

Review

Cognitive Computing and Business Intelligence Applications in Accounting, Finance and Management

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Abstract: Cognitive computing encompasses computing tools and methods that simulate and mimic the process of human thinking, without human supervision. Deep neural network architectures, natural language processing, big data tools, and self-learning tools based on pattern recognition have been widely deployed to solve highly complex problems. Business intelligence enhances collaboration among different organizational departments with data-driven conversations and provides an organization with meaningful data interpretation for making strategic decisions on time. Since the introduction of ChatGPT in November 2022, the tremendous impacts of using Large Language Models have been rippling through cognitive computing, business intelligence, and their applications in accounting, finance, and management. Unlike other recent reviews in related areas, this review focuses precisely on the cognitive computing perspective, with frontier applications in accounting, finance, and management. Some current limitations and future directions of cognitive computing are also discussed.

Keywords: cognitive computing; business intelligence; accounting; finance; management; explainable AI; continual learning; ChatGPT



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1. Introduction

Cognitive computing is an artificial intelligence (AI) subset that mimics human thought with computational algorithms and has the potential to address these issues and to drive automation in works requiring extensive knowledge [1]. AI is a branch of computer science that devises solutions in tasks involving learning and problem-solving, which are often associated with human intelligence [2]. Cognitive computing utilizes tools like deep learning and natural language processing (NLP) to simulate human brain functions [3]. Cognitive computing systems usually have the following four features: adaptability, interactivity, iterative questioning, and contextual ability [4]. This may match human cognition in terms of decision making with uncertain and incomplete information.

Nowadays, human cognition and cognitive functions like reasoning and problem-solving have been successfully replicated to some extent, even though, traditionally speaking, AI systems do not yet process human characteristics like self-awareness, social skills, and prompt adaptability. Complex heterogeneous datasets can be handled by deep learning algorithms to provide meaningful insights [5]. The cognitive computing system with adaptive learning and probabilistic reasoning capabilities can succeed in complex situations of high uncertainty and ambiguity. Schuetz and Venkatesh [4] focused on discussing the

traditional assumptions by information technology scientists on user–IT artifact interactions. Their system learns and then makes responses based on the changing environments. It can also interact with users conveniently. The system keeps trying to inquire, or look for extra information, until the task statement becomes clear enough. It is also able to read and process contextual elements. With these capabilities, cognitive computing systems can adapt to new circumstances, and perceive and interact with human beings. Renuga Devi et al. [6] highlighted the insights and backbone of a cognitive system and its learning methods with some use cases. Singla [7] presented a very brief overview of cognitive computing and its potential real-world applications.

With the introduction of generative pretrained transformers (GPT) in 2018 by OpenAI and the capabilities of the newly developed language models, the performance of cognitive computing tools for tasks, like text summarization and sentiment analysis, have been improving greatly. Generative AI (GenAI) models are AI tools that, based on existing data, are capable of creating new content. OpenAI's GPT models (GPT-2 and GPT-3) are autoregressive in nature, through generating text based on prediction from the preceding words, while Google's BERT is based on transformers, utilizing self-attention mechanisms for handling the dependencies among input data [8]. Zafar et al. [9] focused on the conversational aspect of the AI system to provide human-like dynamics of interactions. Zafar et al. proposed LLMXplorer to review over 205 Large Language Models (LLMs) comprehensively, highlighting social and ethical concerns and their industrial applicability. Figure 1 shows the pipeline of Large Language Models.

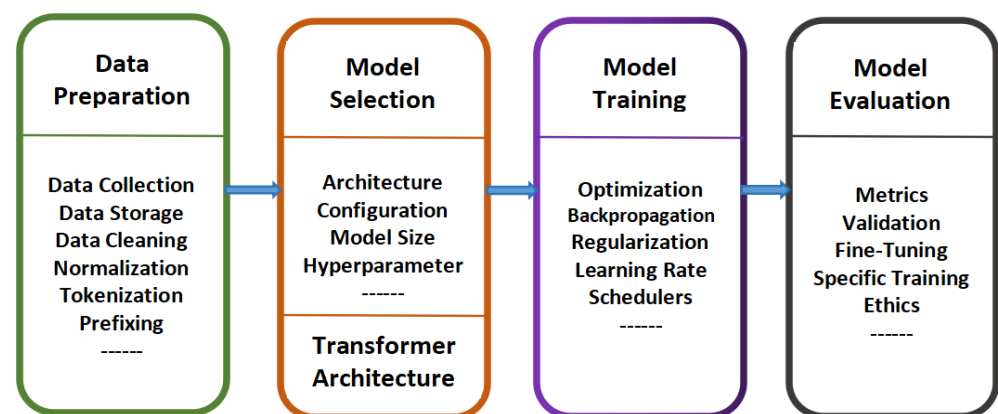


Figure 1. Pipeline of Large Language Models.

Since the release of the first version of ChatGPT (OpenAI's Chat Generative Pre-Trained Transformer) on 30 November 2022, the effects of ChatGPT have been rippling through the accounting industry, finance industry, and management. Its total number of users reached 100 million so quickly that ChatGPT was recognized as the fastest-growing application in Internet history. Because of this, Section 2 focuses on cognitive computing and business applications prior to the launch of ChatGPT, while the other sections focus mainly on cognitive computing applications after the launch of ChatGPT. Section 3 talks about current trends in cognitive computing and accounting. Section 4 focuses on current trends in cognitive computing and finance. Section 5 talks about current trends in cognitive computing and management. Section 6 provides insights on current limitations and future directions. Lastly, Section 7 is the conclusion.

The literature search was conducted on Scopus, an Elsevier database that only indexes peer-reviewed journals of high quality. The scope of the search is "Article title", "Abstract", and "Keywords". For Section 2 on cognitive computing and business intelligence, the two keywords "cognitive computing" and "business intelligence" were used together. A

total of six papers are listed, and the authors selected the relevant two papers that focused squarely on the business context with the applications of cognitive computing technologies. For Section 3 on cognitive computing and accounting, the two keywords “cognitive computing” and “accounting” were used together. A total of eight papers are listed, and the authors selected the relevant two papers that focused squarely on the accounting context with applications of cognitive computing technologies. These two papers were published before Nov. 2022. For Section 4 on cognitive computing and finance, the two keywords “cognitive computing” and “finance” were used together. A total of five papers are listed, and only two were published after Nov. 2022. For Section 5 on cognitive computing and management, the two keywords “cognitive computing” and “management” were used together. A total of fifty-seven papers are listed for the period from 2023 onwards. The authors selected the relevant ten papers on the business management context (excluding articles on data management, knowledge management, etc.) with applications of cognitive computing technologies. One of these ten papers has been included in the section on cognitive computing and finance as well. Because some researchers may not use the term “cognitive computing” in their articles on AI and business, additional papers have been carefully selected and added, based on the expertise of the authors. A summary of the articles on cognitive computing selected from the Scopus database is listed in Table 1, and the tree diagram for grouping the cognitive computing applications selected from Scopus is shown in Figure 2.

Table 1. Summary of the articles on cognitive computing selected from Scopus.

Ref.	First Author	Year	Application Field	Summaries
[10]	Kumar	2017	Business Intelligence	Generalize connection between business processes and machine learning models
[11]	Giacobbe	2019	Business Intelligence	Combine machine learning and business intelligence to raise efficiency of IoTaaS
[12]	Marshall	2018	Accounting	Support the automation of accounting tasks
[13]	Pilipczuk	2020	Accounting	Investigate impacts of cognitive computing in management accounting
[14]	Li	2017	Finance	Deploy cognitive computing on invoice processing in finance operations
[15]	Ryman-Tubb	2018	Finance	Conduct survey on AI methods for payment card fraud detection
[16]	Dwivedi	2021	Finance	Study impacts of AI in different domains like finance and management
[17]	Faccia	2023	Finance and Management	Investigate how cognitive computing helps to identify fraudulent transaction
[18]	Deborah	2024	Finance	Study how cognitive computing helps in the hyperautomation process

Table 1. Cont.

Ref.	First Author	Year	Application Field	Summaries
[19]	Zhang	2023	Management	Apply cognitive computing to quantify and then manage cognitive uncertainty
[20]	Yabanci	2023	Management	Outline AI-powered cognitive computing HRM systems for SMEs
[21]	Gupta	2023	Management	Study relationships between cognitive computing and entrepreneurial quality
[22]	Muthukarup-pasamy	2023	Management	Apply cognitive computing for digital farming management
[23]	Murthi	2024	Management	Propose cognitive computing for smart city infrastructure management
[24]	Sudhakar	2024	Management	Examine the potential of cognitive computing for traffic management
[25]	Kans	2024	Management	Utilize cognitive computing for better maintenance management
[26]	Nowak-Nova	2024	Management	Apply cognitive inference machine in the facility management
[27]	Hildebrand	2025	Management	Conduct review on cognitive computing for business process management

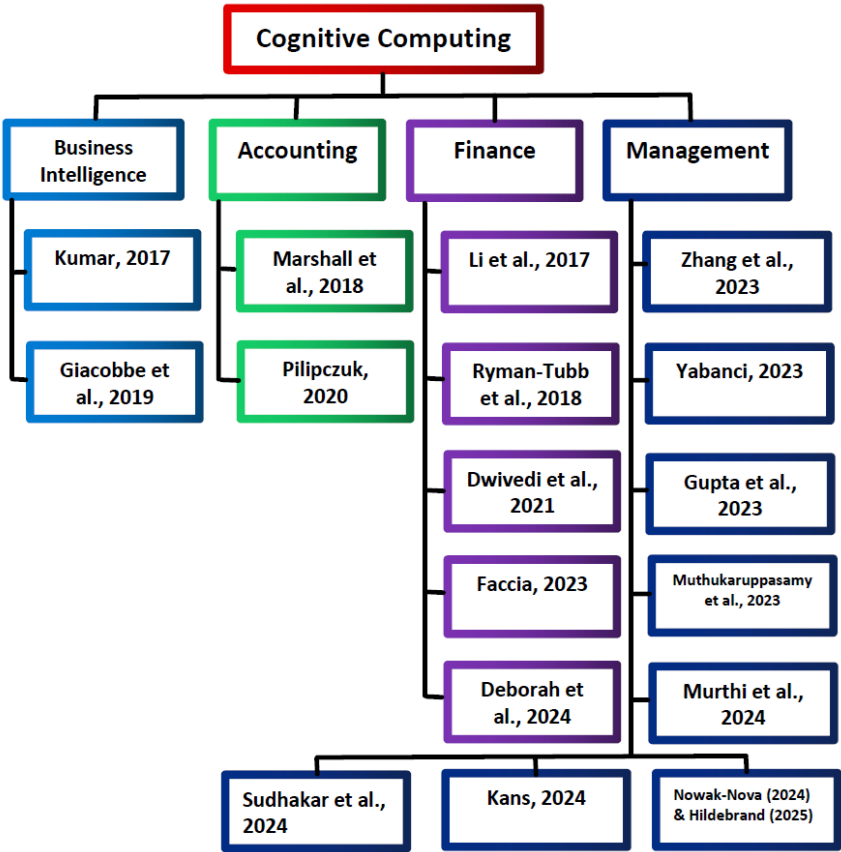


Figure 2. Tree diagram grouping the cognitive computing applications from Scopus [10–27].

The main themes in our accounting section are accounting task automation [12], augmented intelligence [12], managerial accounting [13], and job impact [13]. The main themes in our finance section are language translation [14], invoice processing [14], ERP workflow [14], procure to pay [14,16], fraud detection [15,17], cyber-crime [15,17], transparency [16], customer services [16,18], and process automation [18]. The main themes in the management section are entrepreneurial quality [21], fraud detection [17], risk management [17,19], cognitive risk context [19], smart agriculture [22], human resource management [20], information processing [20,21,25], predictive analytics [22–25], automated models [26], facility management [26], adaptive traffic control [24], infrastructure management [23], industrial maintenance management [25], and business process management [27].

2. Cognitive Computing and Business Intelligence Applications Before the Launch of ChatGPT

Unlike many other systems, cognitive computing is suitable for handling highly complex situations of multi-model data sources, given its interdisciplinary nature [1]. In many real-world business situations, the huge amount of data to process is beyond the capacity of human beings, or too time-consuming and expensive if handled by humans. For example, with the advance of the Internet and social networks, huge amounts of unstructured data of digital content like social media posts, images, audio and video clips, etc., have been generated. The cognitive computing approach is deployed for overcoming the complicated data corpus to generate actionable predictive results, by combining business intelligence with knowledge management for further competitive improvement for intellectual capital application [28]. With advances in deep neural network learning, cognitive computing has the capability to further improve the decision-making process that can mimic how the human brain operates increasingly well. Watson [29] predicted that AI and cognitive computing will obtain dominant coverage in the next generation, as companies are implementing these innovations at an increasing rate. The key areas of interest involve NLP, vision systems, virtual reality, personal assistants, robotics, expert systems, and neural networks. Existing and future business intelligence software may deploy cognitive computing for forecasting model selection, natural language request processing, and visual display selection [29].

On the other hand, business intelligence helps organizations make smart decisions in various fields and bring higher profit margins in return. The “intelligence” part is about the utilization of business knowledge to achieve profitable solutions [30]. This strategy for deploying next-generation decision support systems in business needs to combine traditional business intelligence (BI) with emerging but not yet fully mature cognitive computing approaches [31]. Traditional BI tools focus on handling structured data, while cognitive computing is useful in converting unstructured data into data understandable by the organization for its decision making. This combination strategy may have a lower risk of over-investments and thus lower cost, with satisfactory ROI. IBM, a leader in the cognitive movement, incorporated cognitive solutions into its strategy in 2014 [31].

Business intelligence adoption is found to have significant positive impacts on key performance indicators (KPIs) like customer approval, cost reduction, and revenue increase in the quantitative study of Usman et al. [32]. BI can support continuous improvement in an organization with proactive feedback loops for measuring its KPIs and progress tracking towards its strategic objectives. It is noticed that there exists a strong relationship between business intelligence and knowledge management for obtaining competitive advantage. Competitive intelligence (CI) handles the strategic information of an organization for making decisions in four typical steps: collection, analysis, interpretation, and dissemination [33]. The deployment of BI and CI solutions can lead the organization to

higher levels of customer satisfaction and profitability [34]. The gathering and analysis of information about competitors through CI may offer the organization a competitive advantage over its competitors [35].

Cognitive computing has great potential to further improve decision support in business intelligence, as highlighted in the work of Williams [31], by its ability to analyze vast types of data efficiently. It has been suggested that companies should apply business-driven opportunity analysis when comparing cognitive computing solutions, focusing on how to augment existing decision-support systems. Zhong and Sheng [36] developed a cognitive computing model for better understanding of customer behavior and market strategy optimization for companies. The model is built with deep learning and NLP components to analyze customer sentiment for better demand forecasting. The experimental results support that its two components perform well and both sentiment analysis and forecasting for market strategy decision making achieve satisfactory accuracy. Nevertheless, as noted by Zhong and Sheng [36], their system still faces limitations like generalization ability and interpretability. Models with more explanatory capabilities are needed to better understand the correlations between human emotions and needs in future work. With its natural language processing capability, cognitive computing is able to handle both structured and unstructured data [10]. A precondition for cognitive computing to become capable is the training process, which requires a huge amount of data. As an example in accounting applications, the large amount of accounting data for training the system may come from individual departments. The generalized connection between business processes and machine learning (ML) models is shown in Figure 3, based on the concept from [10].

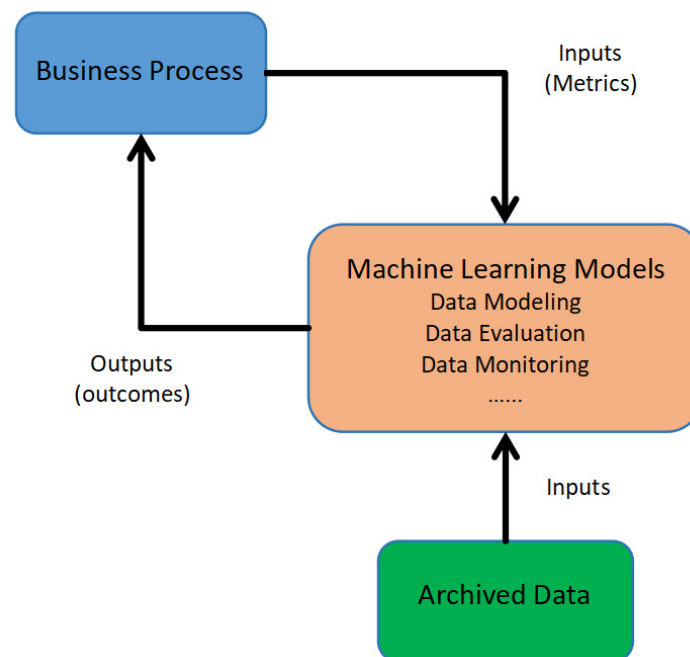


Figure 3. Generalized connection between business processes and machine learning models.

Guptaa et al. [37] conducted a comprehensive survey of how to combine cognitive computing with big data. Cognitive computing features like observation, interpretation, evaluation, and decision fit well with the characteristics of big data, i.e., volume, variety, veracity, velocity, and value, the so-called five Vs. Successful deployments of cognitive computing techniques address many issues facing big data analytics, while big data analytics can lead organizations to get ahead in competition with other businesses [38]. The conclusion of the survey is that cognitive computing will be of increasing importance

in its applications. Ranjan and Foropon [39] outlined a framework for better addressing the current challenges for companies in utilizing big data methods for successful CI implementation.

Cognitive computing has great potential for enriching customer experiences with personal buying advice, based on its ability to learn from experience and to analyze huge datasets of consumer behavior. Cognitive computing improves customer–firm interaction and relationship building and assists organizations in decision making processes in the business world [40]. Marketing co-innovation is achieved with customer engagement and with cognitive computing algorithms to analyze the external data. Chen et al. [41] focused on utilizing cognitive computing to generate marketing co-innovation from user unstructured data. Here, the cognitive computing models obtain valuable insights from vast unstructured external data. The proposed co-innovation process is achieved in the following three steps: idea generation, idea integration, and idea evaluation. The creation of innovation communities leads to more interactive engagement with customers [42], while successful customer engagement is a key factor in providing competitive advantages [43].

At the operational level of the retail industry, cognitive computing systems significantly reduce costs by reducing required human workloads with improved operational efficiency [44]. Nevertheless, there may be factors that hinder consumers' readiness to adopt cognitive computing systems. Barbul et al. [45] investigated the various perceptions of consumers of different genders about cognitive computing applications. It is noticed that women respondents have more concerns about the privacy of their personal information and about insufficient control over cognitive computing systems. It may be worth further investigating the perceptions of various consumer groups about different cognitive computing systems.

Giacobbe et al. [11] outlined an approach that combined machine learning and business intelligence to raise the efficiency of IoT-as-a-Service (IoTaaS). Giacobbe et al. identified cognitive computing as one of the four pillars in the fourth industrial revolution. The role of machine learning is to enable the outlined approach to have the capability to learn from input data and to further improve its performance without need of explicit programming. The advantage of the system is that can it not only provide business insight service but also enrich the knowledge pool by linking with open data. Algorithm 1 and Figure 4 are simplified and modified versions of the approach outlined by Giacobbe et al. [11].

Algorithm 1. Simplified version of data-oriented tasks of digital business platforms

- 1: Data Inputs
 - 2: Data Collection
 - 3: Data Value Chain
 - 4: Data management and storage
 - 5: Data analysis
 - 6: Output by data analysis
 - 7: Machine learning
 - 8: Output by machine learning
 - 9: Business Intelligence
 - 10: Output by business intelligence
-

Business intelligence software may be regarded as an integrated set of methods that transform business data into information to help business decision-making processes [46]. BI software conducts business monitoring and data analysis with reports, charts, and benchmarks while maintaining sufficient security and user interaction. As the cost of

deploying cloud-hosted BI solutions has decreased to very affordable levels, BI applications have reached companies both large and small [47]. A typical BI application involves the following steps of data processing: Collect, Organize, Analyze, Share, and Control. Srivastava et al. [30] presented a comprehensive review of 15 open-source BI software as follows, while comparing their BI features: Birst BI, Board BI, ClicData BI, Cluvio BI, Datapine, Dundas BI, Klipfolio, KyuBit BI, Looker, Microsoft Power BI, Microstrategy analytics, SAP business objects BI, Sisense, Tableau, and Zoho analytics tools. The most recent BI trends on data automation, data quality management, Explainable AI, and data governance were also highlighted, while future features will focus on cognitive computing, NLP, etc.

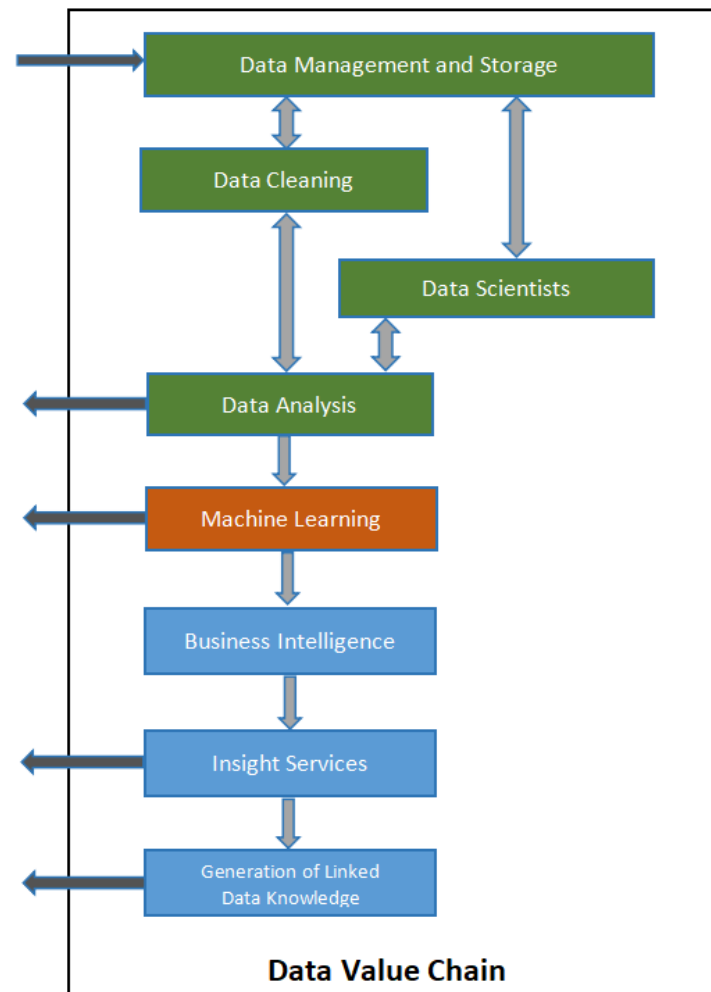


Figure 4. A simplified version of the data value chain for the platform of digital business technology.

Enterprise cognitive computing is helpful to business intelligence software and applications through implementing cognitive computing algorithms into the software that can facilitate organizational business processes [48]. As the volumes of data in enterprises have increased steadily in recent years, it has become more and more challenging for humans to handle. This is a clear opportunity for enterprise cognitive computing to extract meaningful insights from the vast amount of data, and to adapt to new data while maintaining consistency with historical data. Another advantage is that cognitive computing can automate many tasks that would otherwise need human interpretation. Tarafdar et al. [48] presented a brief summary of the opportunities and challenges of enterprise cognitive computing, listing a number of successful business deployments of it. For example, call

centre queries can now be handled by enterprise cognitive computing with suitable NLP capability. Tarafdar et al. also summarized the four main difficulties for business leaders to successfully deploy enterprise cognitive computing, i.e., deciding on the right tools, ensuring the suitability and accuracy of the data, supervising continuously, and clearly allocating responsibility between human users and the software.

3. Current Trends in Cognitive Computing and Accounting

A major transformation in accounting is taking place through AI-powered automation of accounting processes. The tools for automating tasks like data entry have become very sophisticated, and are able to handle input data with extremely high efficiency compared with human accountants [49]. The automated system handles data of different structures from multiple sources efficiently, with minimal human intervention. Figure 5 highlights the main themes in this section of how cognitive computing and its applications are affecting the accounting industry.

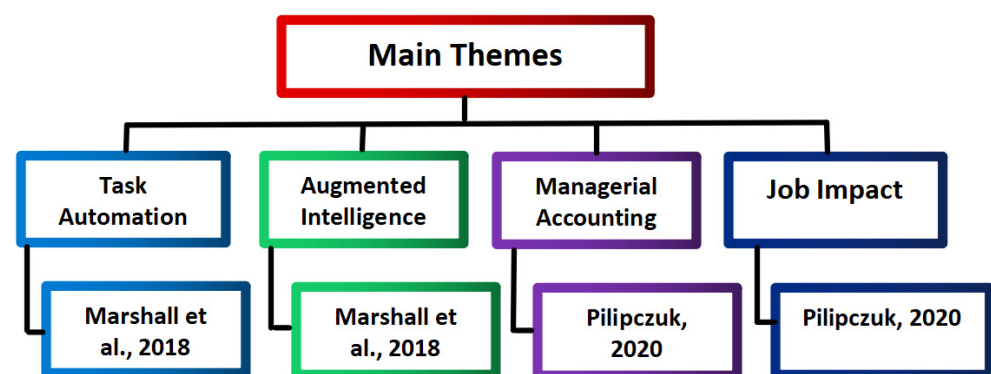


Figure 5. Main themes of the accounting applications identified by our Scopus search [12,13].

The automation of time-consuming data entry, reconciliation, and bookkeeping has not only increased efficiency significantly but also accuracy [50]. Routine jobs like bookkeeping activities, data entry, and reconciliation benefit from automation by reducing human error. Data automation replaces time-consuming entry activities to aid businesses in decision making in their operations [2,51]. A major benefit of AI automation in accounting is cost savings [52]. KPMG International Limited [53] reported that its AI-powered reporting tool can automate accounting tasks to achieve cost reductions for businesses. Another study by Big 4 firms [54] also confirms that AI-powered payroll tax tools enhance the efficiency of tax processing and save costs for businesses. Jejenywa et al. [55] presented a survey on accounting practices with the implementation of AI technology. It is noted that accountants are shifting their job role towards more strategic tasks with state-of-the-art AI technologies instead of routine bookkeeping duties. Furthermore, the likelihood of errors is significantly lower in the AI system than with human beings [55]. The performance of AI models in reconciliation tasks is excellent compared with human processing. With manual reconciliation, it can happen from time to time that intricate patterns in the reconciliation data are overlooked. AI tools have a profound impact on mitigating the risks of discrepancies and thus of regulatory non-compliance [56].

In recent years, AI tools have already outperformed human auditors in the identification of anomalies, discrepancies, errors, fraudulent activities, and irregularities from huge datasets of transaction records. AI has revolutionized the modern accounting industry by raising the competence of financial audits to another level in terms of accuracy, speed, and risk mitigation [57]. AI algorithms also proactively protect the integrity of financial reports [58]. AI-powered predictive analytics are capable of assisting risk assessment and

management, hence aiding the companies to alleviate financial threats [59]. AI tools excel at repetitive tasks so that accountants can instead concentrate on achieving strategic tasks [59]. AI tools generate once labor-intensive financial reports automatically, coherently, and comprehensively with minimal errors, with the advance of AI and NLP technologies. Advances in NLP enable the generation of comprehensive financial reports with deep insights. The extracted insights of AI tools present an enhanced understanding to stakeholders of financial performance [60]. By investigating intricate and human-imperceptible orderliness [61], AI tools enhance the work of accountants and financial professionals with data-driven decision-making analytical capability.

Since the launch of ChatGPT in 2022, there have been consequential breakthroughs in conversational artificial intelligence [62]. Biancone and Chmet [63] assessed the influence of ChatGPT on accounting, with ChatGPT already achieving the automation of some accounting jobs. Table 2 lists recent research on the impact of ChatGPT and other LLMs on the accounting industry.

Table 2. Summary of articles on the impact of ChatGPT and other LLMs on accounting.

Ref.	Main Themes	Summaries
Fu et al. [64]	Financial management	Shows that ChatGPT can be deployed satisfactorily for forecasting, decision making, control, and analysis
Eulerich et al. [65]	Accounting, auditing	Concludes that ChatGPT can match the performance of professional accountants
Shchyrba et al. [66]	Management accounting	Shows that there is a surge in productivity after the adoption of ChatGPT
Biancone and Chmet [63]	Accounting automation	Shows that ChatGPT has already achieved automation of some accounting jobs
Zhao and Wang [67]	Accounting automation	Shows that ChatGPT has the capability to automate accounting duties
Li and Vasarhelyi [68]	User interface (UI), application programming interface (API)	Shows that ChatGPT and other LLMs provide friendly UI and convenient API
Kim et al. [69]	Financial statement analysis	Finds that ChatGPT and other LLMs achieve better performance than human analysts
Rane et al. [70]	Financial analysis, advising, auditing, reporting, customer service	Shows that both ChatGPT and Gemini achieve excellent performance

The details of the research listed in Table 2 are as follows:

- Fu et al. [64] showed that ChatGPT can be deployed satisfactorily for the following four financial management tasks: forecasting, decision making, control, and analysis.
- Eulerich et al. [65] focused on assessment of the capabilities of ChatGPT over accounting and auditing. It was found that ChatGPT 4 is capable of passing the major certification examinations on accounting. The average mark achieved by ChatGPT 4 is 85.1%, which is considered to be high performance in professional accounting examinations. Eulerich et al. concluded that this is the first moment that an artificial intelligence tool has matched the performance of professional accountants on real business accounting tasks.
- Shchyrba et al. [66] found that ChatGPT improved efficiency in management accounting. Their mathematical modelling showed that there is a surge in productivity after adoption of ChatGPT.

- Zhao and Wang [67] noticed that ChatGPT, with its advanced NLP features, brought transformative changes to our society. ChatGPT has the capability to streamline and automate accounting duties.
- Before the launch of ChatGPT, managing complex software and hardware typically required complex programming skills [68]. ChatGPT and other subsequent LLMs provided a friendly user interface (UI) and a convenient application programming interface (API). As a result, ChatGPT and other LLMs have been deployed to different accounting duties. Li and Vasarhelyi noted that about half of these applications use chat-based UI while the other half utilized the API feature, and conducted a comprehensive comparison between UI and API approaches.
- Kim et al. [69] compared the performance of LLMs to that of professional analysts for financial statements analysis. It was found that the LLM achieved better performance than human analysts. The LLM-based trading approaches obtained higher Sharpe ratio and alphas than other approaches.
- Rane et al. [70] investigated the performance of ChatGPT and Gemini in accounting and finance jobs. Both LLMs achieved excellent performance in financial analysis and advising, auditing, reporting, and customer service. ChatGPT provided better user interactions while Gemini held some advantages in terms of accuracy and depth.

Ways to successfully integrate Generative Artificial Intelligence (GenAI) into existing systems by accounting professionals were investigated by Anica-Popa et al. [71]. Even though AI tools automate some accounting processes, human supervision and professional judgment are still necessary to satisfy ethical standards [72]. GenAI, based on Deep Learning and NLP, is capable of making human-like responses. It is noticed that accountants who combine their professional knowledge with GenAI can achieve increased accuracy and efficiency in their work [73]. Nevertheless, improper usage of the AI system may generate irrelevant and inconsistent results. Korzynsky et al. [74] have noted that users lacking sufficient competency in AI Prompt Engineering may lead to ineffective performance of GenAI systems as a result of poor prompt inputs. When deploying GenAI tools, it is desirable that accounting professionals notice that several major risks exist—the model bias risk [75], information/data security risk [76], and the risk of unethical content generation [77].

Pilipczuk [13] focused on the applications and impacts of cognitive computing in management accounting. It is estimated that automation may free accountants from time-consuming process work, while complex work still needs their attention [78]. In other words, technology should augment the accounting field, rather than fully automating it [79]. Pilipczuk [13] identified three groups of competencies that current management accountants needed, i.e., technical skills (accounting skills, IT skills, management skills), cognitive skills, and social and behavioral skills. IT skills and cognitive skills are needed by current management accountants to keep up to date with new advances in accounting software.

Other advanced applications of cognitive computing in accounting include the following:

- Marshall and Lambert [12] showed how cognitive computing models can support the automation of accounting tasks. Task automation typically focuses on data and procedures with structured problems, and is beginning to support less structured problems. With AI as a disruptive innovation, organizations need to face the challenges of how to adopt this disruptive innovation and turn it to their competitive advantage.
- The investigation focused on how blockchain technology has been revolutionizing AI-powered auditing in four areas, i.e., record-keeping, real-time accounting, triple entry-accounting, and continuous auditing [80]. Organizations utilizing blockchain and AI technologies can enhance stakeholder inclusion and facilitate collaboration.
- Anomah et al. [81] focused on investigation of the adaptability of AI by accountants and auditors in developing countries. The authors concluded that policymakers,

professional bodies, and professional leadership are essential for the success of AI adaptability for improved competitiveness.

- Monteiro et al. [82] investigated statistical correlation among manufacturers, AI utilization, internal control systems, and accounting. While emerging AI models are very useful in manufacturing processes [83], a quantitative finding was that AI adoption by manufacturers has positive impacts on the internal control system and thus the accounting system. AI tools are gaining importance in accounting and business management [84].
- Another major future trend is that there will be a shift for accountants towards strategic interpretation for enhanced decision making, with the evolution of new AI technologies into accounting practices [85]. This will free accountants from entry-level data handling, enabling a higher level of interpretation and communicating of findings to clients [51]. Zhang et al. [86] pointed out that low-skilled employees may face the risk of job loss due to the AI-powered automation of some accounting works. Nevertheless, the application of AI in accounting may lead to new employment opportunities for specialized workers/highly skilled experts [87]. AI technologies in accounting have led to efficiency improvements and, at the same time, to the decrease in junior accounting employees [88]. In the panel discussion organized by Efrim Boritz and Stratopoulos, it was concluded that accountants with AI will replace accountants.

4. Current Trends in Cognitive Computing and Finance

Popular applications of AI technologies in finance include predictive and forecasting systems, systems of classification and detection and early warning, big data analytics, and text mining [89]. AI applications have become the new must-haves for central banks and financial institutions, according to the IMF report [90]. This new technology better enables them for market prediction and asset protection. Figure 6 highlights the main themes in this section of how cognitive computing and applications affect the finance industry.

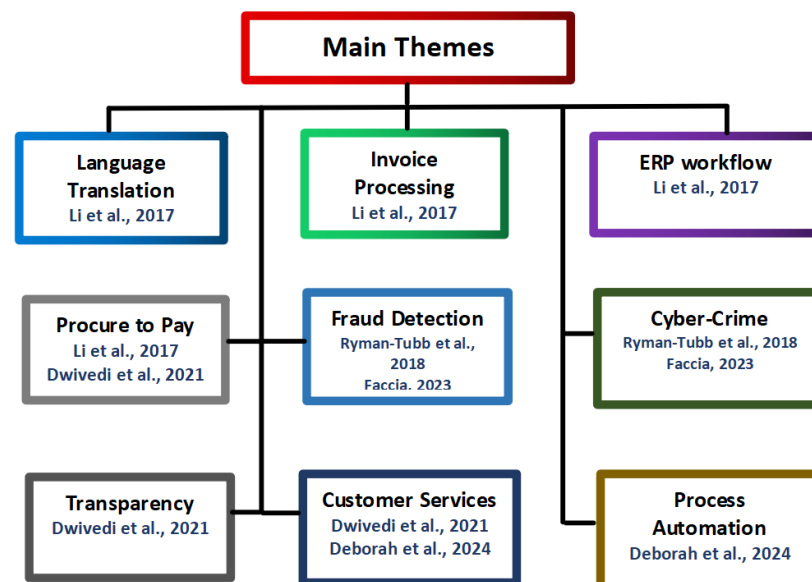


Figure 6. Main themes of the finance applications identified by our Scopus search [14–18].

Since its launch, ChatGPT has had an enormous influence on finance [91]. Not only can it decrease operation costs, but also improve customer satisfaction. ChatGPT is able to handle account management, investment advice, asset management, financial compliance, customer service, etc. According to a BNP Paribas survey of funds with \$250 billion in

total assets [90], hedge funds are adopting generative AI swiftly. More than two-thirds are using ChatGPT for writing marketing materials or summarizing reports. The Basel Committee on Banking Supervision noticed that AI tools are more effective in lending and credit decisions, and money laundering prevention, than traditional ones. Table 3 lists recent research on the impacts of ChatGPT and other LLMs on finance.

Table 3. Summary of the articles of ChatGPT and LLMs and other recent articles on finance.

Ref.	Main Themes	Summaries
Ali and Aysan [91]	Financial management, operation	Concludes that ChatGPT is able to handle account management, investment advice, asset management, financial compliance, customer service, etc.
Dowling and Lucey [92]	Finance research	Concludes that ChatGPT's strength is on identifying financial data and generating ideas
Khan and Umer [93]	Ethical issues	The ethical issues facing ChatGPT included biases, privacy and security, insufficient accountability and transparency, etc.
Zaremba and Demir [94]	Financial application issues	Notes that ChatGPT needs to address issues relating to robustness, explainability, and ethics
Lee et al. [95]	Financial LLM	Finds that FinLLMs since ChatGPT have improved significantly in terms of performance and accuracy
Faccia [17]	Fraud detection	Shows that cognitive computing helps to identify fraudulent transactions
Deborah et al. [18]	Customer services, process automation	Shows that cognitive computing helps in the hyperautomation process

The details of the research listed in Table 3 are as follows:

- Dowling and Lucey [92] found that ChatGPT was capable of assisting finance research remarkably. Its strength is in identifying data and generating ideas, while literature synthesis is its weakness.
- ChatGPT, with its natural language processing capability, has caused a revolution in finance [93]. Khan and Umer focused on identifying ethical issues facing ChatGPT's applications in finance. These challenges included biases, incorporating fake information, privacy and security concerns, and insufficient accountability and transparency.
- Zaremba and Demir [94] noticed that, when deploying ChatGPT in financial applications, the model needs to address issues relating to robustness, explainability, and ethics.
- Lee et al. [95] focused on reviewing the techniques, opportunities, and issues of the Financial LLM (Fin-LLM). Before the launch of ChatGPT, FinBERT-21 [96] and

FLANG [97] only had the parameter size of 0.11 B. After the launch of ChatGPT, for the subsequent FinLLMs, FinMa [98] and BloombergGPT [99] had parameter sizes of 30 B and 50 B respectively, as shown in Figure 7. In comparison tests, Lee et al. [95] found that the FinLLMs since ChatGPT had improved significantly in terms of performance and accuracy.

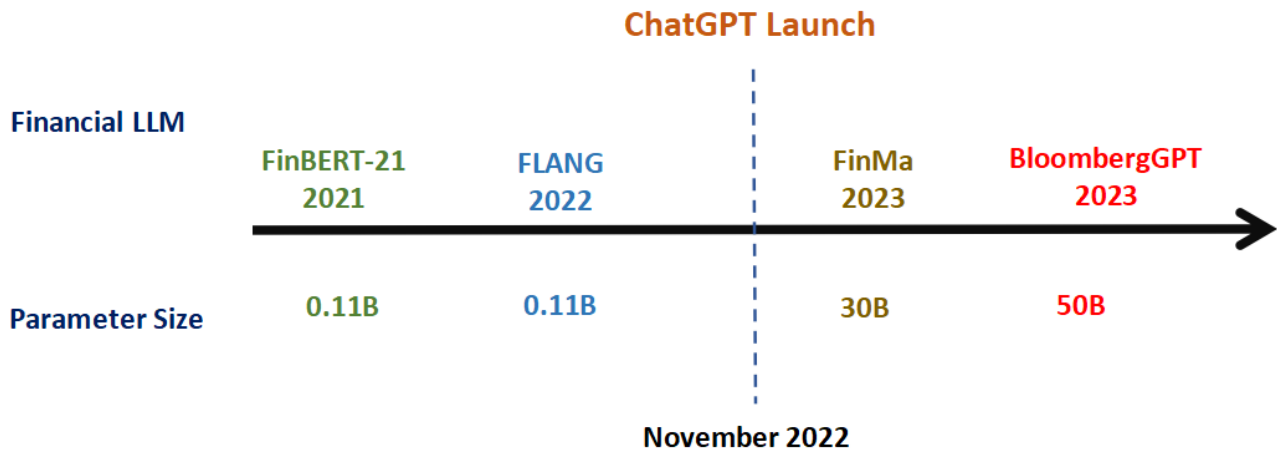


Figure 7. Parameter sizes of Financial LLM before and after the launch of ChatGPT.

Financial institutions in banking, insurance, payments, and wealth management have been adopting GenAI technologies rapidly in the EY report by Chlouverakis [100]. GenAI is deployed in financial sectors with duties like compliance reporting, customer service, risk mitigation, and synthetic data generation in the IMF report [101]. GenAI is used in customer engagement, fraud detection, personalized advice, risk assessment, transaction processing, etc. The European Central Bank, which regulates ten million businesses and organizations, has used AI tools for tasks like automatic data classification [90]. Factors affecting the adoption of business intelligence and analytics (BIA) by banks were examined by Mohammed et al. [102]. The advantages of the BIA system include better customer satisfaction, decision making, operational efficiency, and risk control; and it was found that BIA brings positive benefits to the organization. The Technology–Organization–Environment (TOE) framework plays a significant positive role in BIA adoption [103].

Cognitive models are very valuable for explaining complex decision making to stakeholders to facilitate its adoption [104]. Cognitive computing models have been successfully deployed in finance applications like stock and forex market trading. Chi et al. [105] conducted a holistic survey of AI in data science for finance. Current AI applications in finance, like algorithmic trading, consumer behavior analysis, fraud identification, and market forecasting, were summarized. Nevertheless, Sobhanmanesh et al. [106] noticed that the current literature lacks effective strategies to predict the adoption rate of emerging models. A parametric mathematical model was proposed to forecast the adoption rate of new technologies. For better decision making with more comprehending power, neuroscience, machine learning and deep learning should combine in applications to raise the level of their synergy. Kearns [90] concluded in his IMF report that humans still beat AI in unexpected situations by utilizing a broad set of knowledge for better-informed decision making.

Other advanced applications of cognitive computing in finance include:

- Li et al. [14] presented efforts by IBM towards cognitive computing applications on invoice processing in finance operations. An Internet-based translation function is developed in the invoice system for handling the multiple languages of its global clients. The roles of cognitive computing in this application are to enable domain-

specific and secure translation services. The developed cognitive system was used daily by the offshore team of the IBM delivery center [14].

- Ryman-Tubb et al. [15] presented a survey of payment card fraud detection methods for the industry in 2017. The conclusion is that a gap existed between research and reduction of payment card fraud. The authors highlight that cognitive computing is one of the main future directions worth pursuing.
- Dwivedi et al. [16] combined opinions from a group of AI experts in different industries about the opportunities and impacts of AI in different domains like finance, management, government, and science. They observed that the majority of our society appears to be in catch-up mode with AI innovations. An important question about AI-driven decision making is the extent to which checks and balances are required by management.
- Faccia [17] conducted an investigation on 19 real-world cases to examine how cognitive computing can be deployed for fraudulent transaction identifications. The rising popularity of digital payments has increased the risks of financial fraud in National Payment Switches and International Payment Switches. Faccia found that cognitive computing models can help organizations prepare before the emerging threats and thus preserve their payment system integrity.
- Bormpotsis et al. [107] proposed a modular neural network with a neuroscience-informed feature for utilizing the closing prices and sentiments from online social media and apps, achieving outstanding performance against other state-of-the-art deep learning models.
- Deborah et al. [18] talked about hyperautomation with the help of emerging technologies like cognitive computing. The word “hyper” refers to the combining of technologies that can make exponential gains for the overall system. Cognitive computing models are deployed for handling unstructured data like text and voice in industries like finance and banking.

The gap between fully apprehending the ethics of AI in financial inclusions and its implications is still very large [108]. Yang and Lee [108] conducted a survey of 675 users of AI products in finance to investigate the relationship between AI transparency, accountability, and user perceptions of fairness. They found that higher degrees of transparency, accountability, and legitimacy of the AI system increase its perceived fairness by users. This leads to a significant increase in user satisfaction and user willingness to recommend AI-powered services to others.

- The current explainable AI system is still very difficult for lay users to understand, even though AI firms have begun focusing on the explainability of their AI systems [109]. Werz et al. [109] conducted experiments with focus groups on three AI apps, including a finance application, and found that the expectation of lay users for AI transparency is different to that of AI experts. The topic of transparency in AI is of particular concern, as governments like the EU are preparing regulations to ensure AI transparency for all stakeholders [109].

5. Current Trends in Cognitive Computing and Management

Both Generative AI and LLMs have been revolutionizing management fields since the launch of ChatGPT. Generative AI has the capability to generate original materials, while LLMs have the capability to make human-level text [110]. Figure 8 highlights the main themes in this section about how cognitive computing and applications have been affecting management since ChatGPT’s launch.

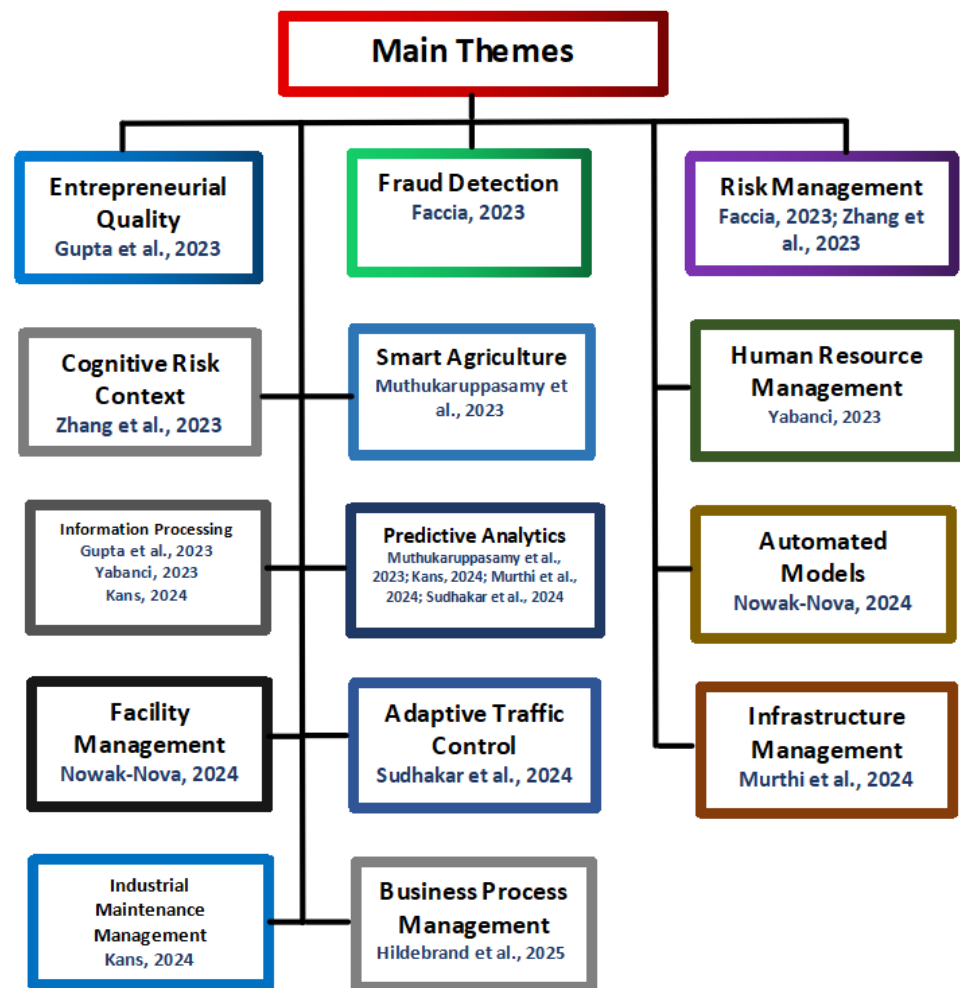


Figure 8. Main themes of management applications identified by our Scopus search [17,19–27].

Table 4 lists summaries of recent research on the impact of ChatGPT and other LLMs on management, while details are discussed in the paragraphs following Table 4.

Table 4. Summary of articles on ChatGPT and LLMs and other recent articles on management.

Ref.	Main Themes	Summaries
Sutrisno et al. [111]	Human resource (HR) management	Finds that ChatGPT has significantly improved HR management
Linkon et al. [110]	AI ethics	Shows that LLMs have the capability to make human-level text, and that there is need for AI regulation and governance
Faccia [17]	Fraud detection, risk management	Shows that cognitive computing helps identify fraudulent transactions
Zhang et al. [19]	Risk management, cognitive risk context	Shows that cognitive computing helps manage cognitive uncertainty
Yabanci [20]	Information processing, human resource management	Shows AI-powered cognitive computing HRM systems for SMEs
Gupta et al. [21]	Information processing, entrepreneurial quality	Studies relationships between cognitive computing and entrepreneurial quality
Muthukaruppasamy et al. [22]	Predictive analytics, smart agriculture	Shows that cognitive computing can be applied for digital farming management

Table 4. Cont.

Ref.	Main Themes	Summaries
Murthi et al. [23]	Predictive analytics, infrastructure management	Shows that cognitive computing can be deployed for smart city infrastructure management
Sudhakar et al. [24]	Predictive analytics, adaptive traffic control	Shows that cognitive computing can be deployed for traffic management
Kans [25]	Information processing, predictive analytics, industrial maintenance management	Supports that cognitive computing leads to better maintenance management
Nowak-Nova [26]	Automated models, facility management	Supports that cognitive inference machines can be used in facility management
Hildebrand et al. [27]	Business process management	Shows that cognitive computing can be deployed for business process management

Cognitive interoperability becomes crucial during the human–machine collaboration and decision-making process. AI systems and cognition capabilities are predicted to become essential, assuming collaborator roles and not just being tools [112]. Based on a review of current AI technologies in the enterprise [112], it is concluded that the existing AI systems cannot match all cognitive abilities yet, with difficulties especially in structuring knowledge representation and recognizing semantic complexity. Desai [113] concluded that, even though data can provide assistance for better decision making, the hardest issues for leaders and managers cannot be entirely solved with hard data and AI technologies. Human endeavors like imagination and conviction are needed in these situations.

Current cognitive computing methods outperform existing traditional approaches in business process management. Cognitive computing has not only been deployed for organizing the business processes efficiently but also been adopted for proactive decision making. Hildebrand et al. [27] conducted a broad and in-depth review of 27 articles that focus on next-generation cognitive computing for business process management. Emerging cognitive computing technologies have the analytical competence to assume more roles in assisting informed decision-making processes than traditional ones. Furthermore, intelligent and cognitive capabilities successfully enhance business process management to a higher level of advanced features like predictive maintenance and better human–computer interaction. Yet, the focus is still on the stage of utilizing the learning and adaptability of cognitive computing for assisting the decision making of business process management. A main challenge for organizations is identified, i.e., the reluctance to initialize transformative changes. The hindering factors identified include organization culture, existing decision-making processes, and workflow. It is concluded that additional approaches are needed for enhancing the transition to cognitive business process management.

Incorporating AI technologies into management accounting has the potential to accomplish both financial data management and strategic decision making. Unlike financial accounting, management accounting needs to be forward-looking and to prioritize data analysis for strategy planning [114]. Almulla et al. [115] conducted a survey of the recent efforts by researchers to apply AI tools in management accounting. Common conclusions by the researchers are that the incorporation of AI tools into management accounting is at a very early stage, but it is expected that this will advance soon. AI-powered automation can augment human accountants.

Cognitive computing methods have been applied to quantify and then manage cognitive uncertainty, which is important for flourishing risk management [19]. A probabilistic linguistic quantification method was deployed for evaluating information qualitatively, enabling decision makers to handle both cognitive and statistical uncertainties. A new

probabilistic linguistic distance measure was developed to quantitatively measure experts' subjective preferences in an environment with risks. Zhang et al. [19] applied the improved prospect theory to more accurately represent the processes of cognitive decision making. The cognitive uncertainty evaluation model was then employed for assessing geopolitical risks thoroughly.

AI-powered cognitive computing systems are able to help small and medium-sized enterprises (SMEs) in human resources management. Yabanci [20] focused on how to help SMEs achieve digitalization of human resources management. Yabanci [20] found that, even though SMEs assume an essential role in both local and global markets, they typically do not utilize information and communication technology effectively for management processes. Factors affecting the adoption of these computing systems were also discussed. In the investigation by Sutrisno et al. [111], it was found that ChatGPT has significantly improved human resource (HR) management communication among HR colleagues. Bharathi and Bhosale [116] investigated how to explore the applications of cognitive computing for sustainability initiatives in human resource management (HRM). A questionnaire was given to human resources managers to understand the problems in HRM and to identify the important cognitive computing technologies for applications in HRM. The focus was on ranking cognitive computing opportunities for assisting informed decision making for HRM managers.

Cognitive computing, machine learning, and visualization models have been utilized for better maintenance management in Industry 4.0 [25]. Interviews with representatives in the maintenance industry were conducted, covering system providers, suppliers, researchers, etc. It was found that the digitalization progress in maintenance management was slow. To facilitate digital transformation, challenges around competence, leadership, and strategy need to be overcome. Pilot studies are needed for initializing the implementation process.

Other advanced applications of cognitive computing in management include the following:

- Gupta et al. [21] investigated the relationships between cognitive computing and entrepreneurial quality. Three hundred companies from China and India were interviewed. The findings supported that the cognitive computing technologies would have a positive impact on entrepreneurial quality, like risk-taking susceptibility, proactiveness, and innovativeness, for the firms in both China and India.
- Muthukaruppasamy et al. [22] focused on the application of digital farming for addressing issues in farming management like resource management and food security, with the belief that digital models would lead to better decision making with savvy managing methods. The agricultural digital platform included data collection, big data, cognitive computing simulation, enquiry, prediction, and transmission. It can provide help in data evaluation, forecasting and decision making for farming management.
- Murthi et al. [23] proposed a cognitive computing model of AI, machine learning, and data analytics for smart city infrastructure management. Case studies confirmed that the cognitive computing system can improve the duration, persistence, and effectiveness of urban infrastructure. It is recognized that cognitive computing has the potential to provide the most operative solution for overcoming frontier city infrastructure challenges.
- Sudhakar et al. [24] investigated the potential of cognitive computing models, like machine learning, natural language processing, and big data analytics, to overcome the problems of traffic management. Cognitive computing can enable the system to have adaptive control instruments to cope robustly with changing environments. Case studies highlighted efficiency enhancement and travel time reduction as benefits of cognitive computing in intelligent traffic management.

- Reddy and Hajarath [117] outlined and discussed how cognitive systems can be developed in the future for enhancing the decision-making process of supply chain management. To achieve this objective, they concluded that more research is needed to connect the cognitive system with the existing enterprise resource-planning solutions.
- Nowak-Nova [26] focused on the application of the cognitive inference machine in facility management, with the combination of automated valuation models with neural network algorithms. The proposed cognitive system can react to changing market situations efficiently, providing managers with information on their operational management.
- Arumugam et al. [118] noted that there are huge effects from applying cognitive technology to human capital management in the banking industry. Arumugam et al. quantitatively investigated, and found a significant correlation between, the transformation of cognitive technology and bank employee performance. They concluded that cognitive technology contributes significantly to human capital management.

Despite the advances in cognitive computing applications in management, limitations remain to be overcome. Future AI tools should have explainability, in other words, telling what the outputs mean [88]. Human experts of diverse experience and thought still outperform AI tools in creativity and product differentiation [119]. Linkon et al. [110] talked about concern for AI ethics, and the need for AI regulation and governance.

6. Insights on Current Limitations and Future Directions

Understanding the limitations of Large Language Models is important to the successful deployment of LLMs [120], despite the fact that hundreds of billions of dollars have been directed to the development of new applications based on the LLMs since the release of ChatGPT. Limitations on reasoning, expertise, understanding, and planning are highlighted. Because of these limitations, it is still essential to deploy LLMs with proper human supervision. Bai et al. [121] found that, like human beings, the current LLMs are still subject to implicit biases. Stereotype biases by LLMs are observed in a diverse range of social classes. Thus, efforts are needed to reduce the effects from implicit biases in LLMs.

Another limitation to the cognitive computing and business applications is the slow adoption by SMEs of cognitive technologies, despite the fact that AI and cognitive computing technologies are very helpful in business applications. Powerful LLMs have been transforming businesses worldwide, especially among large corporations, as highlighted in the previous sections. Addressing slow adoption by SMEs is an especially important topic, given that the majority of businesses in our world are SMEs. For example, in Canada, the total number of employer businesses was 1.22 million in 2022, with 1.19 million small companies. In a recent survey by KPMG [122], for the next three years, 55% of Canadian companies believe that AI/ML are the most important technologies for assisting them to achieve company goals. Nevertheless, it is also found out that only 5% of Canadian organizations are making progress on AI strategy concretely. A Deloitte survey [123] noticed that 26% of Canadian companies had utilized at least one AI deployment, compared to the 34% average globally. Bryan et al. [124] conducted further investigation on the data by Statistics Canada [125] about how businesses in Canada had been utilizing AI over the past 12 months. Only 10.6% of the businesses were planning to utilize AI in their operations for producing goods or services in the coming 12 months. From the above official statistics and private surveys, it is observed that the SMEs are very slow in adopting and utilizing AI technologies.

A major reason for this slow adoption by SMEs of cognitive technologies is that many SMEs do not realize how AI and cognitive computing applications can help their businesses. Most SMEs have not utilized the benefits brought by the new AI technologies,

due to the current limitations of the SMEs, like their AI knowledge and cost concerns. Even though nearly half of SME companies (46%) noted that emerging technologies like AI are of critical importance in the operations of their business, only 23% have had any kind of first-hand experience of deploying AI applications in the survey by Schönberger [126]. Tawil et al. [127] conducted a three-year-long study on trends and challenges for more than 85 UK SMEs in adopting AI and big data technology with funding support from the European Regional Development Fund. It is noted that the SMEs can gain huge benefits with the adoption of data science (AI and big data), like productivity improvement, business growth, and innovation. Based on this three-year investigation, it is concluded with evidence that there exists the need to increase awareness among the SME stakeholders, like owners, entrepreneurs, and managers, about the advantages and challenges of the new digital technologies.

Generative Pretrained Transformers (GPTs), like other neural networks, have a weakness in their interpretability and are often criticized for their transparency issues, despite their outstanding capability [128]. Many of the artificial intelligence methods do not have the power to explain their own decision-making process, which may be called “Black-Box” [128]. This lack of explanation capability may lead to trust and compliance issues, and also hinder efforts to address the bias and fairness of AI methods. Adelakun et al. [59] identified the lack of transparency and accountability in AI systems as the primary concern for its applications in accounting, because it is still difficult to understand and to explain AI’s outputs. Addressing the ethical issues associated with AI in accounting is an essential topic that needs handling to satisfy the ethics and governance requirements.

Explainable AI (XAI) has the potential to address the above interpretability weakness of the GPTs, leading to comprehension of the system’s process of decision making. Explainable AI refers to methods that enhance understanding of the AI outputs for human beings. The XAI has the potential to turn deep learning methods into more accessible and trustworthy models for applications. The challenges of existing XAI approaches include how to build up sound explanations for complex algorithms while also maintaining the balance between transparency and privacy. Hassija et al. [128] presented a comprehensive review of the current XAI methods that are developed to provide interpretation to the black-box methods. To further strengthen the linguistic sophistication of the LLMs, Zafar et al. [9] integrated knowledge graphs with LLMs. Their conversational AI system handles the weakness of many AI systems, i.e., transparency and trustworthiness, within the context of media and journalism. It is shown that the proposed system is able to serve as a precedent for a future AI system that should address not only efficiency but also trustworthiness.

Efforts are needed to understand the susceptibilities of LLMs to further improve LLMs with more reliable mechanisms, and to address the concerns of LLMs over safety, security, and privacy, as highlighted in the review of Zhang et al. [129]. Cartwright et al. [130] investigated the privacy compliance of the popular ChatGPT, Claude, and Gemini. It was found that ChatGPT has issues like access control. On the other hand, Claude was found to exhibit satisfactory privacy compliance and data security. The performance of Gemini for these aspects was not consistent. Motlagh et al. [131] highlighted the importance of defensive strategies in cybersecurity when deploying LLMs. At the organizational level, these involved four steps: identification, protection, detection, and response. As a result, sophisticated research and planning is needed to ensure that the LLMs are capable of satisfying privacy requirements.

Cognitive systems are desired to become a personalized business partner that has the capability of continuously learning. Continual learning, a paradigm of machine learning, is worthy of further investigation for business applications, as continual learning is developed to imitate the capability of human intelligence to learn continuously [132]. When ChatGPT

was developed, it worked similarly to many other language models, by an autoregressive process for generating text [133]. In one sentence, the likelihood of the next word is derived from the previous words. It is interesting to note that this concept of autoregression and neural networks working together existed long before the launch of ChatGPT. The authors of [134] showed that recurrent neural networks can be regarded as a type of nonlinear autoregressive-moving average model (NARMA). Baziyad et al. [133] noticed that there existed linguistic limitations for this autoregression strategy of ChatGPT. New benchmarks need to be set up for cognitive computing systems to achieve human-centric intelligence [6].

7. Conclusions

Our review of cognitive computing and business intelligence applications in accounting, finance, and management, three imperative areas for our society, provides a holistic framework to better comprehend their trends and limitations. In the two Forbes reports by Houston in March and December 2023 [135,136], it was emphasized that accounting is crucial to the successful operation of a business by providing essential financial information to management for key decision making. Furthermore, business finance is indispensable for the management of a business and requires key information from accounting.

Organizations may benefit from these frontier case studies of deploying cognitive computing in different business contexts under our integral schema. First, this review presented an overview of the trends for cognitive computing and business intelligence applications before the launch of ChatGPT. Next, this survey summarized more recent case studies of cognitive computing in accounting, finance, and management after the release of ChatGPT.

New initiatives from governments and organizations are needed to promote awareness in SME owners and managers of the benefits associated with cognitive computing technologies. As the complexity of the computing task increases with the size of data sources, it becomes challenging for small and medium enterprises to allocate enough financial support and resources for successful cognitive computing deployments. More institutional supports must be provided to SMEs for their successful implementation of cognitive computing solutions.

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