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The Evolution of AI in Business: A Topic Model Analysis of Research Trends

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Abstract

Artificial intelligence (AI) is rapidly transforming business practices, with large language models (LLMs) at the forefront of this change. While AI adoption is increasing, the process by which firms develop capabilities to leverage these technologies remains unclear. Here we apply structural topic modeling to over 5,000 research abstracts to map the thematic evolution of AI in business research from 2017 to 2023. We identify four primary themes—Customer Service, Future of Business, AI Adoption, and Ethics—and show an increasing emphasis on Customer Service and AI Adoption, while interest in Ethics has declined. The analysis reveals that forward-looking research on AI's future business impact is most influential in terms of citations. We also find strong links between customer service and AI adoption themes, but a significant gap with technical AI applications, suggesting that strategic considerations have outpaced technical implementation in recent years. Viewed through the lens of dynamic capabilities theory, these insights can inform future research on how businesses develop and navigate the challenges of AI adoption.

Keywords: artificial intelligence; large language models; topic model; dynamic capabilities theory.

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1 Introduction

While artificial intelligence (AI) has existed as an area of research and application for decades, we can arguably trace the current era back to a research team at Google who developed an attention mechanism for transformer neural networks. This attention mechanism revolutionized large language models (LLMs) by simplifying and speeding up the way machines understand and process information by focusing on the most important parts of the data (Vaswani et al., 2017). This novel approach will allow businesses to handle complex tasks more efficiently and offers a break from prior models in its potential for transformational change (Gruetzemacher and Paradice, 2020). LLMs offer a unique set of strengths and weaknesses due to their autoregressive architecture that predicts probable next-tokens. They excel at open-ended tasks such as interactive conversations but are relatively weaker with deterministic tasks such as automating structured data analysis, or with tasks requiring complex reasoning (Karpinska et al., 2024)—at least in the early stages of their development.

As artificial intelligence continues to evolve, its integration across various sectors holds promise for widespread productivity gains. Bresnahan (2024) argues that the economy-wide adoption of AI is poised to catalyze significant boosts in productivity, reminiscent of major technological shifts of the past. While assessments of early AI adoption by McElhran et al. (2024) using 2018 U.S. business survey data pointed to a varied pace among organizations, current trends indicate a more cohesive uptake, signaling a maturing of AI applications in business environments. For example, Humlum and Vestergaard (2024) found substantial engagement with AI tools like ChatGPT across diverse professions in Denmark.

The rapid adoption of AI technologies in business contexts raises questions about how organizations develop capabilities to leverage these new tools effectively. Dynamic capabilities theory offers a framework for understanding this process, as it explains how firms sense opportunities, seize opportunities, and reconfigure their resources to maintain competitiveness in the face of technological disruption (Teece et al., 1997). This theoretical lens can provide insights into how businesses adapt to the unique challenges and opportunities presented by AI, particularly in the context of LLMs with their distinct strengths in open-ended tasks.

Exploring the impact of AI technology through the lens of dynamic capabilities, this study aims to map the thematic evolution of business-related research on AI and LLMs from 2017 to 2023, the era of transformer architecture. Three research questions are explored. First, how have the themes in AI-related business research evolved from 2017 to 2023, reflecting technological advancements and changing market needs? Second, which topics have garnered the most scholarly influence, as measured by citation impact, indicating areas of high interest or emerging trends? Third, what connections exist between different themes in AI business research, as evidenced by their co-occurrence in research projects, revealing potential synergies and gaps for future study? To effectively address these questions, this study employs structural topic modeling as a methodological framework to analyze a corpus of over 5,000 research abstracts centered on AI in business settings. This approach systematically identifies and quantifies prevalent themes and their temporal shifts within the corpus. Structural topic modeling facilitates a granular analysis of how certain topics gain prominence or recede over time and how they correlate with each other, offering valuable insights that could shape future research directions. By examining these trends through the lens of dynamic capabilities, we can gain a deeper understanding of how scholarly attention aligns with the challenges and opportunities businesses face in developing AI-related capabilities. This analysis reveals that future-oriented themes and customer outreach have outpaced attention to technical implementation in terms of prevalence and influence, suggesting that strategic considerations and customer-facing applications of AI in business are advancing more rapidly than the development of more technical application. This imbalance highlights the need for firms to align their strategic AI initiatives with robust technical foundations as they build the dynamic capabilities required to fully leverage AI's potential.

2 Literature review

Recent research has examined the evolving role of AI in business contexts, revealing a rapid growth in AI adoption and capabilities over the past decade (Jorzik et al., 2024). AI is reshaping business practices across industries, from enhancing customer service and marketing efforts to transforming product development and decision-making processes (Kshetri et al., 2023; Kanbach et al., 2024; Shore et al., 2024). Gupta and Yang (2024) investigated factors influencing the adoption of ChatGPT technology by startups, finding that entrepreneurs' perceptions and attitudes toward generative AI play a crucial role in identifying potential risks and opportunities for organizations. However, research also points to challenges in AI implementation, including the need for new management capabilities, ethical considerations, and the importance of aligning AI initiatives with business strategies (Jorzik et al., 2024; Shore et al., 2024). Moreover, studies have highlighted the uneven adoption of AI across different business sectors and sizes, with larger enterprises more likely to implement AI solutions compared to small and medium-sized businesses (Shore et al., 2024). As AI continues to evolve, we should expect its impact on business models and operations to deepen, necessitating ongoing adaptation and innovation from organizations to harness its full potential.

Dynamic capabilities

Dynamic capability theory focuses on how firms adapt and reconfigure their resources and capabilities over time in response to rapidly changing environments (Teece et al., 1997). This emphasis on change and adaptation distinguishes it from static theories of competitive advantage and makes it particularly relevant for analyzing a business landscape impacted by AI. The integration of AI in business practice marks a substantial shift in how industries operate and strategize, fundamentally enhancing efficiency and reshaping customer interactions (e.g., Wang et al., 2022; Kshetri et al., 2023). As such, organizations will seek AI technology to the extent it can help them gain competitive edge amid complex market dynamics. Pursuing competitive advantage through technological innovation aligns closely with principles of dynamic capabilities theory, which provides a framework for understanding how firms adapt and thrive in rapidly changing environments. Dynamic capabilities theory is particularly relevant in the context of AI adoption, as it explains how organizations develop the capacity to sense opportunities, seize them, and reconfigure their resources to maintain competitiveness in the face of technological disruption.

Dynamic capabilities theory offers a framework in strategic management research, aiming to explain how firms achieve and sustain competitive advantage in rapidly changing environments. The theory states that organizations possess higher-order capabilities that enable them to sense opportunities, seize them, and reconfigure their resource base to adapt to environmental changes. Bleady et al. (2018) identify two primary schools of thought within dynamic capabilities theory. The "Teece school" (Teece et al., 1997) conceptualizes dynamic capabilities as specific and identifiable processes, such as product development and strategic decision-making, that integrate, build, and reconfigure internal and external competences. This school emphasizes the importance of managerial and organizational processes, shaped by the firm's asset positions and path dependencies. The second school, linked to Eisenhardt and Martin (2000), emphasizes how firms achieve new resource configurations across varied market dynamics. In highly dynamic markets, Eisenhardt and Martin argue that dynamic capabilities resemble simple, experiential processes with unpredictable outcomes, contrasting with Teece's view of more structured, analytical processes. Elaborating on these foundational perspectives, Helfat and Peteraf (2015) introduced the concept of "managerial cognitive capability" as underpinnings of dynamic capabilities, highlighting the role of managers' mental activities in sensing, seizing, and reconfiguring opportunities.

Recent empirical studies applying this theory to AI adoption and implementation highlight the critical role of sensing, seizing, and reconfiguring capabilities in successfully integrating AI into business operations. Organizations with strong sensing capabilities are better positioned to recognize the potential of AI technologies and their relevance to existing business challenges. For instance, Dubey et al. (2019) emphasize that AI-powered big data analytics enhance firms' ability to sense opportunities by providing valuable insights that improve operational performance. Similarly, Drydakis (2022) illustrates how AI applications during the COVID-19 pandemic enhanced small and midsize firms' ability to sense market trends and financial risks, aiding in the identification of strategic opportunities amidst economic instability. Graham and Moore's (2021) qualitative study of senior managers across various industries revealed that organizations with strong sensing capabilities are better positioned to recognize the potential of AI technologies and their relevance to existing business challenges. Their findings indicated that managers with superior cognitive capabilities for attention and perception were more adept at identifying new AI-related opportunities and threats. Additionally, Sullivan and Wamba (2024) discuss how AI-powered capabilities such as AI-enabled automation and analytics significantly enhance an organization's adaptive response to market changes, further reinforcing the importance of sensing capabilities in dynamic environments.

Seizing capabilities prove equally important in the context of AI adoption, enabling firms to make strategic investments and implement AI solutions effectively. Chen et al. (2023a) highlight that AI tools enhance dynamic marketing capabilities, such as customer relationship management and pricing, which enable firms to seize market opportunities more effectively by allowing them to quickly adapt to changing demands. Additionally, Mikalef et al. (2019) demonstrate that AI-driven big data analytics help firms to seize opportunities through innovation and strategic repositioning, leading to improved competitive performance. These studies suggest that the ability to seize opportunities through strategic decision-making and resource allocation is crucial for translating AI potential into tangible business outcomes.

Reconfiguring capabilities are crucial for firms to optimize resource use to maintain competitive advantage amid technological disruption—certainly a relevant focus for AI adoption. Gallego-Gomez and De-Pablos-Heredero (2020) show that in the banking industry, AI facilitates the development of dynamic capabilities that allow banks to transform traditional processes to create new relationships with customers, enhancing customer service and operational efficiency. Similarly, Graham and Moore (2021) emphasized the role of AI in enabling firms to transform their operations and maintain adaptability in rapidly changing technological environments.

While dynamic capability theory offers a robust framework for understanding AI adoption, the resource-based view (RBV) is another prominent theory in strategic management that may be considered for examining how firms leverage AI technologies. RBV emphasizes the importance of valuable, rare, inimitable, and non-substitutable resources in achieving sustainable competitive advantage (Barney, 2001). However, the RBV's traditional focus on exploiting existing firm-specific resources can be seen as relatively static. While this framework has been influential in explaining competitive advantage, it may be limited in addressing evolving environments like those created by AI. As Krakowski et al. (2023) argue, AI adoption triggers interrelated substitution and complementation dynamics, which both erode traditional human capabilities and create new human–machine capabilities. The RBV's focus on existing resources may not fully account for these shifts in resource value and functionality that AI introduces. Moreover, the theory's emphasis on resource heterogeneity and immobility does not adequately address the need for continuous resource reconfiguration in response to AI advancements. These limitations suggest that although RBV provides insight into the importance of firm-specific resources, it may not fully capture the dynamic nature of AI adoption and implementation in rapidly changing business environments.

While RBV emphasizes the importance of valuable and rare resources for competitive advantage, organizational learning theory offers a dynamic view on how firms can develop and adapt these resources over time. Crossan et al. (1999) propose that firms engage in four key processes—intuiting, interpreting, integrating, and institutionalizing—across individual, group, and organizational levels. This framework is relevant for AI adoption, as it highlights how organizations initially recognize AI's potential through individual insights, then interpret and integrate these insights into coordinated actions before institutionalizing AI technologies to secure competitive advantage. Wijnhoven (2022) illustrates this process in the context of AI adoption, showing how organizations must overcome knowledge transformation and integration challenges to effectively implement AI systems. However, as Easterby-Smith and Lyles (2012) discuss, organizational learning processes can be slow, which suggests they may struggle to keep pace with the rapid changes brought on by disruptive technologies like AI. This limitation raises concerns about whether firms can fully institutionalize AI innovations quickly enough to maintain a competitive edge in fast-evolving industries. In contrast to the static nature of RBV and the incremental approach of organizational learning, dynamic capability theory offers a more appropriate framework for examining the evolution of AI in business. Dynamic capability theory offers a distinctive edge in its ability to explain both the erosion of traditional capabilities and the creation of new ones in the context of AI adoption. Abou-Foul et al. (2023) highlight that AI capabilities function as dynamic capabilities, allowing firms to sense, seize, and reconfigure internal and external resources to address rapidly changing environments. The theory's emphasis on sensing, seizing, and transforming capabilities provides a comprehensive framework for understanding how firms identify AI opportunities, implement AI solutions, and reconfigure their resources and capabilities accordingly. This dynamic perspective is crucial for capturing the continuous adaptation required in AI adoption and implementation, making dynamic capability theory a suitable lens for our study of AI's impact on business practices.

Topic Modeling AI Research

Topic modeling provides scholars a means to systematically map and analyze the thematic landscape of a research field, identifying prevailing trends and shifts over time. For example, Sharma et al. (2021) utilized topic modeling to systematically analyze the progression of information management research across five decades, mapping the field's shift from foundational topics like database management and data processing to more intricate topics such as knowledge management, big data analytics, and sustainability. By employing topic modeling, Sharma et al. were able to highlight the dynamic nature of information management as a discipline, evolving in response to technological advancement and organizational needs.

Mustak et al. (2021) and Vaid et al. (2023) both utilized topic modeling to investigate the expanding role of AI in marketing. Mustak et al. explored a range of AI applications within marketing, identifying key themes such as consumer sentiment analysis and AI-driven strategic marketing innovations. Vaid et al. focused on empirical consumer research, covering a variety of AI applications to study consumer behavior, but also noting that such techniques are relatively underutilized in the field. Both studies offer examples of using topic modeling to explore evolving trends in AI utilization within marketing research. Similarly, Naz et al. (2022) applied topic modeling to investigate the role of AI in sustainable supply chain management, identifying key themes related to efficiency and sustainability. Aziz et al. (2021) also used topic modeling to explore AI applications in finance, identifying trends like algorithmic trading and risk assessment as pivotal areas influenced by AI.

3 Data & analysis

Data for this project were downloaded from the Web of Science (WoS) database. WoS was chosen as the primary data source due to its comprehensive coverage of business and management journals, as well as its inclusion of citation count metadata crucial for assessing the impact of research. Although WoS is not exhaustive, it captures an array of high-quality, peer-reviewed journals in the field, providing a strong foundation for analyzing AI-business research trends.

All research article abstracts mentioning "artificial intelligence" or "large language models" published between 2017-2023 and categorized as business, economics, finance, or information science were collected. The start of the time range was chosen due to the impact of Vaswani et al. (2017) on AI applications. This seminal paper introduced the transformer architecture foundational to the development of large language models and generative AI. The end point of 2023 represents the most recent full year of data available. As displayed in Figure 1, this timeframe adequately captures the exponential growth in research interest in AI and LLMs. This search resulted in a corpus of 5,214 research abstracts. This collection includes metadata in the form of publication date as well as total number of citations at the time of download (June 2024). An average number of citations per year was calculated for each article to make them comparable in terms of impact, since older publications have an opportunity to accumulate more citations than newer publications.

A structural topic model is applied to this collection of business-oriented research abstracts on AI and LLMs. Topic modeling is a statistical method used for uncovering the latent topics that occur in a collection of documents. The foundation of modern topic modeling was laid by Blei et al. (2003) with the application of Latent Dirichlet Allocation (LDA), a generative probabilistic model for collections of discrete data such as text corpora. LDA models each document as a mixture of topics, where a topic is a probability distribution over words. All documents in the corpus are modeled to share the same set of topics, albeit in varying proportions. Subsequent contributions modeled correlations between topics via the covariance structure of topic proportions across documents (Blei and Lafferty, 2006), as well as the dynamic evolution of topics over time that allow for analyzing temporal changes in the thematic content of a corpus (Blei and Lafferty, 2007).

Building on the foundations of LDA and its extensions, Roberts et al. (2014) introduced structural topic modeling (STM), which integrates document-level metadata into the topic modeling process. This innovation allows researchers to incorporate covariates associated with the documents into the model, allowing for additional insights into how latent topics vary across document context.

Topic modeling was chosen as the primary analytical method for this study due to its strengths in analyzing large amounts of text and identifying latent themes. Unlike traditional content analysis methods, topic modeling allows for the systematic identification of thematic patterns across a vast number of documents without needing to pre-define categories. This approach is well-suited to the research goal of mapping the thematic evolution of AI in business research, as it can reveal shifts in research focus over time and co-occurring themes not immediately apparent through manual analysis. Additionally, the ability to quantify the prevalence of topics aligns with the aim to assess the relative importance and interconnectedness of AI-business research themes.

The analysis presented here uses publication dates and average number of citations per year since publication (as reported by WoS) as covariates in modeling topic distributions. STM was implemented via the 'stm' R package (Roberts et al., 2019). Models were conducted that analyze covariation structures in terms of temporality (year of publication) as well as impact of the research (average number of citations per year), as well as the correlation between topics across documents in the corpus. Prior to modeling, standard data cleaning procedures were conducted. This included converting text to lowercase word-stems, and removing punctuation, numbers, and common stop-words ("the", for example).

A 21-topic model was generated, utilizing diagnostic metrics to ensure the quality of the topic extraction. Candidate models ranging from 15 – 30 topics were evaluated for semantic coherence (measuring the co-occurrence of probable words for a topic together at the document level) and topic exclusivity (an indicator that top words for one topic are exclusive to that topic and do not appear as probable words in other topics). These diagnostic scores are reported in Appendix A, showing a 21-topic solution as scoring best across these two measures.

For the assignment of labels to these latent topics, a systematic process was employed. Initially, the most probable word-stems for each topic were examined to understand the core content and orientation of the topics. This was complemented by an analysis of the most frequent and

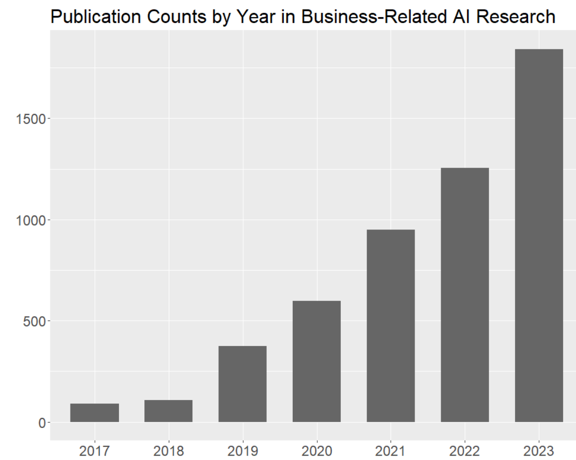

Figure 1. Number of articles included in the corpus by year.

exclusive ("frex") word-stems, which helped in discerning the unique characteristics of each topic. Additionally, to ensure the labels accurately reflected the content of the topics, the 25 most representative abstracts for each topic were manually reviewed. This approach facilitated the assignment of descriptive labels to each topic to aid interpretation.

These topics then underwent further analysis to understand their distribution across the corpus. The prevalence of each topic across the corpus was assessed, providing insights into the dominant themes across business-oriented research on AI. Temporal trends in topic prevalence were also examined, revealing how interests and focuses have shifted over the years. This analysis was also extended to evaluate the topical prevalence associated with average citations per year, offering a perspective on the impact and recognition of the topics within the academic community. Lastly, correlations between topics co-existing at the document level were investigated, highlighting intersections of topical interest, and suggesting areas of thematic overlap.

4 Results

The structural topic model applied to the corpus of 5,214 business-oriented research abstracts on AI and large language models identified 21 latent topics, summarized in Figure 2. This figure displays the top 5 “frex” (frequent and exclusive) word-stems that are most uniquely representative of each topic. The identified topics span a diverse range of subjects related to the application, adoption, and implications of AI technologies in business contexts. Four themes stand out as most prominent—Customer Service, Future of Business, AI Adoption, and Ethics. Beyond these, we see a variety of domains like problem solving, technology management, or innovation. Overall, the model results represent a comprehensive landscape of key areas explored within the scholarly discourse on business AI since 2017.

It is helpful to provide context to what these topics look like at a document-level by examining representative examples. “Customer Service”—the most prominent topic in the corpus—is especially focused on studies of customer experience with AI technology. Many studies scoring high on this topic are concerned with the relationships between business and client as mediated by the very new experience of chatbots, examining the quality of service provided by chatbots (Hsaio and Chen, 2022), customer engagement with voice-enabled AI (Cai et al., 2022; McLean et al.,

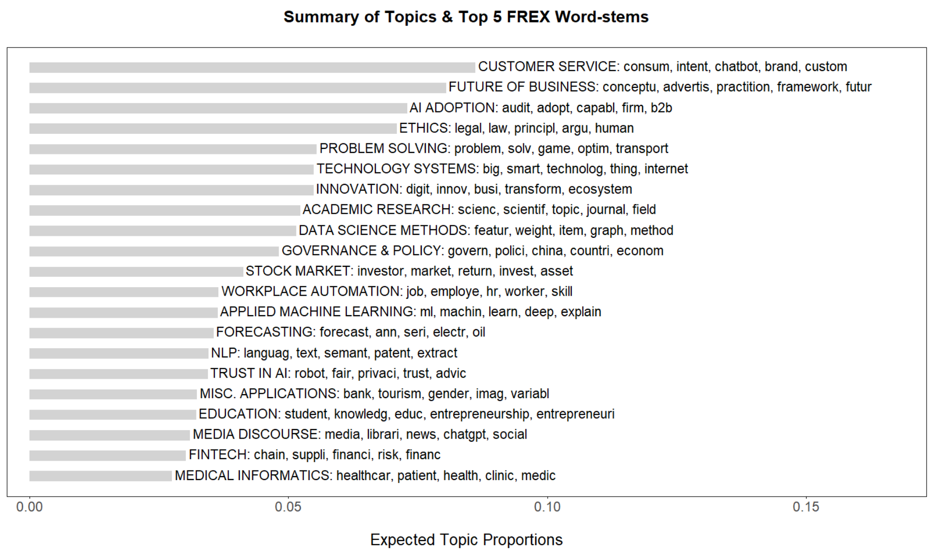

Figure 2. Summary of 21 topics identified in the model, with the top five most frequent and exclusive ('frex') word-stems.

2021), experiments of when customers desire chatbots (Zhu et al., 2022), or appropriate usage of emoticons in chatbots for brand management (Li and Shen, 2021).

The second-most prevalent topic— "Future of Business"—encompasses forward-looking analyses of how emerging technologies are reshaping business landscapes. Authors scoring high on this topic are often introducing new concepts or new challenges caused by generative AI. For example, Gao and Liu (2023) introduce the concept of AI-enabled personalization for interactive marketing, Miao et al. (2022) theorized the use of avatars to achieve effective customer outcomes, and Whittaker et al. (2021) confront the issue of deepfakes for marketing research.

Relatedly, the "AI Adoption" topic focuses on the business experience of integrating AI into organizational processes. Abstracts scoring high on this topic cover a wide variety of examples, including business-to-business relationship management (Chatterjee et al., 2022), AI adoption in hospitals during COVID-19 (Chen et al., 2023b), or organizational barriers to adopting AI in practice (Kar et al., 2021).

Lastly, among the most prominent topics, the "Ethics" theme represents a crucial area of focus within research on AI in business contexts. These studies grapple with the moral and ethical implications of AI deployment across various business practices. As a disruptive technology, many of these studies are concerned with responsibility and accountability, such as corporate responsibility for human rights (Kriebitz & Lütge, 2020), military defense contracting (Meerveld et al., 2023), or existing blind spots to recognize as businesses delegate decision-making to AI (Bolander, 2019). Ultimately, studies under this topic seek ethical frameworks or governance structures to address the profound impact that AI has and will have on business and society, so practice can align with societal norms and respect individual rights.

We can further analyze the results of this topic model by exploring how prevalence varies across temporal dynamics, topical influence on academic impact as measured by citation rates, or the relationship between topics based on patterns of co-occurrence within the same documents.

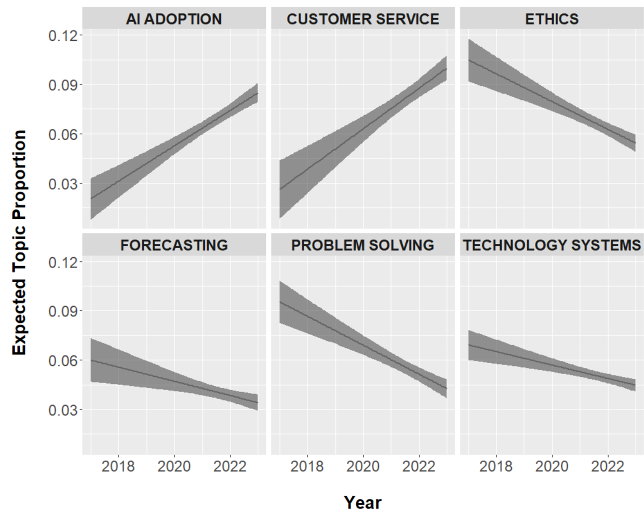

Figure 3. Temporal trends in expected proportions for selected topics.

Temporal Dynamics

While many topics remain steady in their prevalence during the 2017-2023 time range, Figure 3 presents some notable exceptions. Two of the most prominent topics in the model—AI Adoption and Customer Service—stand out on a clear uptrend of scholarly attention. Both topics more than triple in the amount of scholarly attention by the end of 2023. By contrast, the Ethics topic was the most prominent at the start of the time range but declined by half across the period.

Other topics also displayed a noteworthy decline in prevalence. The "Problem Solving" topic generally addresses complex optimization problems, ranging from dynamic programming in pursuit of profit maximization (Kim and Kim, 2022) to tree search heuristics for project scheduling (Liu et al., 2023). Overall, the Problem Solving topic displays a similar temporal prevalence trend as the Ethics topic, starting as one of the most prominent topic proportions and finishing at an average endpoint.

A modest downward trend is seen in the prevalence of the "Forecasting" and "Technology Systems" topics over time. The Forecasting topic encompasses a range of studies focused on predictive analytics across various domains, such as forecasting crude oil prices (Li et al., 2019) or wind power generation (Jafarian-Namin et al., 2019). The Technology Systems topic reflects discussions of strategizing around complex and emerging systems, such as the impact of the Internet-of-Things (IoT) on pricing (Zhang and Yue, 2020) or integrating big data analytics with Industry 4.0 processes (Javaid et al., 2021).

Impact Dynamics

Beyond observations on the temporal trends of topic prevalence, exploring the impact of topics (as measured by average amount of citations) adds another layer of understanding AI-related research in the academic business discourse. Table 1 presents the Pearson correlation coefficient between each topic with the average number of annual citations across all abstracts in the corpus.

In addition to being one of the most prevalent topics in the model, the Future of Business topic is clearly the most influential in terms of attracting scholarly attention, with the highest correlation between an abstract's average citations and topic proportion ($\rho = 0.172$). Customer Service, the most prevalent topic overall and the topic with the sharpest uptrend in recent attention, is the second-most prominent in attracting scholarly citations ($\rho = 0.102$). AI Adoption, another recently trending topic, also displays a positive though weaker correlation ($\rho = 0.053$).

Although lower in prevalence, the "Workplace Automation" topic stands out in its association with citation impact ($\rho = 0.071$). This topic focuses on the evolving labor dynamics in workplace settings, particularly how automation and AI reshape job roles and workflows. This includes a variety of examples such as striking appropriate balances between task automation and expertise in professional services (Sampson, 2021), the automation of talent recruitment (Black and van Esch, 2021), and even the increasing need for skills related to emotional intelligence in a landscape where analytical tasks are increasingly automated (Huang et al., 2019).

Conversely, some topics such as Problem Solving, Stock Market, and Academic Research (focused on systematic reviews of existing scholarship) display negative correlations between topic proportion and citations. This suggests that these areas, while valid and of interest to various audiences, seem to attract fewer scholarly citations relative to their prevalence in the research corpus. Overall, there are clear trends evident in some topics exerting more impact than others in the business scholarship on AI.

Table 1. Pearson correlation coefficient of expected topic proportions and average annual number of citations.

Topic	ρ	Topic	ρ	Topic	ρ
Future of Business	0.172	Technology Systems	0.019	NLP	−0.057
Customer Service	0.102	Ethics	−0.003	Forecasting	−0.063
Workplace Automation	0.071	Medical Informatics	−0.005	Misc. Applications	−0.063
AI Adoption	0.053	Fintech	−0.019	Education	−0.063
Applied ML	0.048	Media Discourse	−0.037	Academic Research	−0.068
Trust in AI	0.034	Governance & Policy	−0.043	Stock Market	−0.068
Innovation	0.029	Data Science Methods	−0.056	Problem Solving	−0.075

Note: Values calculated as the Pearson correlation between average annual number of citations and topic proportion values.

Topic Correlations

Figure 4 graphically displays the correlations between the 21 topics in the model. Each node represents a distinct topic, with node size reflecting the overall prevalence of each topic in the corpus. In this correlation structure, ties indicate a greater tendency of topics to co-occur within the same abstract; ties with a strength less than 0.05 were deleted to clarify relationships. This network graph presents an overview of the business-oriented AI research landscape, complementing previous analyses by revealing clusters of overlapping interests.

Starting with the most prominent topic, Customer Service, we see a primary connection to the "Trust in AI" topic. Malodia et al. (2022) offers an example of research at the intersection of these topics, exploring barriers to consumer adoption of AI-enabled voice assistants. Branching out from there, we see a connection between Trust in AI with Ethics, illustrated by Martin's (2019) commentary on the responsibility for consequential decisions shaped by algorithms.

The Ethics topic bridges Trust in AI and Customer Service with the Future of Business and Workplace Automation topics to create the most prominent cluster seen in the model. Tied to the Future of Business are the AI Adoption and Innovation topics. This series of interconnections underscores a thematic alignment of ethical considerations and trust in AI with practical applications for customer engagement and organizational integration. Leonardi and Treem's (2020) work conceptualizing behavioral visibility in organizational settings caused by digital connectivity offers an example of research that spreads across this cluster of topics. Setting up new types of research questions for organizational scholars, this study exemplifies the forward-looking discussion implied by the intersection of these topics, as businesses and scholars alike grapple with the long-term impacts of AI technologies.

Another notable cluster comprises topics such as Problem Solving, Forecasting, Data Science Methods, and Applied Machine Learning (ML). This group branches out to the Stock Market and Fintech topics and represents a more technical and application-focused segment of the research corpus, where the emphasis is on leveraging AI for optimization and predictive analytics. The connections from this cluster highlight the interdisciplinary nature of AI research, where methodologies and insights from one domain (e.g., forecasting) are applied to solve problems in another (e.g., equity investing). This cluster not only underscores the potential for cross-disciplinary innovation but also indicates the critical role that AI technologies play in driving advancements across various business sectors. It also implies an interplay between technical expertise and sector-specific challenges, and we could expect future research reflecting these interests to further explore AI's capabilities to optimize business operations and strategic decision-making.

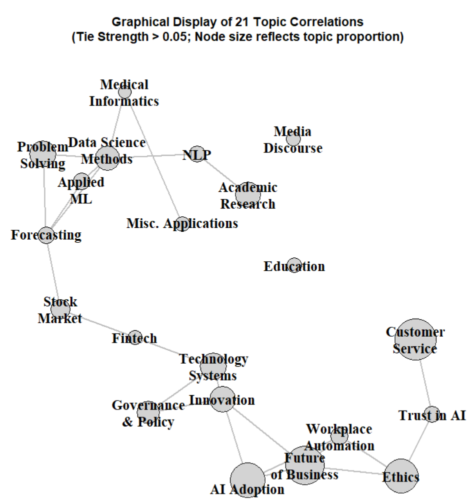

Figure 4. Topic correlation graph. Ties indicate a greater likelihood that topics are co-discussed within common research abstracts.

5 Discussion

This research provides a high-level synthesis of business-oriented AI research over a pivotal period of technological development from 2017 to 2023, revealing distinct thematic patterns through a structural topic model of 5,214 abstracts. The results illuminate core themes across this research area, with particular emphasis on customer service, future business directions, AI integration, and ethical considerations.

The resonance of these themes with prior research offers some validation to these results. The prominence of Customer Service reflects the widespread application of AI technologies aimed at enhancing customer interactions and satisfaction. This aligns with research by Gallego-Gomez and De-Pablos-Heredero (2020) and Wang et al. (2022), focused on AI practices that change and improve customer outreach and service. The scholarly focus on AI Adoption and Future of Business aligns with findings from Mikalef et al. (2019) and Sullivan and Wamba (2024), focused on firms' use of AI to strategically adapt to changing competitive environments. The observed decline in the Ethics theme, despite its initial prominence, might reflect a shift towards more pragmatic concerns as firms move from theoretical discussions to practical implementations of AI, mirroring trends observed by Teece et al. (1997) and Eisenhardt and Martin (2000) regarding the fluid nature of dynamic capabilities in high-velocity markets. This shift is indicative of a broader trend where businesses prioritize actionable insights and tangible benefits from AI applications over abstract ethical considerations.

The temporal dynamics explored in this study reveal the evolving nature of scholarly attention towards AI in business contexts. The recent rise in attention to customer service and AI integration acknowledges the increasing opportunities for practical application of general purpose LLMs, innovating a new era of service. By contrast, the slight decline in recent years given to the Ethics topic perhaps indicates a stabilization of this discussion—or, it may just be overwhelmed relative to the attention given to understanding the practical import of AI in business processes.

In terms of scholarly impact, this analysis shows that topics associated with higher average citations are those that engage with forward-looking and strategic elements of AI application, such as the Future of Business and Workplace Automation. This insight is indicative of the high value placed on research that not only addresses the current capabilities of AI but also anticipates its future developments and implications. This knowledge can illuminate how businesses can integrate a powerful and emerging technology that is ushering in a new era of applications, strategy, and risk (Griffy-Brown et al., 2020; Leavy, 2023).

The network of topic correlations depicted in Figure 4 reveals thematic clusters within AI business research. The largest and most impactful cluster centers around AI adoption, automation, the future of business, ethics, trust, and customer service. This forward-looking set of themes is at the forefront of application and theorizing. Notably, the location of "Ethics" as a bridging topic within this cluster suggests that ethical considerations are not just isolated discussions but integral to understanding the broader implications of AI adoption in business contexts. Still, the absence of stronger connections between highly technical topics and those dealing with ethical or strategic considerations could serve as an underexplored intersection for future research. This could set up research questions that probing whether AI capabilities can be applied to enhance ethical business practices, in addition to present discussions on ethical dilemmas. At the other end of the correlation network, the relative lack of scholarly attention to the more applied clusters could be mined for potential knowledge transfer from research that may target narrower academic communities.

The emergence of LLMs as a primary driver of recent AI applications presents an intriguing lens to view dynamic capabilities in the context of AI adoption. With their autoregressive architecture that effectively predicts probable next-tokens, transformer LLMs excel at open-ended tasks, such as conversational customer service, but are comparatively less adept at deterministic tasks like data analysis or tasks that require complex reasoning. This characteristic aligns with the topic model results presented here, which show an increasing emphasis on "Customer Service", potentially reflecting firms' recognition of LLMs' strengths in these areas. This trend seems to support Eisenhardt and Martin's conceptualization of dynamic capabilities in high-velocity markets as "simple, experiential and fragile processes with unpredictable outcomes" (2000: 1105). The open-ended nature of LLM applications in customer service and other domains requires firms to develop capabilities that are more fluid and adaptable. This shift toward customer service may explain the declining prominence of the "Ethics" topic in the model, as firms move from theoretical considerations to practical AI implementation. Furthermore, the prominence and influence of the "Future of Business" topic aligns with Teece et al.'s (1997) emphasis on dynamic capabilities to confront rapidly changing environments. However, the relative weakness of LLMs in structured data analysis and complex reasoning—at least during the early stages of their development—may indicate a potential limitation in current AI-driven dynamic capabilities, possibly explaining the relative marginalization of more technical-focused AI areas of focus by business researchers.

The results of the topic model also suggest dynamic capabilities as a strong framework to understand broad trends in AI and business. The prominence of the Customer Service and AI Adoption themes illustrates the development of sensing capabilities, as firms leverage AI to better recognize and anticipate market needs. For example, the increasing attention to Customer Service, which has tripled over the years, reflects the ability of firms to utilize LLMs to enhance customer interactions and satisfaction. This supports the idea that sensing capabilities are enhanced by AI, as firms are better equipped to detect and respond to shifts in consumer preferences and behaviors (Sullivan and Wamba, 2024).

Seizing capabilities are highlighted by the AI Adoption theme, where businesses are actively integrating AI into their processes to enhance operational efficiency and strategic decision-making. The study shows that AI tools improve dynamic marketing capabilities, such as customer relationship management and pricing strategies, allowing firms to seize market opportunities more effectively. This finding aligns with Chen et al. (2023a), who demonstrate that AI adoption leads to significant improvements in marketing performance, illustrating how firms strategically implement AI to capture value from emerging opportunities.

Transforming capabilities are essential for firms to continuously reconfigure their resources and maintain competitiveness amid technological disruptions. The Future of Business theme captures forward-looking analyses of AI's role in reshaping business landscapes, indicating how firms are transforming their operations to incorporate AI. Dubey et al. (2019) show that AI enhances transforming capabilities by enabling firms to reconfigure their operational processes and integrate new technologies. As firms adapt their structures and processes to leverage AI, they sustain a competitive advantage by remaining agile and responsive to market changes, aligning with Graham and Moore's (2021) emphasis on adaptability in dynamic environments. Overall, the observed trends in AI business research can be effectively interpreted through the lens of dynamic capabilities theory.

Managerial Implications

The increasing prominence of Customer Service and AI Adoption themes suggests that organizations should prioritize AI integration in customer-facing operations and overall business processes. Gama and Magistretti's (2023) taxonomy of AI applications as "replace," "reinforce," and "reveal" provides a useful framework for managers to evaluate and prioritize AI initiatives. Their study also emphasizes the importance of developing both "enabling" capabilities (e.g., functional competence, cybersecurity management) for initial AI deployment, and "enhancing" capabilities (e.g., augmented decision-making, process optimization) to fully leverage AI's potential. Managers should also foster closer collaboration between technical teams and business units to address the gap between customer service/AI adoption themes and technical AI applications. Prasad Agrawal (2024) emphasizes the importance of technological resource proficiency, which includes IT infrastructure and capabilities, in successful AI adoption. Creating cross-functional AI task forces or implementing job rotation programs could enhance knowledge sharing and align technical development with strategic business needs. This approach helps bridge the divide between technical expertise and business application, ensuring AI initiatives are both technologically sound and strategically aligned with organizational goals.

To effectively develop and leverage dynamic capabilities for digital transformation, managers must focus on building a comprehensive system of AI-enabled capabilities that span sensing, seizing, and transforming functions. Ameen et al. (2024) advise managers to prioritize developing AI skills in data management, human expertise, and organizational flexibility. By integrating AI with strategic agility, firms can quickly adapt, innovate, and improve product development. Managers should also foster ambidexterity—balancing exploration with operational efficiency—while leveraging external support, such as government policies, to strengthen AI's impact and ensure long-term success. Kemp's (2024) situated AI framework offers valuable insights for future-oriented planning, emphasizing the importance of grounding, bounding, and recasting activities. Managers should strategically orchestrate these situating activities to anchor AI in the firm's unique experiences, relational systems, and strategic goals. This approach can help firms develop AI-driven capabilities that are firm-specific, cost-effective, and aligned with emerging opportunities in dynamic environments, positioning the organization for sustained competitive advantage in an AI-driven future.

As managers navigate the complex ethical landscape of generative AI adoption, they must prioritize responsible implementation. Renewed attention to this area is crucial given the observed decline in AI ethics research. Andrieux et al. (2024) offer a straightforward Two-Rule Method of ethically analyzing AI focused on "Do no harm" and "Do good" principles. Managers should proactively establish clear policies that make AI decision-making transparent, designate AI champions within their organizations, and foster continuous learning about AI capabilities and ethics. Keeping a "human in the loop" can address trust issues in AI and ensure accountability. As generative AI advances, managers will likely encounter dilemmas where efficiency with fairness and organizational values conflict.

Limitations

While this study offers valuable insights, it of course carries some limitations. Most importantly, we must not mistake scholarly attention as a perfect mirror of empirical practice. The topics and trends identified in this study reflect the interests and focus of academic researchers, which may not always align precisely with the practical realities of AI adoption and implementation in business settings. Furthermore, the rapid pace of AI development means that there may be a lag between emerging business practices and their reflection in academic literature, potentially leading to an underrepresentation of the most recent AI applications and challenges.

Methodologically, the reliance on abstracts rather than full-text papers inevitably loses some information. Running a topic model on full papers would likely yield different and perhaps more detailed results. However, authors distill the main contribution of their research into their abstracts, so we can have some confidence that these findings adequately capture prevailing trends and provide valid insights into this research landscape, at far less computational cost than would be required by modeling full-text papers.

While WoS provides a robust dataset for this analysis, it does not provide an exhaustive dataset. Other databases such as Scopus, IEEE Explore, or ScienceDirect may contain additional publications relevant to this analysis but not captured by WoS. This limitation may introduce bias in the results presented here; for example, IEEE Explore might offer more comprehensive coverage of technical AI applications, or ScienceDirect may have a wider range of business journals (though it does not offer citation count metadata). Future studies could consider merging results from multiple databases. Despite this limitation, we believe the WoS dataset provides a representative picture of mainstream academic research on AI in business.

Future Directions

The insights identified in this study not only shed light on the current state of AI research in business contexts but also provide direction for future scholarly inquiries. As AI technology matures and businesses continually integrate AI into core operations and strategies, academic research must keep pace to address the opportunities and challenges created by these technologies. Conceptually, scholars can begin differentiating categories across the AI landscape. For example, Hermann and Puntoni (2024) differentiate between convergent and divergent thinking within generative AI, directing attention to contexts of domain-specific tasks versus broader, creative, and potentially more innovative AI applications. Such distinctions can help researchers better understand how different types of AI can influence organizational decision-making, innovation processes, or strategic outcomes. Moreover, exploring AI's role in creating competitive advantages can help scholars better refine which business environments are best suited for creating value from AI integration (Sullivan and Wamba, 2024).

Relatedly, as the technology matures and business adoption increases, scholars will have the opportunity to further explore the costs or unintended consequences associated with the disruptive aspects of AI. Perhaps most obviously, AI will lead to some forms of job displacement (e.g., Chen et al., 2022), which carries political risks of regulatory reaction. Beyond displacement, underexplored is the possibility that AI adoption could lead to disadvantage. Rana et al. (2022) offered a framework to study the unintended consequences of AI integration that can lead to a firm's competitive disadvantage via suboptimal decision-making caused by poor training or data quality. Amid the hype and optimism associated with AI, such pitfalls will inevitably develop and deserve attention from researchers, reinforcing the point from Teece et al. (2016) that the pursuit of organizational agility comes at a cost and invites risk.

Given the fast-changing landscape of generative AI and some of its unprecedented characteristics, researchers could also focus on practitioner experience to help bridge the gap between academic output and real-world implementation as a means of identifying emerging trends. To this end, interview projects could complement systematic reviews like the current study, anticipating trends such as the growing demand for soft skills (Cardon et al., 2024). While few in-depth case studies exist at present, Kanbach et al. (2024) offer categorical guidance for business model innovation across industries. Conducting detailed case studies within specific industries could provide practical insights, best practices, and common challenges, possibly validating the findings from the topic model analysis.

We should expect a diverse and extensive engagement with the topic of AI for years to come, as researchers further explore topics such as new business models made possible by AI capabilities, the ethical aspects of AI in business decisions, or new risks induced by AI. This ongoing research agenda will be crucial in navigating the complexity of AI applications in business contexts, potentially contributing to sustainable business practices, and fostering innovative and ethical AI integration strategies.

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7 Appendix

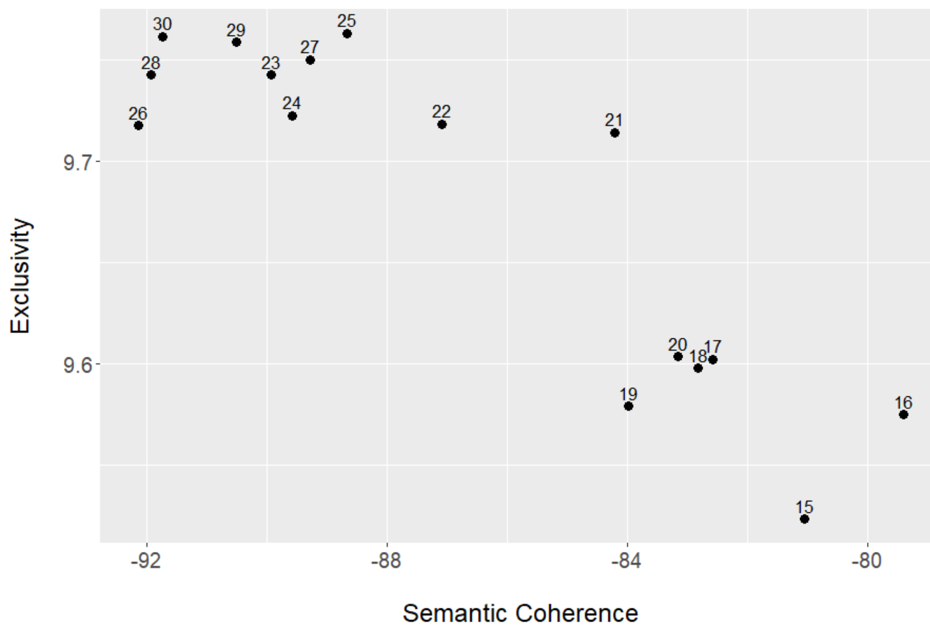

Figure 5. Generality Scores Indicating Topic Exclusivity and Semantic Coherence in Models Defined by *k* Topics

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