Machine Learning Use Case Discovery and Implementation in the Finance and Accounting Domains of Companies

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ABSTRACT

This research paper presents an approach for identifying and implementing machine learning use cases in finance and accounting in an agile setting. The study aims to address the gap in the literature, which predominantly covers the individual advantages of using machine learning in accounting and finance; however, it lacks a comprehensive view of the generation of use cases in this field. Furthermore, the study provides insights for companies in creating machine learning-driven solutions, improving productivity, attaining operational excellence, generating cost savings, and fostering profitable growth. The proposed methodology includes a comprehensive step-by-step strategy comprising 18 distinct process phases categorized into five main clusters.

Keywords: *Machine Learning in Finance and Accounting, Digital Transformation, Use Case Generation, Agile Management*

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INTRODUCTION

In the current digital era, companies must adjust their strategies and operations to effectively respond to rapid development, growth, innovation, and disruption. To maintain competitiveness, companies must develop a comprehensive digital transformation plan encompassing heightened awareness, well-informed decision-making, and swift execution (Albukhitan, 2020). Indeed, the COVID-19 pandemic has sped up the necessity for transforming products and services, highlighting the increasing importance of technology and providing a chance to enhance the field of digital transformation (Cavalcanti et al., 2022). Hence, adopting digital transformation has become essential for companies to survive fiercely competitive environments (Luo et al., 2023).

In digital transformation, the significance of artificial intelligence (AI) and machine learning (ML) cannot be overlooked. The use of AI and ML in business practices has become more critical in the present era of fierce competition, characterized by rapid globalization and the continual appearance of disruptive technologies. These approaches are essential for companies to adapt and flourish in this challenging environment (Warner & Wäger, 2019). In addition, AI has witnessed significant progress in algorithmic ML and autonomous decision-making, which has led to the possibility of enhancing and substituting human jobs across many domains. The rapid transformation rate in the current era of AI technology is remarkable, giving rise to novel prospects for innovation. The potential ramifications of AI are considerable, with the potential to disrupt several sectors like banking, healthcare, manufacturing, retail, supply chain, logistics, and utilities (Dwivedi et al., 2021).

In addition to being widely regarded as imperative in contemporary business practices, digital transformation engenders a multitude of advantages for companies. From the perspective of company performance, it can be observed that the digital transformation process positively influences a company's profitability. This is achieved through reducing costs, enhancing operational efficiency, and facilitating innovative results. Consequently, these factors collectively contribute to the attainment of better performance (Zhai et al., 2022). In addition, such strategic initiatives maximize resource use, promote innovation, enhance the overall customer experience, and increase operational efficiency (H. Zhang & Dong, 2023). It is worth mentioning that the use of digital technologies such as AI, ML, big data, and cloud computing is the engine of transformation, empowering businesses to embrace novel development models, dismantle outdated management paradigms, and construct innovative organizational frameworks that ultimately contribute to heightened productivity and profitability (Cui & Wang, 2023). Within the accounting and finance operations framework, digital technology facilitates financial innovation, resulting in a monetary framework characterized by extensive reach, enhanced productivity, and reduced expenses. Moreover, it significantly influences the decision-making patterns exhibited by companies (Sun et al., 2023). At the macroeconomic level, the adoption of digital finance has been found to favor technological advancements. Specifically, integrating digital finance in various economic sectors can contribute to a greater overall economic growth rate (Xiao et al., 2023). However, digital transformation is a significant challenge for companies, requiring a thorough reassessment of their current capabilities, structures, and culture to find pertinent technologies and effectively integrate them into organizational operations. Companies are faced with the challenge of effectively managing the integration of innovative practices while mitigating the potential disruptive effects to successfully adopt novel business models (Saarikko et al., 2020).

Regardless of size or age, companies have undertaken initiatives to integrate digital innovation as a fundamental element of their strategy for creating and capturing value (Nambisan, 2018). In this sense, corporate digital transformation is an imperative strategic approach companies employ to enhance their vitality and get a competitive edge in the market. The advent of digital technology and the intensification of market competitiveness have prompted companies to prioritize expeditious adaptation rather than deliberating on the necessity of such adaptation (Y. Zhang et al., 2023). When considering corporate digital transformation as a strategic approach, it is crucial to address specific key components. Firstly, intangible capital is a valuable asset in implementing digital transformation strategies, primarily linked to the comprehensive technical framework inside a company. In essence, achieving effective digital transformation is contingent upon the capabilities exhibited by data architecture and data-centric operational models. Additionally, ensuring coherence in data architecture is of particular significance in developing ML skills and providing efficient products and services (Cao & Iansiti, 2022). Secondly, digital transformation encompasses the continuous utilization of emerging digital technology within the operational framework of a company, such as AI and ML, as streamlined operational processes. These processes acknowledge the significance of agility as the primary mechanism for strategically revitalizing an organization's business model, collaboration practices, and, ultimately, its culture (Warner & Wäger, 2019). Thirdly, incorporating agile methods is a critical and essential element of a sustainable transformation strategy since digital transformation is closely linked to agility. The digital transformation process allows companies to transition into agile organizations, facilitating prompt market responsiveness and tackling difficulties in a competitive and fast-paced business environment (Wiechmann et al., 2022).

This study aims to propose a comprehensive agile methodology that elucidates the process by which companies may identify and apply ML use cases in finance and accounting inside their organizational frameworks. Agility is a fundamental organizational concept that facilitates prompt responsiveness to fluctuations in a dynamic corporate environment. Emerging from the realm of software development and information technology endeavors, this concept has evolved into a valuable asset for modern-day companies, effectively harmonizing the need for stability with adaptability (Ciric et al., 2019). Agile project management is an adaptable methodology that prioritizes iterative and test-driven techniques, exemplified by frameworks like Scrum and Kanban. In contrast to traditional waterfall methodologies, agile approaches adopt a condensed planning timeframe and reduced level of commitment, enabling adaptable decision-making and a more malleable project execution strategy that facilitates prompt adaptation to evolving client demands (Thesing et al., 2021). Agile methodologies promote the establishment of self-organizing teams with a significant degree of autonomy. These teams collaborate with managers and customers on project management tasks, including estimating, planning, and eliciting requirements (Hoda & Murugesan, 2016).

The proposed methodology aims to guide companies in developing ML-based solutions in the accounting and finance field. The business implications of the solutions include improving efficiency, enhancing process excellence, generating operational savings, and contributing to profitable growth. Ultimately, this methodology aims to support the overall digital transformation process of the company in an agile setting. This study is organized in the following manner: Section 2 of this paper elaborates on current research in the literature focusing on ML applications in the accounting and finance area. Section 3 concisely describes the research methodology employed in the study. Section 4 of the study provides a comprehensive exposition of the suggested approach for the recognition and execution of ML use cases. The last section concludes.

LITERATURE REVIEW

The scholarly literature has witnessed a significant rise in the use of AI and ML methodologies within finance and accounting, particularly since the beginning of 2015 (Ahmed et al., 2022). The growing interest in this particular domain may be categorized into three broad groups: the analysis of portfolio construction, valuation, and investor conduct; the investigation of financial misconduct and distress; and the exploration of sentiment inference, forecasting, and strategic decision-making (Goodell et al., 2021). The application areas also include forecasting company failure, comprehending the dynamics of financial risk, concluding credit scoring models, applying sentiment indicators derived from textual data to provide insights into stock prices and financial markets, forecasting highly volatile assets, and establishing a network of shareholders to gain an understanding of company ownership structures (Consoli et al., 2021).

In the context of fraud detection and anomaly determination, Femila Roseline et al. (2022) presented an approach for credit card fraud detection by introducing a Long Short-Term Memory-Recurrent Neural Network (LSTM-RNN) ML model with an attention mechanism. Seify et al. (2022) investigated a conceptual design methodology for fraud detection in supply chains. The authors' strategy involved utilizing supervised ML techniques to identify and mitigate instances of fraud and disinformation. Achakzai & Peng (2023) constructed a sophisticated fraud detection model capable of identifying fraudulent entities by including financial and non-financial factors per existing scholarly research. The authors presented the dynamic ensemble selection method as a novel addition to the existing research on fraud detection that dynamically integrated several individual classifiers to get a final prediction. In addition, Lahann et al. (2019) employed a supervised learning classifier to make predictions about tax subjects and their respective tax rates based on the relevant voucher information found in journal reports. The authors identified possible abnormalities and instances of non-compliance.

Concerning default risk, Wang et al. (2022) examined the prediction of corporate financing risk. Their study conducted comparative tests utilizing the LightGBM, k-nearest-neighbors (KNN) algorithm, decision tree method, and random forest algorithm on an identical dataset to predict the financing risk profile of 186 companies. The experimental findings demonstrated that LightGBM outperformed the other three algorithms. Sigrist & Leuenberger (2023) focused on estimating multi-period corporate default risks by integrating tree-boosting and a latent frailty model inside a hybrid econometric-machine learning framework. The model had superior prediction accuracy to linear models, particularly for longer prediction horizons when the disparities were more pronounced. In their study, Murugan & T (2023) analyzed and processed extensive datasets using three ML algorithms: KNN, logistic regression, and extreme gradient boosting (XGBoost). Their investigation aimed to assess these algorithms' predictive capabilities in determining loan defaults and estimating the likelihood of their occurrence. The authors put up KNN and XGBoost ML models as potential approaches for financial risk management.

Customer churn models are another field in which ML approaches may bring additional benefits. Intending to guide the most effective ML method for predicting early customer churn, Prabadevi et al. (2023) used stochastic gradient boosting, random forest, logistic regression, and KNN approaches to conduct customer churn analysis.

Concerning financial performance, sales, and profits, Saha et al. (2023) examined forecasting the financial performance of companies in registered industrial sectors inside emerging countries using ML techniques. Analyzing the registered manufacturing companies in India's food processing industry, it was observed that ML techniques exhibited higher accuracy in predicting sales than profits. Specifically, the Bayesian ML algorithm, BART, had superior predictive capabilities compared to alternative methods. Chakri et al. (2023) employed exploratory data analysis techniques to examine financial accounting data, including balance sheets, income statements, and cash flow statements, to ascertain the profitability level. Furthermore, the researchers made predictions about the overall revenue by utilizing four distinct ML models: linear regression, KNN, support vector regression, and decision tree. The decision tree model was the most beneficial approach for performance analytics. Evdokimov et al. (2023) assessed the efficacy of nine ML algorithms and ARIMA as a comparative benchmark in predicting free cash flow (FCF) growth rate. The authors demonstrated that ML algorithms provided statistically significant evidence of outperforming traditional methods in projecting the growth rate of FCF across a sample of 100 companies, in which the KNN algorithm outperformed the rest. Zema et al.(2022) conducted a study on predicting alternative leasing prices in Polish companies using deep learning algorithms. Van Der Heijden (2022) revealed that employing an ML methodology and utilizing ML classifiers enabled accurate prediction of a company's industry sector based on its financial statement data. In the banking sector, Uçan and Bayazıt (2018) put forth a credit scoring model that incorporated fuzzy rough set theory to handle the inherent uncertainty present in current models effectively. The suggested approach assessed the similarity of data samples in determining a consumer's credit eligibility. The authors reported that the findings indicated a relatively superior performance. The study conducted by Yetiz et al. (2021) investigated customer forecasting within the Turkish banking sector by employing ML techniques such as artificial neural networks and support vector machines. The researchers integrated monthly data from depositary banks from 2011 to 2020, encompassing key variables such as branch count, personnel count, aggregate deposit amounts, and aggregate loan amounts. The customer number projections had implications for strategy formulation in identifying target customers.

Regarding asset price forecasting, Aygün and Kabakçı Günay (2021) conducted a comparative analysis of different statistical techniques and ML methodologies to forecast the future price of the Bitcoin cryptocurrency. The authors employed the Wilcoxon-Mann-Whitney nonparametric statistical test to assess the performance of the investigated models. The results indicated that the ML approach RNN exhibited superior predictive performance compared to the other methods.

In conclusion, the current body of research on utilizing AI and ML methodologies in accounting and finance in companies focused on specific application areas and emphasized the resulting advantages for businesses. However, the existing body of literature lacked comprehensive coverage of the processes involved in recognizing, evaluating, validating, and implementing use cases in companies. The primary aim of this study is to address the existing gap by presenting an approach consistent with agile principles, designed explicitly for the identification and implementation of ML use cases within the financial and accounting fields.

METHOD

The study adopted a methodology that established a theoretical framework for identifying and implementing ML use cases in accounting and finance in companies. The method was a comprehensive step-by-step strategy that consisted of 18 distinct process phases, covering the whole process from the initial concept generation to the conclusion of financial ML applications. In this context, the various stages of the process were delineated and expounded upon in five main clusters. Furthermore, the suggested framework demonstrated compatibility with the agile approach.

PROPOSED FRAMEWORK

The proposed ML use case generation framework in finance and accounting includes 18 successive process steps. The framework is categorized into five main clusters: the ideation, identification, validation, implementation, and post-implementation stages.

As for the initial cluster, the ideation covers spreading the idea of ML, approaching potential customers within the company, and gathering possible use case ideas from specialists in the finance and accounting domains. Secondly, the identification cluster involves the use case evaluation and prioritization steps. Thirdly, the training data snapshot is defined and modeled in the validation cluster. The organized data is then used for exploratory analysis and ML model training. In the fourth implementation cluster, the requirements for the productive system are evaluated, productive data is ordered and modeled, visualization and authorization needs are clarified, the application is tested, and the final application is released. In the last cluster of post-implementation, users are trained, and the ML performance is monitored. The sequential context is presented in Table 1.

Table 1: Methodological Process Steps for ML Use Case Discovery and Implementation

Process Step	Process Cluster	Process Definition
1	Ideation	Spread the Idea of ML
2		Approach the Customer
3		Collection of Possible Use Cases
4	Identification	Use Case Evaluation
5		Use Case Prioritization

6	Validation	Training Data Definition
7		Data Ordering for Training Data
8		Data Modelling for Training Data
9		Exploratory Data Analysis
10		ML Model Development
11	Implementation	Requirements Evaluation for Production
12		Data Ordering for Productive Data
13		Data Modelling for Productive Data
14		Visualization and Authorization
15		Team Testing and Customer Testing
16		Release and Go Live
17	Post-Implementation	User Training
18		Monitoring

The process steps are described as follows:

Spread the Idea of ML: This phase refers to all kinds of activities related to creating awareness of the application areas and benefits of ML-based solutions within the company. This initial phase might be conceptualized as an internal marketing endeavor to facilitate collecting prospective pain points and ideas in the succeeding stages. Within this context, the team tasked with promoting ML within the company may adopt a structured approach known as the why-how-what framework. This approach may first emphasize the underlying rationales for incorporating ML techniques in finance and accounting. Subsequently, the team may highlight the advantages of utilizing ML methods, elucidate how ML strategies align with the overarching vision and strategy of the company, and introduce the individuals who will assume responsibility for the whole ML implementation process.

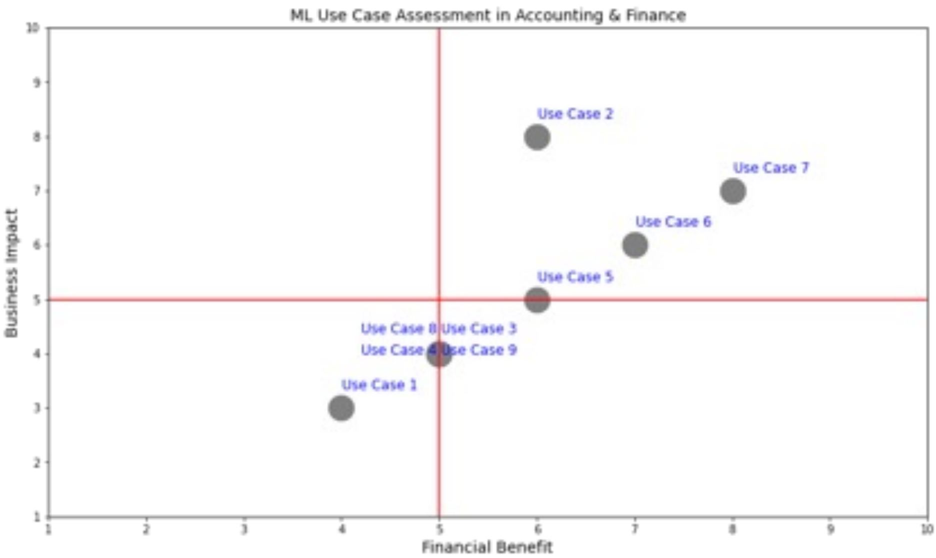
Approach the Customer: When discussing ML-enhanced solutions as an internal service, the customer typically refers to finance and accounting professionals with operations and process management expertise. During this stage, individuals with expertise in operations and processes within the financial domain are identified and engaged to promote the introduction and presentation of ML approaches. The anticipated result of this stage is collecting information about possible pain points within finance and accounting processes. Data collection can take the form of interviews, which aim to uncover the primary bottlenecks in daily operations and processes without providing immediate answers. In addition to consulting domain specialists, conducting interviews with senior executives within the company may also be beneficial to gain a comprehensive understanding of the organization's present financial status, existing difficulties, and future priorities.

Collection of Possible Use Cases: During the last stage of the ideation cluster, the focus is collecting and documenting prospective use case ideas. The collection of ideas can be achieved by either a bottom-up method, including engagement with specialists in the finance and accounting area, or a top-down approach, which is drawn from the expectations set by executives within the company. The top-down method primarily focuses on assessing the appropriateness of key financial performance indicators for ML applications. Those tasked with deploying ML solutions should exercise caution in independently selecting and initiating use cases. Instead, they should seek alignment with domain specialists possessing specialized finance and accounting knowledge. The recommended approach for the implementation team is to maintain a neutral stance and execute the tasks the customer assigns.

Use Case Evaluation: The identification cluster begins with evaluating use cases. During this process, the primary objective is to assess whether or not a use case possesses sufficient merit to warrant further examination and potential implementation. The initial assessment can be conducted by considering specific criteria. These criteria include the clarity of the business problem or pain point, the explicitness of the target condition, the measurability and quantifiability of the benefits, the broadness of the potential impact area of an ML solution, and the presence and accessibility of relevant data within the company's IT landscape or ERP system.

Use Case Prioritization: After completing the use case evaluation in the previous stage, a decision is made to proceed with the submitted concept. The reviewed ideas are then ranked using a two-dimensional technique. In this context, prioritizing is executed by directing attention towards the anticipated business impacts and financial benefits. Figure 1 depicts a proposed visual approach for prioritizing. Consequently, the prioritization of use cases is determined based on their potential for significant business impact and financial benefits. Furthermore, it is recommended that the decision-making process regarding prioritization be conducted collaboratively by a committee comprising representatives from company management, associates responsible for the implementation process (likely the product owner of the ML stream in finance and accounting within the agile framework), subject matter experts, internal customers, and functional department leaders. In the context of agile project management, Kanban boards can serve as a valuable tool for visualizing the progression of use cases. These boards can be leveraged to represent various stages of use case development, including initial ideas in the backlog, elaborated concepts ready for prioritization, prioritized cases undergoing technical evaluation, use cases in implementation, and finalized use cases.

Figure 1: Prioritization of ML Use Cases in Accounting and Finance



Training Data Definition: After completing the prioritizing cluster, the validation cluster's initial stage involves establishing the training dataset's parameters. The training dataset is utilized to derive first business insights, identify trends and patterns in the data, and choose and validate ML models. In this process step, the relevant data necessary for addressing the use case or business challenge is determined, and its accessibility is confirmed. Furthermore, the business rationale is elucidated, and the technical evaluation is conducted. The phase includes the identification of the time scope, variables, and volume of the training dataset.

Data Ordering for Training Data: After assessing the suitability of the training dataset based on its alignment with the business logic and technological feasibility, the training data is made available in the company data warehouse, most probably in its raw form.

Data Modelling for Training Data: During this stage, the raw data undergo a series of procedures, including cleaning, processing, structuring, and ultimately being stored in a database.

Exploratory Data Analysis: In this phase, the structured data go through analysis and visualization to extract valuable insights for business purposes. The insights obtained from the analysis are afterward shared and validated with professionals in finance and accounting. This process aims to ascertain the critical elements within the dataset that have the most significant impact and may be utilized as the primary input for building the ML model in the next step.

ML Model Development: The features of the ML model are engineered and selected based on the findings of the exploratory data analysis. During this iterative step, ML models are chosen, the hyperparameters of the selected model are adjusted, and the final model is assessed to determine its capacity to generalize. The ultimate validation of the model involves evaluating the model's performance indicators concerning the customers' expectations. To conclude this procedural stage, the internal customer confirms the transition to the productive system.

Requirements Evaluation for Production: The initial step in the implementation cluster involves conducting a requirements evaluation. This evaluation entails assessing the business logic, including the productive data schema and structure. Additionally, it involves discussing the customer's expectations regarding the visualization of the final application and the authorization concept. The process step is finished upon verification of technical feasibility.

Data Ordering for Productive Data: The live productive data are ordered from the company's data landscape and made technically available.

Data Modelling for Productive Data: The productive dataset is modeled and deployed in the database.

Visualization and Authorization: The visualization process often involves the creation of live dashboards, which are designed following the customer's specific requirements. Furthermore, the customer's final needs develop the concept of authorization, which defines who will have access to the dashboards within the company.

Team Testing and Customer Testing: The development team first tests the final application, followed by the customer's further testing. In this context, the customer defines and provides the test cases.

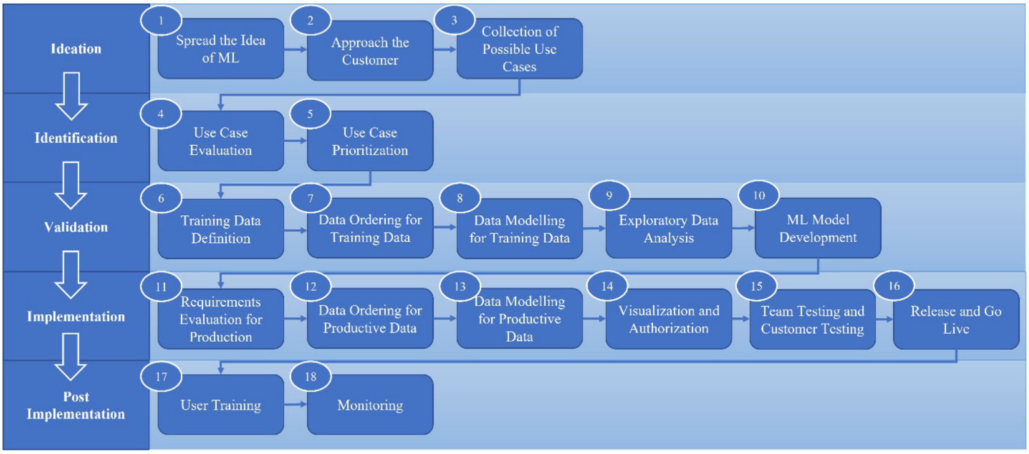
Release and Go Live: The concluding step in the implementation is the release phase. In this stage, it is ascertained that the technical documentation is comprehensive, and the ML adheres to the corporation's IT, compliance, and data security requirements.

User Training: This section entails the preparation of training materials such as user manuals and technical implementation details.

Monitoring: The performance of the ML models is to be continuously monitored, and the need for re-training of the model is to be regularly checked. Monitoring processes may be carried out through model performance dashboards.

The comprehensive framework is concisely represented as a flow chart in Figure 2, depicted below.

Figure 2: Flow Chart of ML Use Case Generation Framework



CONCLUSION

Companies must modify their strategies and operational approaches to sustain their competitive edge in today's digital environment. The strategic process of corporate digital transformation encompasses integrating AI and ML applications, data architecture, and agile practices. AI and ML technologies have become vital components within the accounting and finance industry due to their ability to improve profitability and operational efficiency and foster innovation significantly. While the current body of literature on the uses of AI and ML in accounting and finance primarily emphasizes the individual advantages of specific cases, there is a limited amount of comprehensive research on the generation of use cases in this field. This study aimed to fill this gap by proposing an agile approach for identifying and implementing ML use cases in finance and accounting. The proposed framework had a total of 18 process steps, which were organized into five primary clusters. These clusters serve as a comprehensive guide for companies seeking to engage in the various stages of ideation, identification, validation, implementation, and post-implementation of ML use cases. As for the business consequences, the methodology sought direction in developing ML-driven solutions, enhancing efficiency, achieving process excellence, realizing operational savings, and contributing to profitable growth.

Regarding the study's limitations, it should be noted that the effectiveness of the proposed framework in an agile environment may require a proficient team comprising product owners, scrum masters, data scientists, data modelers, data engineers, ML engineers, visualization developers, and domain experts. The composition of such a team is contingent upon the company's scale. Small and medium-sized enterprises (SMEs) may have challenges establishing a team to implement the provided framework. Hence, the proposed framework would be more suitable for implementation in larger firms, including global companies.

There has been a growing trend for companies to use cloud resources to store and compute data in addition to on-premise resources. In line with this trend, future research may focus on expanding the suggested framework in cloud computing settings such as Microsoft Azure and Amazon Web Services. Another aspect for future research could be establishing a framework for developing use cases that leverage Generative AI methodologies in companies' finance and accounting domains.

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