to their creators, which limits the ability of regulators to assess compliance or ensure fairness. In response, there is growing advocacy for the institutionalisation of algorithmic audit mechanisms, similar to financial audits, to regularly evaluate models for compliance, bias, and systemic risks (Mariani and Dwivedi, 2024). These could be complemented by enforceable requirements for transparency reporting, including disclosures on training data composition, intended uses, known limitations, and incident logs.

Several policy proposals have also emphasised the importance of embedding ethical and societal impact assessments into the GenAI product lifecycle. Rather than treating ethics as an afterthought, regulators and companies alike are exploring frameworks such as Human Rights Impact Assessments (HRIAs) and Algorithmic Impact Assessments (AIAs), which proactively evaluate risks related to discrimination, misinformation, and autonomy infringement during development and deployment.

Ultimately, a harmonised, adaptive, and context-sensitive regulatory strategy is required to manage the risks of GenAI without stifling innovation. This includes cross-border cooperation among governments, the private sector, and civil society to align on standards, enforcement mechanisms, and safeguards that balance technological advancement with the public good.

4.4 Organisational and societal implications

The integration of GenAI into business operations is not merely a technological shift but a catalyst for profound organisational and societal transformation. Within firms, GenAI adoption reshapes traditional work structures, redefines roles, and challenges long-standing assumptions about human–machine collaboration. While GenAI offers immense potential for boosting productivity, accelerating innovation, and enhancing responsiveness, it also introduces risks of structural imbalance, particularly when leveraged primarily for task automation rather than skill augmentation (Schmitt, 2023; Wang and Zhang, 2025). In such cases, core human competencies, such as problem-solving, interpersonal communication, and judgment, may become underutilised or devalued, leading to what scholars refer to as 'organisational deskilling'.

Moreover, the rapid substitution of generative tools for cognitive labour (e.g., in writing, design, analysis) risks displacing mid-level knowledge workers, particularly in sectors such as marketing, media, legal, and finance. This technological displacement could contribute to workforce polarisation, as high-skilled creative and technical roles remain in demand while routine intellectual tasks become automated. As Schmitt (2023) argues, the challenge is not just about job loss, but about a reconfiguration of work identities and responsibilities, raising questions about employee motivation, meaningfulness of work, and long-term organisational learning capacity.

Another critical issue lies in the erosion of human judgment and critical reflection. Over-reliance on GenAI for decision-making may promote a 'technocratic drift', wherein the speed and convenience of automated recommendations overshadow deliberative processes and contextual sensitivity (Salazar and Kunc, 2025). This can reduce cognitive diversity within teams and impair resilience, especially in complex or volatile environments where nuanced judgment is essential. Organisations must thus establish clear boundaries and governance frameworks to ensure that GenAI complements rather than overrides human expertise.

At the societal level, GenAI's diffusion exacerbates existing digital inequalities. Access to computational infrastructure, high-quality training data, and AI literacy remains uneven across regions, sectors, and social groups. This asymmetry risks reinforcing power imbalances between technology-rich and resource-constrained organisations, as well as between digitally fluent and marginalised populations (Wilson and Daugherty, 2024). Without deliberate policy and design interventions, the benefits of GenAI could disproportionately accrue to large corporations and elite institutions, leaving SMEs, public-sector entities, and underserved communities behind.

To counteract these trends, inclusive innovation strategies are imperative. This includes proactive investment in workforce upskilling and reskilling programs, especially in prompt engineering, ethical AI governance, and hybrid human-AI collaboration techniques. Companies must also adopt participatory design approaches that involve end-users, especially those from vulnerable or underrepresented backgrounds, in shaping GenAI applications. On a broader scale, national and international stakeholders should promote equitable access to GenAI infrastructure and research resources, supporting a more balanced and just technological transition.

In sum, while GenAI presents a transformative opportunity for businesses and societies, its full potential will only be realised if accompanied by thoughtful organisational restructuring, ethical design practices, and inclusive governance frameworks that mitigate its risks and amplify its shared value.

Table 4 Summary of emerging challenges in GenAI deployment

Challenge area	*Key issues*	*References*
Ethics and fairness	Bias amplification, explainability, misinformation	Kasneci et al. (2023), Gupta et al. (2024), Islam and Greenwood (2024)
Privacy and security	Data leakage, unauthorised data usage, malicious use	Feuerriegel et al. (2024), Şahin and Karayel (2024)
Regulatory landscape	Legal ambiguity, lack of standards, cross-domain use case complexity	Helberger and Diakopoulos (2023), Dwivedi et al. (2023)
Societal implications	Job displacement, loss of human skills, digital inequality	Schmitt (2023), Wilson and Daugherty (2024), Wang and Zhang (2025)

5 Future research agenda

As GenAI continues to evolve, its influence on business practices, strategic decision-making, and organisational transformation opens new and important avenues for academic inquiry. The rapid adoption of GenAI across sectors, ranging from marketing and finance to healthcare and logistics, has catalysed a wave of empirical studies and practitioner reports. Yet, despite this momentum, the academic literature remains fragmented and uneven in its treatment of the subject. Key conceptual foundations are often underdeveloped, empirical studies are methodologically inconsistent, and cross-disciplinary integration is still limited.

Most current research focuses on immediate applications and performance metrics, often overlooking deeper theoretical implications. For example, how GenAI reshapes traditional views of value creation, decision autonomy, or cognitive work remains insufficiently theorised. Similarly, there is a need to critically assess how GenAI interacts with existing strategic frameworks, such as dynamic capabilities, ambidexterity, or resource orchestration, especially under conditions of high uncertainty and technological disruption.

Moreover, methodological diversity remains a challenge. While some studies rely on qualitative case analysis or experimental interfaces, others employ large-scale data simulations or proprietary model audits, making cross-study comparisons difficult. This methodological fragmentation suggests a need for greater convergence around robust, replicable approaches that can measure GenAI's impact on both operational performance and organisational learning outcomes.

In addition, the ethical, legal, and socio-technical dimensions of GenAI are often treated in isolation rather than as integral to innovation and value realisation. There is a clear gap in multi-level frameworks that connect micro-level design practices with meso-level organisational routines and macro-level societal consequences. This is particularly pressing given the stakes involved in GenAI's use in critical infrastructure, public decision-making, and citizen-facing platforms.

Against this backdrop, the following sections outline a targeted research agenda. It identifies priority topics, proposes methodological pathways, and encourages greater engagement between disciplines such as information systems (IS), operations management, organisational theory, and business ethics. By doing so, this agenda aims to move beyond fragmented insights and toward a more integrated, rigorous, and forward-looking body of knowledge on GenAI in business.

5.1 Gaps in current research

Despite growing academic and practitioner interest, the research landscape on GenAI in business remains highly fragmented and emergent. Much of the current literature is sector-specific, emphasising immediate applications in healthcare (Ning et al., 2024; Bhuyan et al., 2025), education (Bahroun et al., 2023), and manufacturing (Ghobakhloo et al., 2024). While these domain-focused studies offer useful insights into practical deployments, they often fail to articulate cross-sectoral mechanisms or generalisable patterns of GenAI-enabled transformation. As a result, a cohesive understanding of GenAI's strategic, operational, and organisational implications at the firm level is still underdeveloped.

Furthermore, there is a noticeable emphasis on short-term deployment outcomes, such as efficiency gains, content generation, or user interaction metrics, without adequate consideration for longer-term organisational consequences. The integration of GenAI into core business processes raises foundational questions that remain largely unexplored. For instance, how do generative systems alter firm-level capabilities related to innovation, agility, and learning? What structural or cultural shifts are required to embed GenAI into decision-making and value creation systems sustainably? As Jorzik et al. (2024) and Gupta et al. (2024) suggest, GenAI does more than automate tasks, it reconfigures workflows, power dynamics, and even definitions of expertise within organisations. Yet, these deeper transformations are not sufficiently theorised or empirically tested.

In addition, the literature rarely engages with the evolving role of GenAI in shaping strategic differentiation over time. While many firms adopt GenAI tools for efficiency or novelty, the mechanisms through which these tools contribute to sustained competitive advantage are not well understood. Does GenAI strengthen existing resource positions, or does it create entirely new sources of value and risk? How do firms balance the benefits of automation with the need to preserve human creativity, judgment, and ethical accountability? These questions call for longitudinal and comparative research designs that trace the organisational journey of GenAI adoption, adaptation, and routinisation over time.

Finally, there is a theoretical gap in integrating GenAI into established frameworks in strategic management, IS, and organisational studies. Concepts such as dynamic capabilities, absorptive capacity, and ambidexterity remain underutilised in explaining how firms harness GenAI for innovation and adaptation. Addressing this gap requires not only empirical rigor but also conceptual clarity, linking GenAI's technical affordances with its socio-organisational consequences.

5.2 Methodological issues and innovations

Current research on GenAI in business is characterised by a proliferation of conceptual commentaries, exploratory case studies, and highly technical assessments focused on model architecture or computational performance. While these early contributions are instrumental in shaping the initial contours of the field, they often fall short in terms of empirical generalisability, methodological rigor, and theoretical integration. As such, there is a pressing need to expand the methodological toolkit applied to GenAI studies, particularly in contexts where business decisions, human-AI interaction, and strategic transformation are at stake.

Future research should adopt mixed-method approaches that combine qualitative inquiry, quantitative analysis, and computational experimentation. Studies integrating grounded interviews with system developers and users, coupled with econometric modelling of performance data, can yield richer insights into the mechanisms through which GenAI influences business processes and outcomes (Singh et al., 2024; Salazar and Kunc, 2025). In particular, longitudinal field studies that track GenAI deployment across time and contexts are critical to capture dynamic effects such as organisational learning, technology assimilation, or capability development.

An emerging methodological frontier lies in the use of scoping reviews, bibliometric analysis, and topic modelling to trace the intellectual evolution of GenAI research. Techniques such as latent Dirichlet allocation (LDA) or dynamic topic modelling allow scholars to map thematic shifts and disciplinary convergence across large academic corpora (Gupta et al., 2024). This meta-analytical approach is especially useful for a rapidly expanding domain like GenAI, where new terminologies, applications, and ethical concerns continuously emerge.

Equally transformative is the use of GenAI itself as a research assistant. Advanced language models can support academic workflows by automating literature summarisation, generating hypotheses from structured databases, or even simulating business scenarios under uncertainty (Robertson et al., 2024). However, the integration of GenAI into the research process introduces new epistemological and methodological dilemmas. For example, the problem of hallucination, where GenAI generates plausible yet false information, raises concerns about the reliability of AI-augmented research. Similarly, issues of data leakage, training set contamination, and model bias must be carefully managed to preserve the integrity of empirical findings.

To mitigate these risks, it is essential to establish methodological guidelines for the use of GenAI in academic research. Transparency regarding the scope and limits of AI-generated content, clarity in authorship attribution, and explicit disclosure of AI involvement in data processing or analysis are critical components of ethical research design. Moreover, academic institutions and journals must work toward developing frameworks to assess the validity and replicability of studies that employ GenAI as a tool for inquiry.

In sum, advancing the methodological foundations of GenAI research requires a dual strategy: embracing the power of computational tools while embedding them within robust empirical and ethical protocols. Only then can GenAI research mature into a theoretically sound and practically relevant discipline.

5.3 Cross-disciplinary research opportunities

GenAI stands at the confluence of multiple academic disciplines, AI, strategic management, operations research, IS, and innovation studies. However, the majority of research remains confined within disciplinary silos, with technical studies prioritising model development and performance metrics, and managerial studies focusing on application scenarios or strategic implications. This fragmented approach limits the development of integrative frameworks that could guide both scholarly inquiry and organisational practice. As GenAI continues to diffuse across sectors, cross-disciplinary research becomes essential to fully grasp its multifaceted implications.

One promising avenue involves the fusion of innovation management and human-computer interaction (HCI) to explore how GenAI can support co-creation processes, augment creativity, and foster user-centred innovation practices. Mariani and Dwivedi (2024) argue that GenAI technologies, when integrated with design thinking methodologies, can fundamentally reshape ideation and prototyping workflows. Interdisciplinary collaboration here could produce actionable models of GenAI-enabled innovation ecosystems that combine technical feasibility, user desirability, and business viability.

Another critical intersection lies between business ethics and computer science, particularly in the development of governance frameworks and value-sensitive design. As GenAI systems become embedded in decision-making and content generation, questions of accountability, fairness, and autonomy gain prominence. Insights from ethical theory can help computer scientists identify and mitigate algorithmic harms, while technical understanding is necessary to translate normative principles into system-level design constraints (Kasneci et al., 2023; Helberger and Diakopoulos, 2023). Such collaboration could lead to the establishment of ethical AI development protocols, redress mechanisms for harm, and compliance-by-design strategies.

Additionally, IS research offers well-developed frameworks for understanding digital transformation, which can be extended to capture the unique dynamics of GenAI adoption. Storey et al. (2025) and Wang and Zhang (2025) highlight that GenAI does not merely digitise existing processes, it reconfigures entire business architectures, from customer touchpoints to internal value creation activities. A cross-disciplinary approach combining IS with operations management and organisational theory can help model how GenAI technologies diffuse within firms, reshape workflows, and generate emergent capabilities. Cross-disciplinary synthesis also opens the door to more robust methodological triangulation. For example, pairing ethnographic studies of GenAI adoption with computational social science methods can uncover the human, cultural, and systemic dimensions of AI integration. Likewise, collaboration between legal scholars and systems engineers could foster the co-design of regulatory sandboxes and audit tools tailored to GenAI applications.

Ultimately, GenAI's profound societal and organisational impact demands research that transcends traditional boundaries. Interdisciplinary collaboration will not only produce richer theoretical insights but also enhance practical relevance by informing policy, guiding ethical design, and shaping education for a future shaped by intelligent automation. It is through such convergence that academia can support the responsible and innovative deployment of GenAI across industries and societies.

Table 5 Directions for future research on GenAI in business

Research area	*Key priorities*	*References*
Theoretical gaps	Organisational learning, value creation mechanisms, and innovation models	Gupta et al. (2024), Jorzik et al. (2024), Wilson and Daugherty (2024)
Methodological innovation	Mixed methods, GenAI-assisted research, longitudinal studies	Salazar and Kunc (2025), Robertson et al. (2024)
Ethical and governance studies	Bias, accountability, AI literacy, policy integration	Kasneci et al. (2023), Helberger and Diakopoulos (2023)
Cross-disciplinary integration	AI + Strategy, AI + Ethics, AI + Innovation Management	Mariani and Dwivedi (2024), Storey et al. (2025)

6 Conclusions

GenAI represents a profound technological shift, redefining the boundaries of what machines can autonomously create, simulate, and decide. Unlike earlier paradigms of AI, which primarily focused on classification, optimisation, or automation of routine processes, GenAI introduces a new frontier, one where machines are capable of generating novel content, reasoning through prompts, and engaging in complex creative and strategic tasks. This paper has examined the technological foundations, strategic implications, ethical concerns, and emerging research directions of GenAI in business, with the aim of offering an integrated and forward-looking perspective.

Technologically, GenAI stands out through the sophistication and adaptability of its underlying architectures. Transformer-based models like GPT and LaMDA have set new benchmarks for language understanding and generation, while GANs, VAEs, and diffusion models are revolutionising the creation of synthetic images, prototypes, and even scientific hypotheses. These tools are no longer confined to the research lab, they are increasingly embedded within enterprise workflows, enabling new forms of interaction between humans and intelligent systems.

From a strategic standpoint, GenAI has become a key enabler of BMI. It empowers organisations to experiment with value creation and delivery mechanisms at unprecedented speed and scale. Firms can now simulate future demand, generate synthetic personas for market testing, or craft hyper-personalised services, all within a few iterations of prompt engineering. The implications extend far beyond operational efficiency; GenAI contributes directly to strategic agility, competitive positioning, and long-term resilience. Business leaders can use GenAI to detect weak signals, anticipate disruptions, and prototype responses in complex environments.

Operationally, GenAI facilitates the automation and augmentation of analytics, reporting, forecasting, and decision support. These capabilities unlock new efficiencies in supply chain planning, financial modeling, and risk management. At the same time, GenAI enables more nuanced human–AI collaboration by generating interpretable narratives and visualisations that support managerial sensemaking. In customer-facing functions, GenAI offers unprecedented personalisation at scale, reshaping marketing strategies, product design, and service delivery. In human capital management, GenAI is transforming recruitment, learning, and performance evaluation through adaptive content generation and predictive modeling.

However, the adoption of GenAI is not without risks or trade-offs. This paper has highlighted significant ethical, legal, and societal concerns, including the reproduction of bias, opacity of decision-making, threats to data privacy, and challenges in accountability. These issues are not peripheral, they are central to how GenAI will be perceived, governed, and scaled in the years ahead. The dual-use nature of GenAI (i.e., its potential for both beneficial and harmful applications) requires that developers, users, and regulators work in tandem to establish robust safeguards, including transparency standards, red-teaming protocols, ethical impact assessments, and sector-specific governance mechanisms.

The paper also identifies critical gaps in current research and proposes a forward-looking agenda. Many existing studies on GenAI remain either narrowly technical or overly conceptual, lacking empirical grounding and cross-disciplinary integration. There is an urgent need for longitudinal studies, field experiments, and system-level analyses that examine how GenAI reshapes organisational processes, roles, and capabilities over time. Methodological innovation, such as the use of GenAI itself as a research assistant or as a subject of simulation-based inquiry, can open new frontiers in scholarly work.

Moreover, the future of GenAI research must be deeply interdisciplinary. Business transformation through GenAI cannot be fully understood or managed from a single disciplinary lens. Insights from organisational theory, IS, ethics, law, and design science must converge to produce integrated frameworks for responsible innovation. Equally, educators and training institutions must update curricula to prepare the workforce for augmented intelligence environments, where creativity, judgment, and ethical reasoning are as important as technical proficiency.

In conclusion, GenAI is not merely a technological advancement, it is a socio-technical revolution. Its impact spans industries, functions, and societal institutions, offering new opportunities for value creation while simultaneously introducing new forms of risk, inequality, and disruption. The challenge for business leaders, researchers, and policymakers is to embrace this transformation thoughtfully and inclusively. Organisations must craft adaptive strategies that leverage GenAI's creative and analytical capabilities while safeguarding human agency, equity, and trust. Scholars must develop robust theories and methods that account for GenAI's dynamic, generative, and evolving nature.

This paper invites a collaborative and open dialogue across sectors and disciplines: to co-create a future in which GenAI contributes to productivity, innovation, and progress, without compromising ethical integrity, human dignity, and social cohesion. Only through such a balanced and inclusive approach can GenAI fulfil its transformative promise for business and society alike.

Declarations

All authors declare that they have no conflicts of interest.

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