Generative Artificial Intelligence in Applied Business Contexts: A Systematic Review, Lexical Analysis, and Research Framework

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Generative Artificial Intelligence (GenAI) is transforming business practices with potential applications in customer service, code generation, risk analysis, and HR functions. GenAI may simultaneously create or exacerbate ethical, legal, and security concerns in the business context despite its promise. Thus, researchers should be interested in its role and impact, especially in the applied business context. This multi-method systematic review examines GenAI literature in applied business research, revealing dominant themes like ChatGPT and language models but noting a scarcity of business-based studies. Analysis of GenAI research features in applied business studies identifies a limited focus on theoretical frameworks, data collection methods, and data analysis processes. We suggest frameworks for future research to assess GenAI's impact on system and information quality, user satisfaction, and organizational outcomes based on our findings. This review provides a vital foundation for understanding and advancing GenAI in applied business research contexts.

Keywords: generative artificial intelligence, systematic review, lexical analysis, applied business research

INTRODUCTION

The concept of Generative Artificial Intelligence (GenAI) has impacted multiple fields and applications in a relatively short timeframe. At its core, GenAI serves as a tool for generating unique content by employing machine learning algorithms to sift through extensive datasets. These algorithms utilize trained data, considered most pertinent to a given input, as a foundation for constructing responses (Aydin & Karaarslan, 2023). The crucial role of Natural Language Processing (NLP) in this technology cannot be overstated, as it underpins the interpretation of inputs, indexing, and training reference data, and producing output in desired languages (Chowdhary & Chowdhary, 2020). GenAI is a tool and a field of study, emphasizing its capability to create new information and the underlying potential for advancing various industries and disciplines through innovative applications.

Business and the Use of GenAI

GenAI can potentially enhance customer service skills, code generation, risk analysis, and HR functions (Mondal et al., 2023). While the potential of GenAI is expansive, its integration into mainstream use has stirred controversy (Sia, n.d.). The utility of GenAI as a thinking supplement prompts questions about the necessity for human intervention in validating, extending, or constraining its outputs, particularly in business applications. As a result, common concerns focus on its ethical, legal, organizational culture, and operational dimensions.

For example, businesses can leverage GenAI's specialized data to craft marketing materials based on in-depth analyses of target groups and create dynamic social media content. GenAI can also provide recommendations to companies regarding business innovation (Kanbach et al., 2023). Moreover, its impact transcends content creation, potentially automating customer service interactions and incorporating decision support based on financial analysis and market trends (Chen et al., 2023).

Although GenAI may positively transform business practices, it simultaneously may create or exacerbate trust, ethical, legal, data privacy, and security risks inherent in business (Pratt, 2023; Tese & Silvanio, 2023; Tilley, 2020; Weitzman, 2023). Therefore, GenAI should be of interest to applied business research which is "a type of inquiry tailored for specific organizations" to solve problems and facilitate managerial decision-making for managers (Norris, 2015). Specifically, researchers are examining GenAI's role in organizations since applied business research is centered on the desire to solve problems experienced by organizations (Hair et al., 2020).

Emerging Applied AI Research Issues

Artificial intelligence (AI), a broad term encompassing advanced computer systems, has its roots in the seminal 1950 work of Alan Turing. A subfield of AI, machine learning (ML), has gained prominence with the rise of big data, leading to the development of artificial neural networks (ANN) and, subsequently, deep learning (DL). GenAI, a subset of deep learning, creates new content based on learned patterns from existing content. GenAI applications span across media, business/marketing/healthcare, and the education/code development/metaverse. Examples of popular AI applications in each category are provided in Table 1.

TABLE 1
POPULAR AI APPLICATIONS BY TYPE

Type	AI Applications
Media	DALL.E 2, Imagen, Dreamfusion, Magic 3D, Flamingo, Visual GPT, Phenaki, AudioLM, Jukebox
Business/Marketing/Healthcare	ChatGPT, LaMDA, Meta AI, AlphaFold
Education/Code Development/Metaverse	Codex, Alphacode, Metaverse AI

Despite successes in GenAI development, challenges persist, including interpretability, data bias, and ethical use. As a result, initiatives have been created to establish norms and principles to guide the deployment of GenAI applications. For instance, the Partnership on AI and Stanford University established the National AI Research Resource, which hosts programs such as the Congressional Boot Camp on AI, the AI Audit Challenge, and the Tech Ethics and Policy Summer Fellowship (Stanford University, 2023). Microsoft's Responsible AI Standard emphasizes accountability, inclusiveness, reliability, safety, fairness, transparency, and privacy and security (Zhang, et al., 2021).

As GenAI applications evolve, those who develop and use the applications must ensure both safety and responsibility in their deployment. Specifically, this process must emphasize standard design principles, algorithmic improvements, and attention to efficiency, explainability, fairness, and accountability (Jovanović & Campbell, 2022). Moreover, Sohail et al., (2023) identify ethical concerns regarding false information generated by conversational GenAI models.

Research Questions

GenAI exists in a multifaceted landscape with implications across diverse sectors. Scholars and practitioners must understand its current role in applied business research to uncover insights that may guide practical applications of GenAI in business contexts. Therefore, this multi-method systematic review aims to explore the current features and themes of GenAI literature in applied business research. An investigation of these areas is needed to (a) uncover foundational insights that may guide practical applications of GenAI in business contexts, (b) identify major recurring themes in empirical business research, (c) increase our comprehensive understanding of current discourse, and (d) highlight potential gaps or areas that need further exploration. Additionally, our findings may detect essential aspects necessary for the informed, ethical, and responsible integration of GenAI in applied business contexts. As a result, the following research questions were examined:

RQ1: *What themes exist in GenAI research studies?*

RQ2: *What are the features of GenAI research in applied business studies?*

METHODOLOGY

Systematic Review

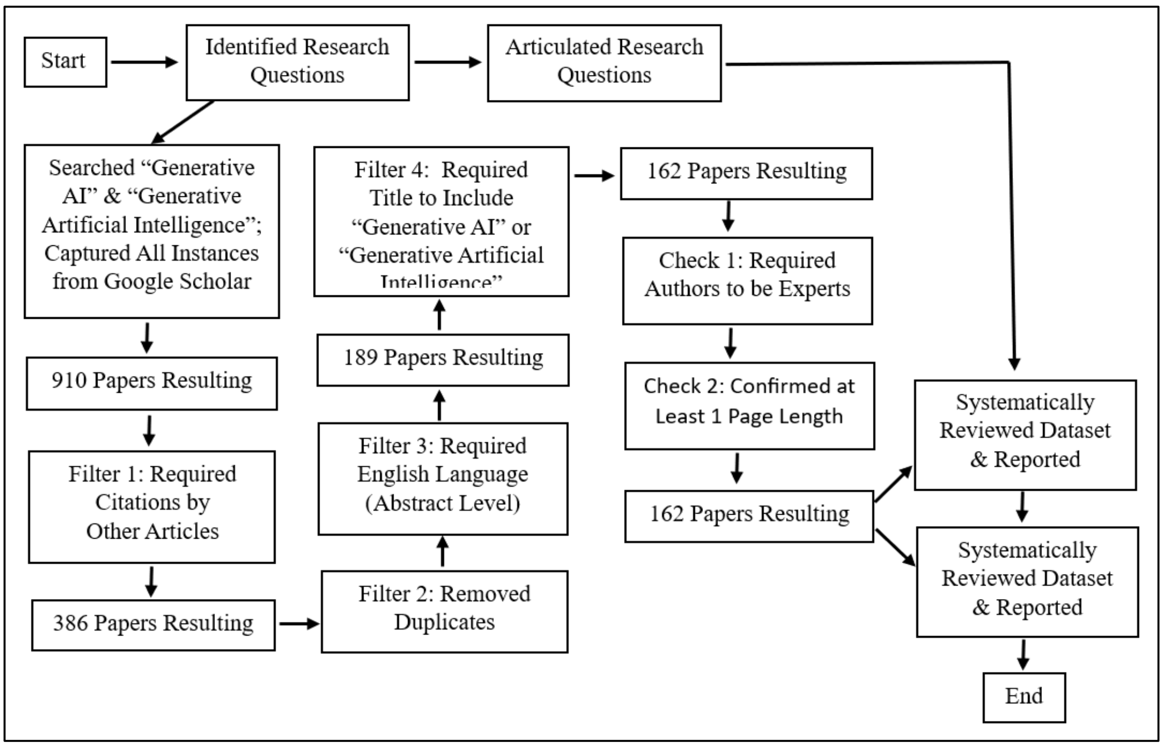
The present study examined the empirical GenAI literature using the widely leveraged approach of systematic review to reveal emergent trends, methodologies, contexts, and potential implications in applied business settings (Borges et al., 2021). Specifically, researchers captured and summarized all empirical GenAI research studies that fit the articulated eligibility requirements. Additionally, a lexical map was produced of the data (e.g., abstracts, introductions) utilizing Leximancer (Leximancer Pty Ltd, 2018) software for thematic counts and cluster analysis to support the findings (Lemon & Hayes, 2020).

A systematic review may be conducted when the academy has published enough research on a given concept that there is instability in understanding that concept. Thus, the systematic review can stabilize a comprehension of that phenomenon. Our review models the steps in previous studies to analyze the most important and highest quality GenAI research (Gilstrap & Gilstrap, 2023; see Kitchenham & Brereton, 2013). First, review questions were developed. Second, a review protocol was generated. Third, study selection criteria and processes were articulated. Fourth, the qualities of the studies were assessed. Fifth, lexical and human analysis were applied, and summarized data extraction and synthesis results were presented and interpreted.

Dataset Protocol

To generate a complete dataset of research literature, the authors first conducted a capture of all relevant research articles (n=910) based upon the search phrases "generative artificial intelligence" and "generative ai" utilizing a Python-based tool to scrape and order entries from Google Scholar. Using a modification of the PRISMA approach (Page et al., 2021), the dataset was filtered with a sort/filter/remove method utilized in past systematic reviews (see Gilstrap & Gilstrap, 2023) (see Figure 1). Specifically, the collection of articles was initially filtered based on four requirements: (1) articles were cited by at least one other paper (n=386), (2) article titles were required to contain at least one of the search phrases (n=189), (3) articles were required to be published in English and (4) duplicates were removed (n=162). Additionally, dataset articles were analyzed to determine that at least one author of each article was an expert (i.e., published previously on the topic or identified as trained in the field) and that each included article be at least one full page in length. No additional articles were added back to the field due to the recency and saliency of filters applied. Finally, the final dataset (n=162) was prepared for systematic review and lexical analysis in .doc and .pdf file formats.

FIGURE 1
DATASET & REVIEW PROTOCOL



Lexical Analysis

The dataset was analyzed using the textual analysis software Leximancer to create outputs for research questions (Çakar & Aykol, 2022). Leximancer uses a machine learning iterative process of seeding word definitions from frequencies and co-occurrences of words counted within blocks of text over a dataset to identify key concepts, which it groups into themes (Leximancer Pty Ltd, 2018). It has been used in many disciplines to assess scaled qualitative datasets.

For this study, Leximancer was utilized to assess 162 articles for the clear concepts (direct counts) and themes (i.e., terms with strongest co-occurrences) that emerge in this GenAI literature given 1,524,298 words emerged in the dataset (roughly fifteen very large novels in size) (e.g., Cretchley et al., 2010; Gilstrap & Gilstrap, 2023; Wilk et al., 2019).

The temporal distribution of the final dataset of GenAI peer-reviewed journals (PRJs) is as follows: 2020 or earlier: n=6; 2021: n=6; 2022: n=20; 2023: n=130. The year 2023 saw significant growth in the number of GenAI studies and position papers. These articles' major fields of study included computer science, education, engineering, public policy, and business. Although the present study lexically examines the broader GenAI dataset for textual information, additional focus will be given to the business-based articles for applied business research.

FINDINGS

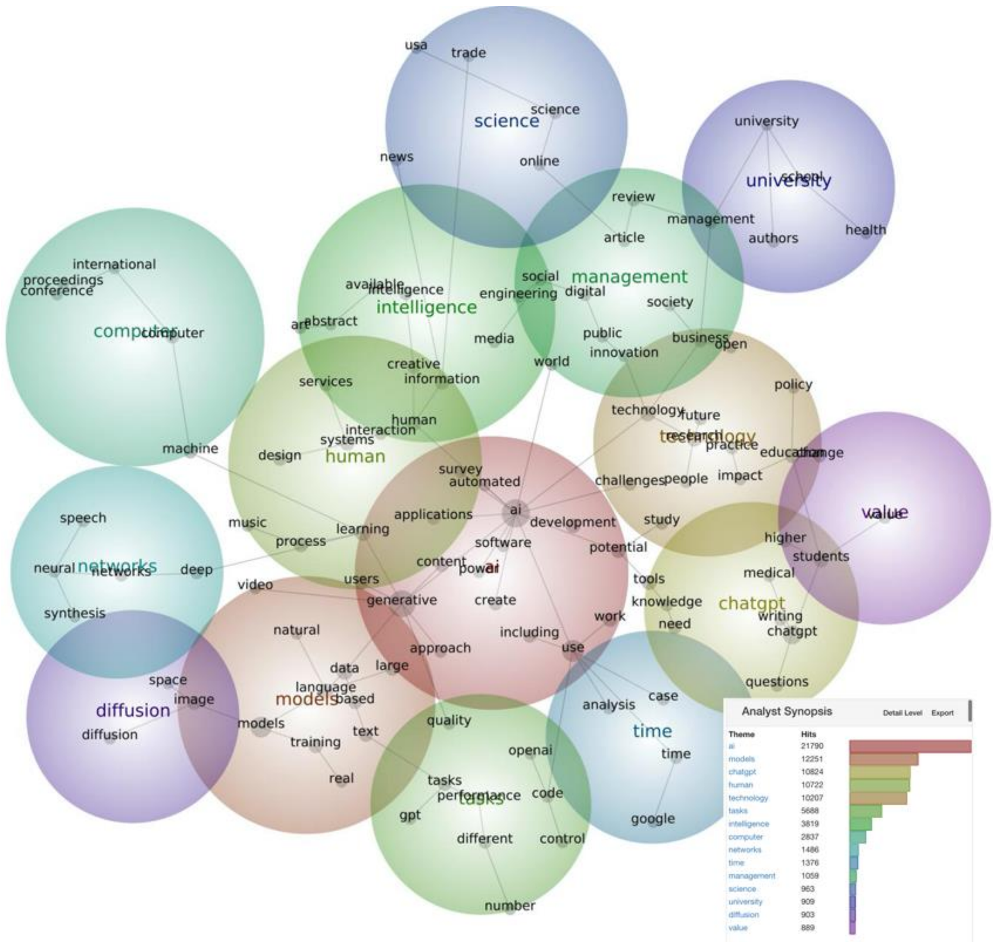
We organize findings according to our research questions. The first research question attempts to identify themes in GenAI research studies (Section 3.1). The second research question investigates specific features of GenAI research in applied business studies (Section 3.2)

Lexical Analysis of GenAI Dataset

The list of co-occurrence terms found via Leximancer's lexical calculations of the complete GenAI dataset (n=162 articles) indicates business terminology is not common within it. Frequency counts of the top 20 common terms across the dataset reveal only the 19th (i.e., "training") and 20th most frequent terms (i.e., "development") are most closely related to the business context. The next most frequent business term is "performance" at the 41st slot, and "management" at the 48th slot. Across the top 110 most frequent terms within the dataset, only two terms (i.e., training, development) implicate business while two additional terms (i.e., management, innovation) impact business but appear somewhat broader in contextual consideration. The term "business" does not appear until the 63rd slot in the frequency list, demonstrating that business is not a prominent research context in GenAI literature. Beyond Leximancer, a basic search count of "business" in the larger dataset identifies only 902 instances, clearly not enough to impact the top frequencies within the larger, complete GenAI articles dataset. For example, "usa" is the least term of the top 110 lexically calculated list and emerged 207 times.

Figure 2 reveals the Leximancer counts and calculations of the complete GenAI dataset where the most impactful concepts shown clustered are those terms that emerge through tabular count and highest co-occurrence. Each top-level theme is represented by a colored sphere showing the additional, co-occurring terms that cluster around it. Considering the top fifteen themes, it is clear the majority of GenAI articles focus on ChatGPT as a leading GenAI model, how information is utilized and created through large language models, the impact of these models on society and humans, how GenAI models learn using data capture and analysis as well as training technology, and what educational tools and technological outcomes impact university students and project management. Unfortunately, the GenAI dataset analysis findings do not identify where or how business is impacted beyond management.

FIGURE 2
LEXICAL ANALYSIS FINDINGS FOR COMPLETE GENAI ARTICLE DATASET WITH MOST FREQUENT, CO-OCCURRING THEMES

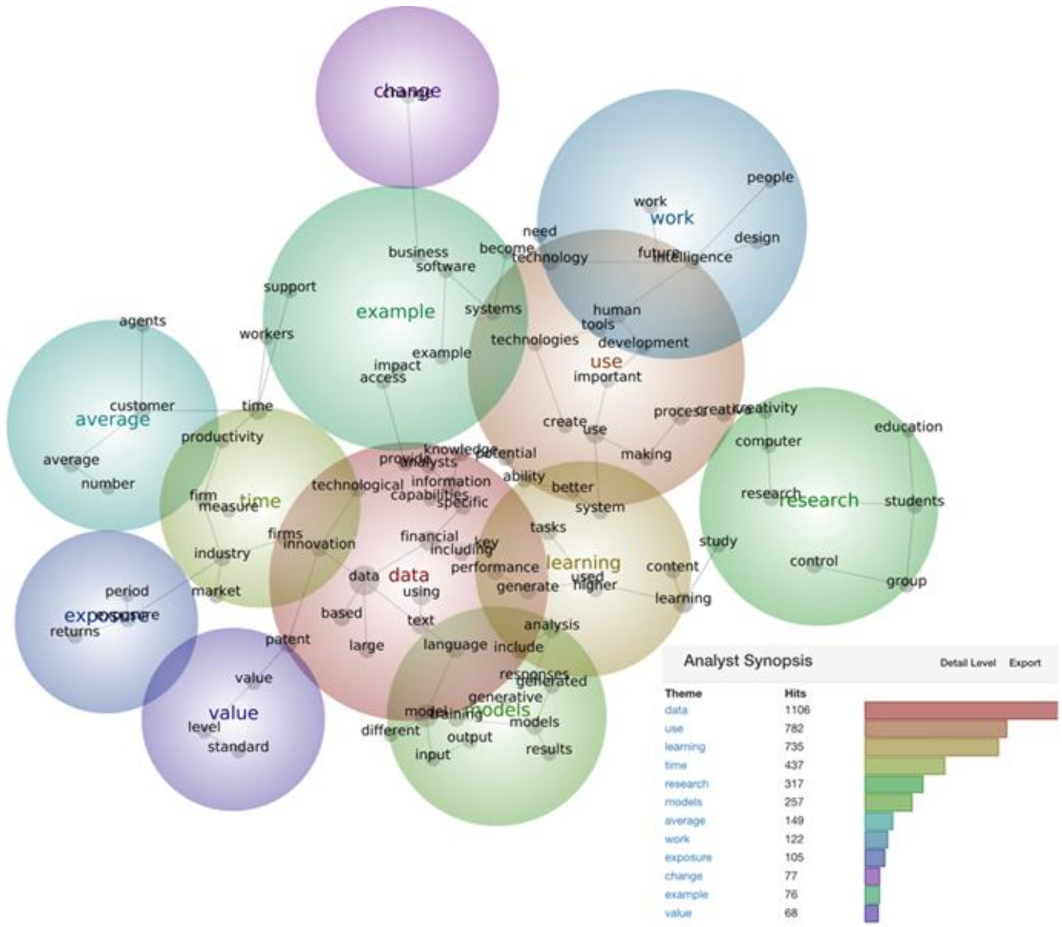


Lexical Analysis of GenAI-Applied Business (AB) Data Business

Drawn from the complete dataset, the applied business dataset (GenAI-AB) is comprised of twenty articles. The articles are focused on applied business contexts and disciplines including general business (Beerbaum, 2023b; Brynjolfsson et al., 2023; Eisfeldt et al., 2023; Houde et al., 2020; Inie et al., 2023; Korzynski et al., 2023; Zhong et al., 2023; Zq et al., 2020), management (Bilgram & Laarmann, 2023; Kanitz et al., 2023; Korzynski et al., 2023; Lim et al., 2023), marketing (Mayahi & Vidrih, 2022), finance (Krause, 2023b, 2023a, 2023c), accounting (Beerbaum, 2023a), and information systems (Euchner, 2023; Ferrag et al., 2023; Mollick & Euchner, 2023).

Leximancer was used to generate a lexical count and co-occurrence calculation of the most frequent terms across the GenAI-AB dataset. The top themes begin to incorporate business-related concepts through work and computer-based research. While the most common themes demonstrate the importance of data, learning, and modeling for GenAI within applied business contexts, industry ("time"), innovation ("time," "data"), firms ("time," "data"), and intellectual property ("patent" within "data") are observed emerging to support the top-level themes. More specifically, these business-related themes emerge through frequency counts and are found clustered with the top-level themes.

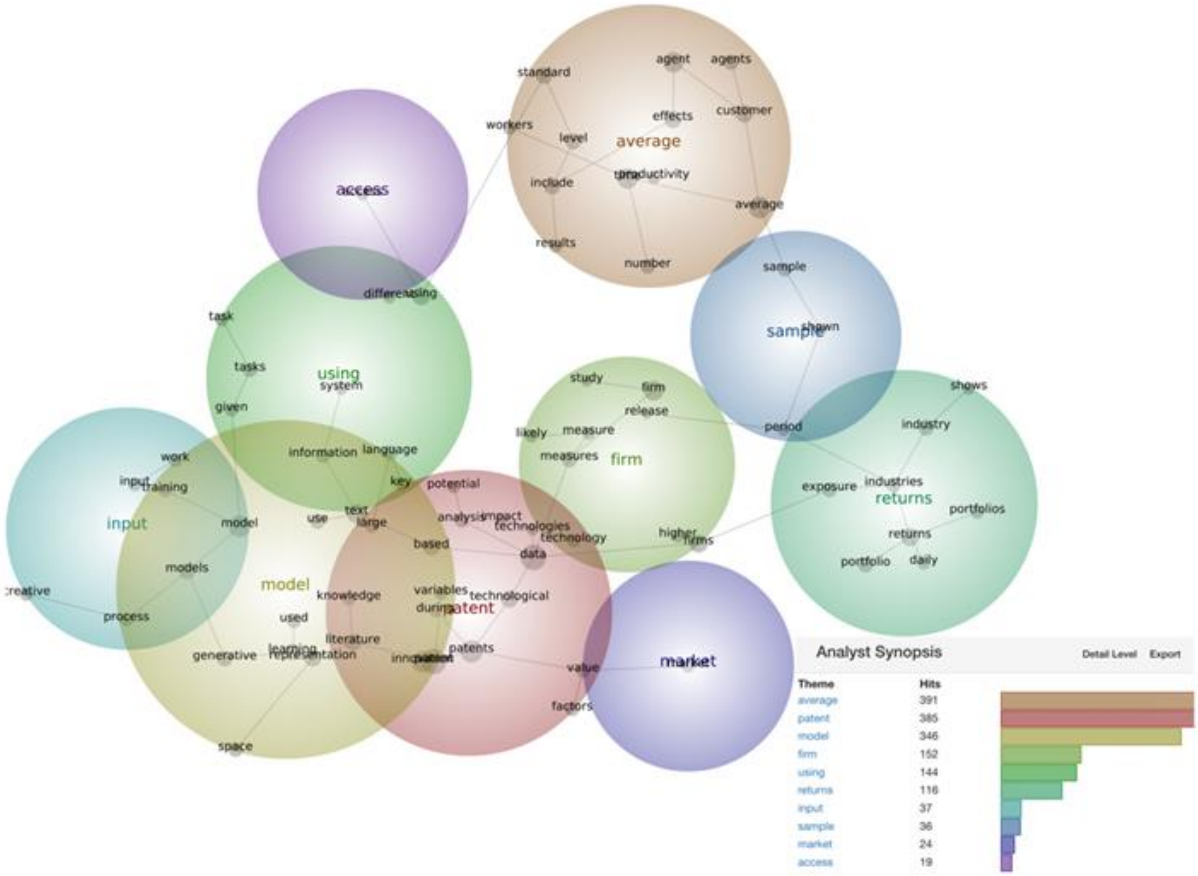
FIGURE 3
LEXICAL ANALYSIS FINDINGS FOR APPLIED BUSINESS DATASET WITH MOST FREQUENT, CO-OCCURRING THEMES



Lexical Analysis of GenAI-Applied Business Empirical Research (GenAI-AB-Emp) Data Subset

Only five of the GenAI-AB articles are applied in nature and thus comprise the applied business empirical research (GenAI-AB-Emp) dataset (Brynjolfsson et al., 2023; Eisfeldt et al., 2023; Inie et al., 2023; Zhong et al., 2023; Zq et al., 2020). The AB-Emp dataset offers a valuable lens into research applied business disciplines may choose to explore and extend. For the lexical purposes of this paper, this sub-subset likewise allows examining and comparing how traditional research into GenAI-AB may be counterposed against those published articles offered as theoretical or monograph-style articles. The lexical findings indicate the “firm,” “patent”-based intellectual property, and “market” analysis of the value created by GenAI are prominent themes across the GenAI-AB-Emp dataset (see Figure 4). Additionally, the findings highlight additional themes within empirical applied business research, including “customer,” “agents,” “standards,” “workers,” “tasks,” “industries,” “portfolios,” and “exposure.” GenAI-AB demonstrates a robust entre into GenAI thought within the applied business realm given the contextual nature of GenAI technologies, the business processes enhanced, human and firm implications, intellectual property impacts, intellectual capital expended, firm modifications and adaptations, and organizational affordances that this new technology offers.

FIGURE 4
LEXICAL ANALYSIS FINDINGS FOR APPLIED BUSINESS EMPIRICAL DATASET WITH FREQUENT, CO-OCCURRING THEMES



GenAI Research Features in Applied Business Studies

Research question 1 examined the attributes of GenAI research published in empirical applied business studies. Specifically, three features were examined in each study: theoretical framework, data collection, and data analysis processes. As noted in Table 2, the applied business studies examine GenAI through five primary theoretical frameworks, utilize both quantitative and qualitative data to examine GenAI phenomenon, and primarily rely on quantitative methodologies to examine their data. Additionally, our findings highlight the lack of GenAI studies in applied business studies. Specifically, at the time of data collection, only five of the 162 examined GenAI articles focused on the applied business context.

TABLE 2
GENERATIVE AI APPLIED BUSINESS RESEARCH FEATURES & STUDIES

Structural Feature	Topics	Studies
Theoretical Framework	Copyright Protection and Accountability	Zhong et al. (2023)
	Customer Service Support	Brynjolfsson et al. (2023)
	Disentangled Representation Learning	Cheng et al. (2023)
	Firm Values	Eisfeldt et al. (2023)
	Participatory AI/Participatory Design	Inie et al. (2023)
Data Collection	Archival Images	Zhong et al. (2023)
	Computing System Patents	Cheng et al. (2023)
	Firm Earning Call Transcripts	Eisfeldt et al. (2023)
	Firm-Occupational Employment Data	Eisfeldt et al. (2023)
	Generative AI Captured Conversational Text	Brynjolfsson et al. (2023)
	Occupation Task Statements/Data	Eisfeldt et al. (2023)
	Performance Statistics	Brynjolfsson et al. (2023)
	Qualitative Surveys	Inie et al. (2023)
	Social Media Posts	Eisfeldt et al. (2023)
Data Analysis	Chat-GPT Scoring	Eisfeldt et al. (2023)
	Computer-Aided Sentiment Analysis	Brynjolfsson et al. (2023)
	Data Aggregation	Eisfeldt et al. (2023)
	Frechet Inception Distance (FID)	Zhong et al. (2023)
	Frequency Distribution & Regression	Brynjolfsson et al. (2023) Cheng et al. (2023) Eisfeldt et al. (2023)
	Generative Adversarial Network (GAN) & Norm Calculations	Zhong et al. (2023)
	Natural Language Pre-Processing Techniques	Eisfeldt et al. (2023)
	Qualitative Thematic Analysis	Inie et al. (2023)
	Quantitative Textual Analysis	2023

DISCUSSION

The thematic analysis of the GenAI research corpus, as reflected by the Leximancer software's lexical metrics, offers a nuanced view of the field's dominant conversations. The prominence of platforms, such as ChatGPT, within the analysis, highlights a concentrated interest in how advanced language models redefine information synthesis and their ripple effects on societal structures. Furthermore, the analysis casts light on the learning methodologies of GenAI, with a particular focus on how data is harnessed and interpreted, underlining its significance in sectors like education and project oversight. These insights are pivotal, providing granular insight into GenAI's role in reshaping business and technological landscapes—a critical factor for assessing these systems' efficacy.

Themes From GenAI Research Studies

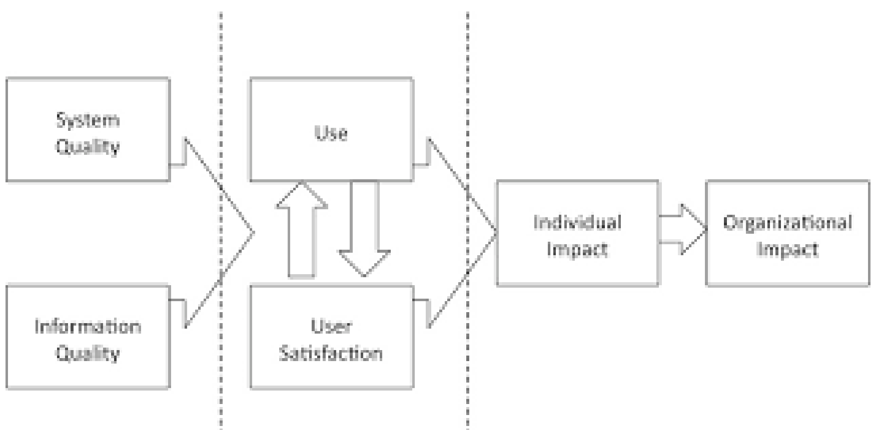
Lexical findings indicate the "firm," "patent"-based intellectual property, and "market" analysis of the value created by GenAI are prominent themes across the GenAI-AB-Emp dataset (see Figure 4). Additionally, the findings highlight additional themes within empirical applied business research including "customer," "agents," "standards," "workers," "tasks," "industries," "portfolios," and "exposure." These findings are instructive because they highlight the current themes that appear to be service-focused and data-focused. Additionally, they provide a macro view of the dataset from Figure 4, have an IP bent, and include workers, work, and risk.

Frameworks for Future Research

The Information Systems (IS) Success Model is a comprehensive, widely used, and well-tested framework to assess the success of information systems within organizations (Delone & McLean, 2004; see Pushparaj et al. 2023). The model suggests IS success is a multidimensional construct composed of six dimensions: system quality, information quality, use, user satisfaction, individual impact, and organizational impact (DeLone & McLean, 1992) (see Figure 5). For example, researchers can utilize the system quality dimension to evaluate the technical aspects of GenAI systems, such as the performance, reliability, and security of GenAI models and platforms, as part of business system solutions. Findings may help researchers gain insights into how well GenAI systems meet the technical requirements of businesses and contribute to their overall success relative to existing systems that are absent GenAI capabilities. Additionally, the model's information quality dimension is a useful framework to investigate output generated by GenAI systems in business, including how accurately and timely GenAI-generated information meets the needs of businesses.

Knowing the well-documented limitations of existing information (i.e., GenAI input) and hallucinations (i.e., GenAI output) could provide insights about GenAI-generated information reliability, relevancy, and usefulness for decision-making processes. Finally, future research should employ the organizational impact dimensions to assess the adoption and impact of GenAI in the business context. For instance, researchers should examine GenAI's organizational-level impact on firm performance, innovations, process improvement and transformation, and product and service customization. Moreover, inquiries should focus on user satisfaction and end-user needs to fully comprehend potential avenues and hurdles of GenAI's social dimensions in business, including user interaction and gratification.

FIGURE 5
IS SUCCESS MODEL



(DeLone & McLean, 1992)

Researchers can also explore factors influencing the acceptance and usage of GenAI by employees, including its effects on user satisfaction and individual-level outcomes such as job performance, creativity, trust, information ownership, and behavioral impacts. Existing theoretical lenses, such as the Technology Acceptance Model (Venkatesh et al. 2003)), Task-Technology Fit (Goodhue & Thompson, 1995), and Cognitive Fit Theory (Vessey & Galletta 1991) provide useful frameworks to explore GenAI's acceptance, use, and individual-level efficiency in business contexts. Furthermore, critical research should assess how and if traditional theoretical lenses are still effective when managing GenAI in business contexts given its complexity and transformational potential.

CONCLUSION

This systematic review fills a gap in the literature by articulating the current state of GenAI research relative to traditional academic scholarship. Specifically, the findings highlight that research in applied business contexts is anemic and largely guided by quantitative research within service sectors but with little consistency in theoretical frameworks or data collection approaches. Given this paucity of inquiry and lack of direction across applied business research into GenAI, we provide useful frameworks to investigate the extensive effects of GenAI across the corporate and social spectrum. It is critical to consider the organizational impact of GenAI, including its influence on business achievements and congruence with communal ethos. Thus, applied business researchers must adopt a comprehensive approach that embraces the complex consequences of GenAI to ensure that advancements in business technologies are directly beneficial to the wider community.

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