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Artificial Intelligence for Market Risk and Opportunity Forecasting in Small and Medium-Sized Businesses: A Critical Review and Future Research Agenda

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Abstract

Small and medium-sized businesses (SMEs) operate in increasingly volatile and competitive markets characterized by demand uncertainty, price fluctuations, supply chain disruptions, and rapid technological change. In recent years, artificial intelligence (AI) has emerged as a powerful tool for market risk assessment and opportunity forecasting, enabling data-driven decision-making that was previously accessible mainly to large corporations. This review critically examines the state of the art in artificial intelligence–driven market risk and opportunity forecasting models applied to SMEs, to synthesize existing knowledge, identifying methodological trends, and outlining future research directions. Drawing on peer-reviewed literature across business analytics, information systems, and applied machine learning, the review evaluates commonly used AI techniques, including traditional machine learning algorithms, deep learning models, ensemble methods, and hybrid analytical frameworks. Particular attention is paid to how these models are used to predict market demand volatility, revenue risk, customer churn, pricing dynamics, and emerging growth opportunities in SME contexts. The review also assesses the types of data employed, such as transactional records, financial statements, social media data, and macroeconomic indicators, and discusses the implications of data limitations typical of SMEs. The findings reveal that while AI-based forecasting models often outperform traditional statistical approaches in predictive accuracy, their adoption among SMEs is constrained by challenges related to data quality, computational resources, model interpretability, and organizational readiness. Furthermore, the literature shows a strong bias toward accuracy-focused evaluations, with limited emphasis on explainability, managerial usability, and real-world economic impact. This review contributes by developing a structured conceptual framework linking AI capabilities, data sources, and forecasting objectives to SME strategic outcomes. It concludes by proposing a future research agenda emphasizing explainable AI, integration of alternative data sources, ethical and governance considerations, and scalable AI solutions tailored to the unique constraints of small and medium-sized businesses.

Keywords: Small and Medium Enterprise (SME); Artificial Intelligence (AI); Market Risk Forecasting; Opportunity Forecasting; Business Analytics; Machine Learning; Data-Driven Decision-Making

1. Introduction

Small and medium-sized businesses (SMEs constitute over 90% of enterprises worldwide and play a critical role in employment generation, innovation, and economic growth, particularly in developing and emerging economies (OECD, 2019; World Bank, 2020). Despite their importance, SMEs are disproportionately exposed to market risks such as demand volatility, price uncertainty, competitive pressure, and macroeconomic shocks due to limited financial buffers and restricted access to advanced analytical tools (Beck & Demirgüç-Kunt, 2006; Ayyagari et al., 2011). Effective forecasting of market risks and opportunities is therefore essential for SME survival, resilience, and sustainable growth.

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Traditional market forecasting approaches used by SMEs have largely relied on linear statistical models and managerial intuition, which often fail to capture nonlinear patterns, structural breaks, and complex interactions inherent in modern markets (Makridakis et al., 2018; Fildes & Goodwin, 2007). In recent years, artificial intelligence (AI) and machine learning (ML) techniques have transformed predictive analytics by enabling the processing of large, heterogeneous datasets and uncovering hidden patterns that enhance forecasting accuracy (Jordan & Mitchell, 2015; Davenport & Ronanki, 2018). These capabilities position AI as a promising solution for addressing market uncertainty faced by SMEs.

AI-driven market prediction models, including supervised learning algorithms, deep learning architectures, ensemble methods, and hybrid systems, have demonstrated superior performance in forecasting demand, sales, customer behavior, and financial risk across various industries (Ahmad et al., 2015; Chen & Guestrin, 2016; Fischer & Krauss, 2018). For SMEs, such models offer the potential to identify emerging opportunities, anticipate adverse market movements, and optimize strategic decision-making under uncertainty (Wamba et al., 2017; Rialti et al., 2019). Moreover, the increasing availability of cloud computing and software-as-a-service (SaaS) platforms has lowered the entry barrier for AI adoption among resource-constrained firms (Margherita et al., 2021). However, despite growing interest, the adoption of AI for market risk and opportunity forecasting among SMEs remains uneven and underexplored. Existing studies highlight persistent challenges related to data scarcity, model interpretability, technical expertise, and organizational readiness (Bughin et al., 2018; Jarrahi, 2018). In addition, much of the current literature prioritizes predictive accuracy over practical usability, explainability, and economic impact—factors that are crucial for SME managers and policymakers (Doshi-Velez & Kim, 2017; Shmueli & Koppius, 2011).

Furthermore, the literature on AI-driven forecasting in SMEs is fragmented across disciplines, including information systems, operations management, finance, and entrepreneurship, making it difficult to derive a coherent understanding of methodological trends, application domains, and research gaps (Rai et al., 2019; Dwivedi et al., 2021). There is a growing need for integrative reviews that critically evaluate existing models, assess their relevance to SME contexts, and articulate future research directions that align technological advances with managerial and policy needs.

Against this background, this review provides a comprehensive and critical synthesis of AI-based market risk and opportunity forecasting models applied to SMEs. By systematically examining existing studies, the review aims to (i) identify dominant AI techniques and data sources, (ii) evaluate their predictive and strategic relevance for SMEs, (iii) highlight key limitations and adoption barriers, and (iv) propose a forward-looking research agenda. In doing so, this article contributes to both academic scholarship and practice by clarifying how AI can be responsibly and effectively leveraged to transform market uncertainty into strategic advantage for small and medium-sized businesses.

2. Conceptual Foundations of Artificial Intelligence in SME Market Forecasting

The conceptual foundations of artificial intelligence (AI) in small and medium-sized enterprise (SME) market forecasting are rooted in advances in computational intelligence, data analytics, and decision science. AI broadly refers to computational systems capable of performing tasks that traditionally require human intelligence, such as learning, reasoning, pattern recognition, and prediction (Russell & Norvig, 2016; Jordan & Mitchell, 2015). Within the context of market forecasting, AI enables firms to process large volumes of structured and unstructured data to anticipate market risks and identify emerging opportunities with greater accuracy than traditional methods (Ahmad et al., 2015; Makridakis et al., 2018).

Market forecasting in SMEs has historically relied on heuristic judgment and linear statistical models, including regression analysis and time-series techniques (Fildes & Goodwin, 2007; Armstrong, 2001). While these approaches provide interpretability and simplicity, they are limited in their ability to capture nonlinear interactions, high-dimensional relationships, and rapidly changing market conditions (Zhang et al., 1998; Hastie et al., 2009). AI-based models, particularly machine learning (ML) algorithms, overcome these limitations by learning directly from data without prespecified functional forms (Mitchell, 1997; Shmueli & Koppius, 2011). From a theoretical perspective, AI-driven forecasting aligns with the resource-based view (RBV), which posits that firms gain competitive advantage by developing unique, difficult-to-imitate capabilities (Barney, 1991). Predictive analytics capabilities enabled by AI can be considered strategic resources that enhance SMEs' ability to sense market changes and respond proactively (Rialti et al., 2019; Wamba et al., 2017). Similarly, the dynamic capabilities theory emphasizes the role of data-driven learning in adapting to volatile environments, a core challenge faced by SMEs (Teece et al., 2016; Dubey et al., 2019).

AI models used in SME market forecasting typically fall into four broad categories: supervised learning, unsupervised learning, deep learning, and ensemble methods (Hastie et al., 2009; Jordan & Mitchell, 2015). Supervised learning algorithms, such as linear regression, support vector machines, decision trees, and k-nearest neighbors, are widely applied for demand prediction, sales forecasting, and customer churn analysis (Ahmad et al., 2015; Kim, 2003; Vapnik, 1998). Unsupervised learning techniques, including clustering and dimensionality reduction, support market segmentation and opportunity identification (Jain et al., 1999; Wedel & Kamakura, 2012). Deep learning architectures, particularly recurrent neural networks (RNNs) and long short-term memory (LSTM) models, extend AI forecasting capabilities by modeling temporal dependencies and complex nonlinear dynamics in market data (Hochreiter & Schmidhuber, 1997; Fischer & Krauss, 2018). Ensemble methods such as Random Forests and gradient boosting combine multiple learners to improve robustness and predictive performance, making them attractive for noisy and data-scarce SME environments (Breiman, 2001; Chen & Guestrin, 2016).

Another critical conceptual pillar is the data–information–knowledge–decision (DIKD) hierarchy, which frames AI as a mechanism for transforming raw data into actionable market intelligence (Davenport & Harris, 2017; Provost & Fawcett, 2013). For SMEs, AI-driven forecasting systems act as decision-support tools that augment managerial judgment rather than replace it, consistent with the human–AI collaboration paradigm (Jarrahi, 2018; Rai et al., 2019). However, the conceptual adoption of AI in SME forecasting is constrained by issues of explainability and trust. The emergence of explainable artificial intelligence (XAI) reflects the need to balance predictive accuracy with transparency, particularly for managerial decision-making and regulatory compliance (Doshi-Velez & Kim, 2017; Ribeiro et al., 2016). This conceptual shift is especially relevant for SMEs, where decision-makers often require interpretable insights to justify strategic actions under uncertainty. The conceptual foundations of AI in SME market forecasting integrate computational learning theory, strategic management frameworks, and decision science. These foundations underscore AI's potential to enhance market risk assessment and opportunity identification while highlighting the importance of contextual adaptation to SME-specific constraints.

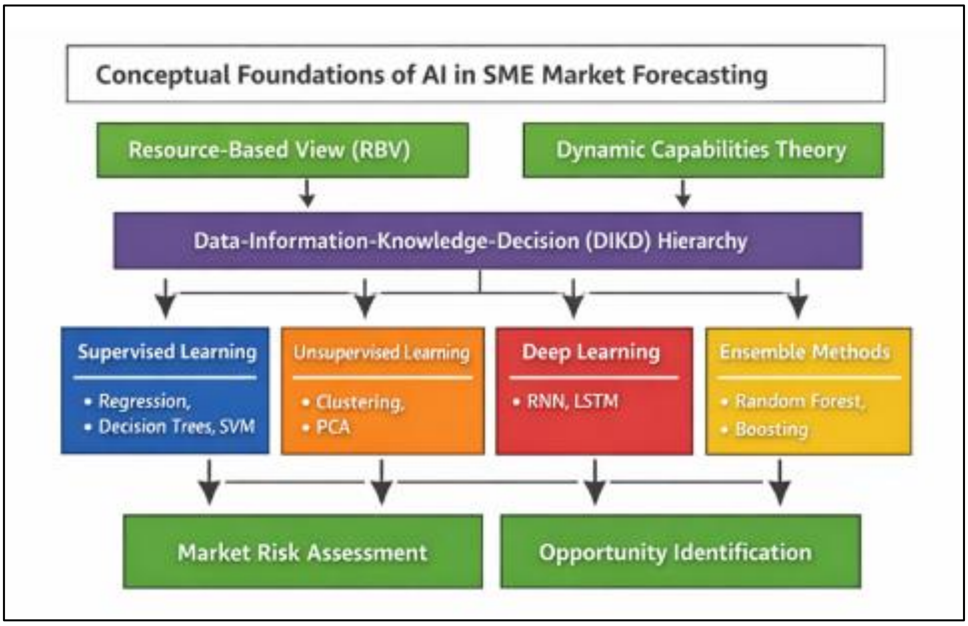

Figure 1 Conceptual framework for AI-driven SME market forecasting. It links strategic theories (Resource-Based View, Dynamic Capabilities) and the DIKD hierarchy to various AI techniques, including supervised learning, unsupervised learning, deep learning, and ensemble methods. The framework illustrates how these AI approaches enable SMEs to achieve key outcomes, such as market risk assessment and opportunity identification. AI Models for Market Risk Prediction in Small and Medium-Sized Enterprises

3. Market Risk Prediction

Market risk prediction is a critical strategic function for small and medium-sized enterprises (SMEs), as these firms are particularly vulnerable to demand uncertainty, revenue volatility, competitive shocks, and macroeconomic instability (Beck & Demirgüç-Kunt, 2006; OECD, 2019). Artificial intelligence (AI)–based predictive models have increasingly been adopted to enhance SMEs' ability to anticipate adverse market conditions and mitigate downside risk through data-driven decision-making (Ahmad et al., 2015; Shmueli & Koppius, 2011). Early applications of AI in market risk prediction relied primarily on supervised machine learning models, including linear regression, logistic regression, decision trees, and support vector machines (SVMs) (Kim, 2003; Vapnik, 1998). These models are widely used to forecast sales declines, customer churn, and revenue shortfalls, offering improved predictive accuracy over traditional statistical techniques while maintaining a degree of interpretability (Makridakis et al., 2018; Zhang et al., 1998). For

SMEs, such models provide an accessible entry point into AI-driven analytics due to their relatively low computational requirements.

Tree-based ensemble models, such as Random Forests and Gradient Boosting Machines, represent a major advancement in market risk prediction. By aggregating multiple weak learners, these models reduce overfitting and improve robustness in noisy, data-constrained environments typical of SMEs (Breiman, 2001; Chen & Guestrin, 2016). Empirical studies demonstrate that ensemble methods outperform single-model approaches in forecasting revenue volatility, demand downturns, and price instability across multiple business contexts (Rialti et al., 2019; Wamba et al., 2017). The emergence of deep learning models has further expanded the scope of AI-based market risk forecasting. Recurrent neural networks (RNNs) and long short-term memory (LSTM) architectures are particularly effective in capturing temporal dependencies and nonlinear dynamics in market data (Hochreiter & Schmidhuber, 1997; Fischer & Krauss, 2018). These models enable SMEs to anticipate prolonged downturns, seasonality-driven risk, and delayed market responses that are difficult to detect using conventional methods (Sezer et al., 2020).

In addition to purely quantitative models, hybrid AI frameworks integrate machine learning with econometric techniques and business rules to enhance contextual relevance and managerial interpretability (Atsalakis & Valavanis, 2009; Dubey et al., 2019). Such hybrid systems align with the human–AI collaboration paradigm, in which predictive outputs support rather than replace managerial judgment (Jarrahi, 2018; Rai et al., 2019). However, the increasing complexity of AI models raises concerns regarding transparency and trust. The adoption of explainable artificial intelligence (XAI) methods, such as SHAP values, LIME, and rule-based approximations, has become central to market risk applications in SMEs (Ribeiro et al., 2016; Doshi-Velez & Kim, 2017). Explainability enhances managerial confidence, facilitates regulatory compliance, and supports actionable risk mitigation strategies. AI models for market risk prediction provide SMEs with powerful tools to detect early warning signals, allocate resources efficiently, and enhance strategic resilience. Yet, their effectiveness depends on data quality, organizational readiness, and the alignment of predictive outputs with business objectives.

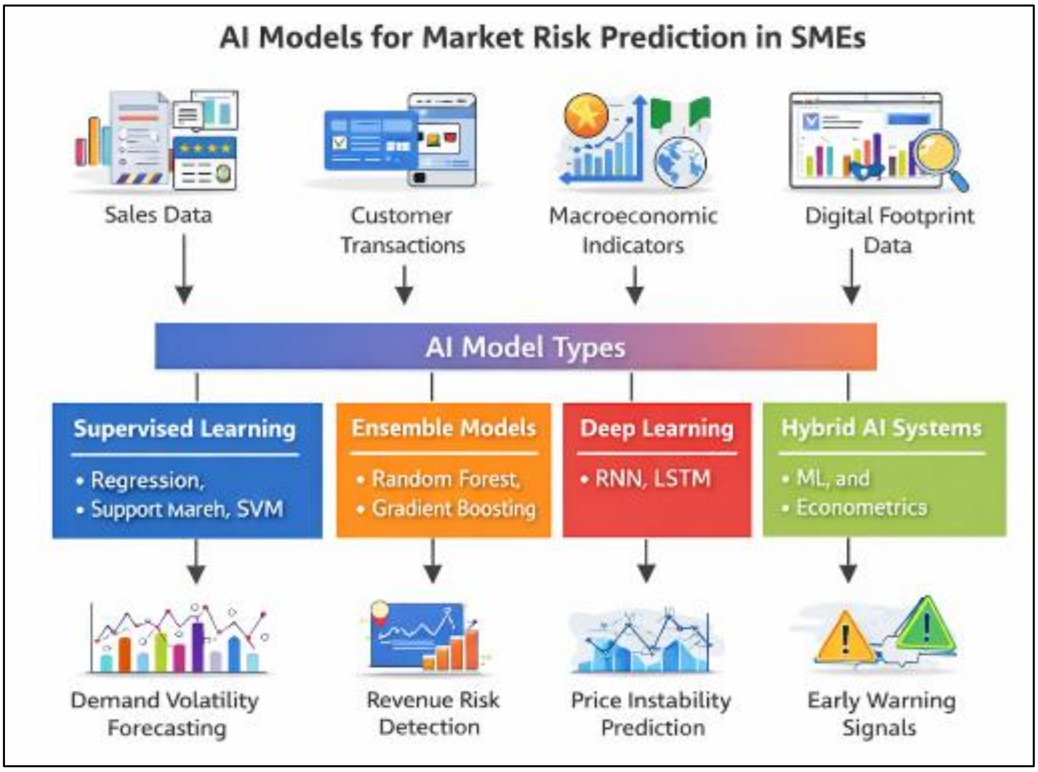

Figure 2 The conceptual architecture of AI-driven market risk prediction in SMEs. Multiple internal and external data sources feed into AI model classes, including supervised learning, ensemble methods, deep learning, and hybrid frameworks. These models generate actionable market risk insights that support proactive decision-making and strategic risk mitigation for small and medium-sized enterprises

4. AI Models for Opportunity Identification and Growth Forecasting

Artificial intelligence (AI) has become a critical enabler for identifying market opportunities and forecasting growth trajectories in small and medium-sized businesses (SMEs). Unlike traditional forecasting approaches that rely heavily on historical averages and linear assumptions, AI-driven models leverage complex, nonlinear relationships within large and heterogeneous datasets to uncover latent growth signals and emerging market opportunities (Witten et al., 2016; Brynjolfsson & McElheran, 2016; Cao et al., 2021). For SMEs operating under resource constraints and high environmental uncertainty, such predictive capabilities offer substantial strategic value (Chatterjee et al., 2021; Verma et al., 2022). Supervised machine learning models are widely applied in opportunity identification tasks, particularly for sales growth forecasting, customer lifetime value estimation, and new market entry analysis (Ahmad et al., 2015; Huang et al., 2018; Olson & Wu, 2019). Regression-based models, decision trees, and support vector machines (SVMs) are commonly used to predict revenue expansion, product adoption rates, and regional demand growth (Cortes & Vapnik, 1995; Breiman, 2001; Fan et al., 2019). These models enable SMEs to quantify growth potential across products, customer segments, and geographic markets with improved accuracy compared to classical econometric methods (Fildes et al., 2019; Makridakis et al., 2020).

Unsupervised learning techniques play a complementary role by discovering hidden patterns and opportunity clusters without predefined outcome variables (Jain et al., 1999; Aggarwal, 2018). Clustering algorithms such as k-means, hierarchical clustering, and self-organizing maps are used to segment customers, identify underserved niches, and detect emerging consumption trends (Wedel & Kannan, 2016; Li et al., 2020). These insights are particularly valuable for SMEs seeking innovation-driven growth in dynamic markets (Rialti et al., 2019; Kumar et al., 2021). Deep learning models further enhance opportunity forecasting by capturing temporal and contextual dependencies within complex datasets (LeCun et al., 2015; Goodfellow et al., 2016). Recurrent neural networks (RNNs) and long short-term memory (LSTM) architectures are increasingly used for long-horizon sales forecasting, demand growth prediction, and innovation diffusion modeling (Hochreiter & Schmidhuber, 1997; Bandara et al., 2020; Sezer et al., 2020). These models are particularly effective when SMEs integrate alternative data sources such as online search trends, social media sentiment, and platform-based transaction data (Gandomi & Haider, 2015; Liu et al., 2022).

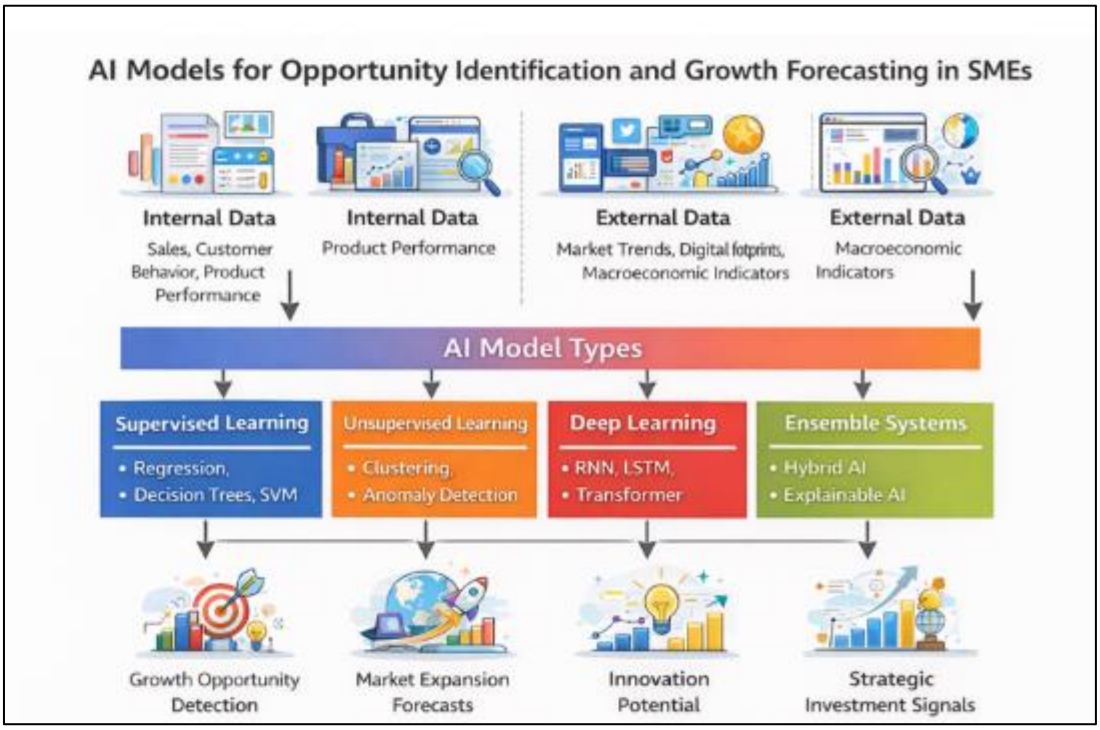

Figure 3 AI-driven opportunity identification and growth forecasting framework for SMEs

The figure will illustrate how internal business data (sales, customer behavior, product performance) and external data (market trends, digital footprints, macroeconomic indicators) feed into AI model categories, supervised learning, unsupervised learning, deep learning, and ensemble systems, to generate outputs such as growth opportunity detection, market expansion forecasts, innovation potential, and strategic investment signals for SMEs.

Ensemble and hybrid AI models represent a growing frontier in SME growth forecasting research (Zhou, 2012; Wolpert, 1992). By combining machine learning, deep learning, and traditional forecasting techniques, ensemble frameworks improve robustness and reduce prediction uncertainty (Dietterich, 2000; Zhang et al., 2021). Recent studies emphasize the importance of explainable AI (XAI) in opportunity identification, enabling SME managers to interpret model outputs and translate predictions into actionable growth strategies (Doshi-Velez & Kim, 2017; Ribeiro et al., 2016; Dwivedi et al., 2023).

5. Data Sources and Analytics Infrastructure for Small and Medium-Sized Enterprises

The effectiveness of artificial intelligence (AI)–driven market forecasting in small and medium-sized enterprises (SMEs) is fundamentally dependent on the availability, quality, and integration of data, as well as the robustness of the supporting analytics infrastructure (Wamba et al., 2017; Gandomi & Haider, 2015). Unlike large corporations, SMEs often operate under constraints related to data volume, technical expertise, and financial resources, which shape both the type of data they can access and the analytics architectures they can deploy (Margherita et al., 2021; Verma et al., 2022).

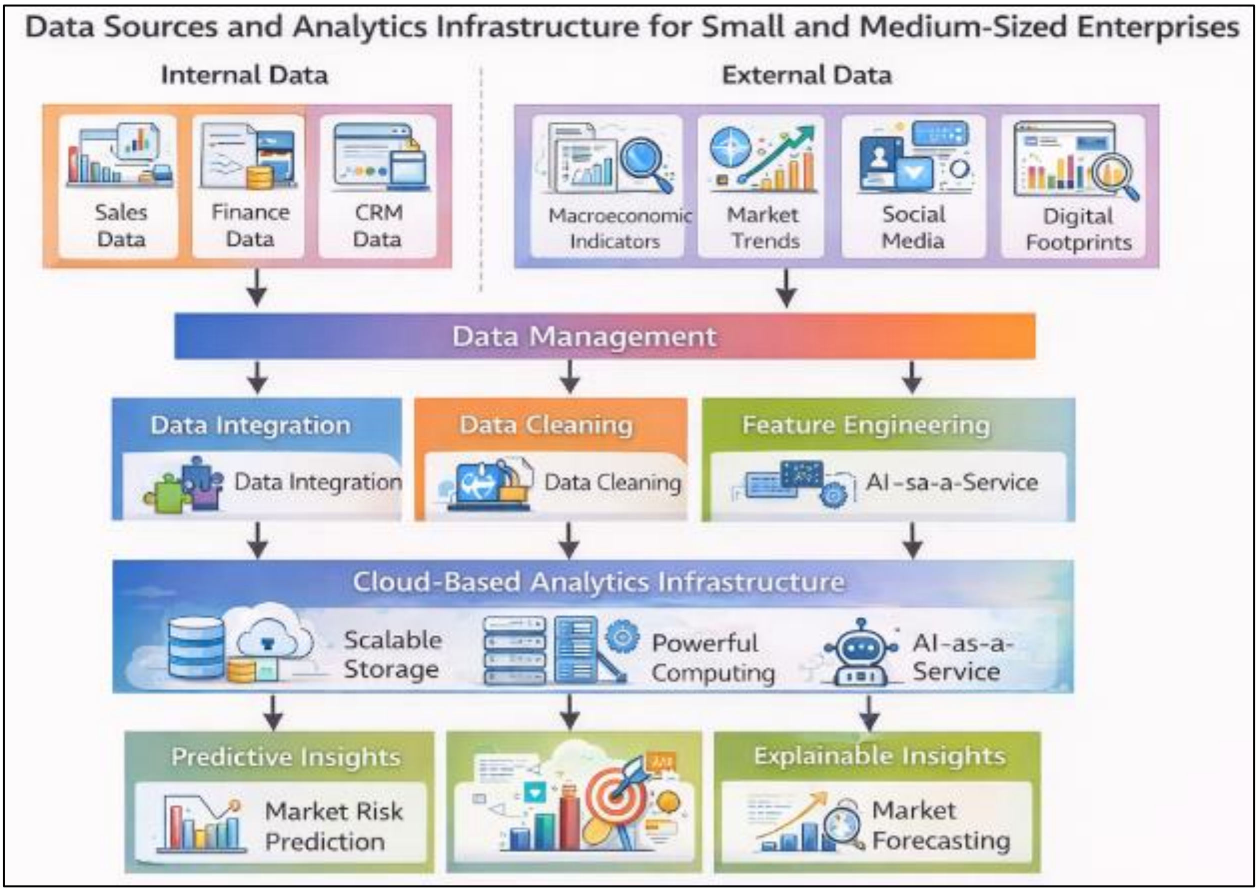

Figure 4 Summary of data sources and analytics infrastructure for AI-driven market forecasting in SMEs. The figure summarizes the integrated data and analytics framework that supports AI-driven market forecasting in small and medium-sized enterprises. It distinguishes internal and external data sources, which are consolidated through centralized data management processes to ensure data quality and usability. These processed datasets are analyzed within a scalable, cloud-based infrastructure that enables the application of advanced AI models. The framework ultimately delivers predictive and explainable insights for risk assessment, growth forecasting, and opportunity identification, supporting data-driven decision-making and scalable AI adoption in SMEs

SME data sources can broadly be classified into internal and external categories. Internal data typically includes transactional sales records, customer relationship management (CRM) data, accounting and financial statements, inventory logs, and operational performance metrics (Ahmad et al., 2015; Huang et al., 2018). These structured datasets form the backbone of predictive analytics applications such as demand forecasting, revenue growth estimation, and risk assessment (Makridakis et al., 2018; Fildes et al., 2019). However, internal data in SMEs are often fragmented across departments and stored in non-standardized formats, limiting their immediate usability for advanced AI models (Rialti et al., 2019; Fan et al., 2019). External data sources significantly enhance forecasting performance by providing contextual and forward-looking information (Liu et al., 2022; Cao et al., 2021). These include macroeconomic indicators, industry reports, competitor pricing data, social media sentiment, web search trends, and platform-based transaction data (Gandomi & Haider, 2015; Wedel & Kannan, 2016). The integration of alternative and unstructured data has been shown to improve opportunity identification and early risk detection, particularly in volatile markets (Sezer et al., 2020; Dwivedi et al., 2023).

From an infrastructure perspective, SMEs increasingly rely on cloud-based analytics platforms to overcome capital and scalability constraints (Armbrust et al., 2010; Marston et al., 2011). Cloud computing enables on-demand access to storage, computing power, and AI services, facilitating the deployment of machine learning and deep learning models without extensive in-house infrastructure (Davenport & Ronanki, 2018; OECD, 2019). Software-as-a-service (SaaS) analytics tools further democratize AI adoption by offering prebuilt models, automated feature engineering, and visualization dashboards tailored to managerial decision-making (Chatterjee et al., 2021; Verma et al., 2022). Data preprocessing and pipeline automation represent critical components of SME analytics infrastructure. Processes such as data cleaning, normalization, feature extraction, and real-time updating directly influence model accuracy and reliability (Kelleher et al., 2020; Jordan & Mitchell, 2015). Recent studies emphasize the role of data governance and security frameworks in ensuring data integrity, privacy, and regulatory compliance, especially as SMEs adopt AI-driven decision systems (Bughin et al., 2018; Rai et al., 2019).

The convergence of diverse data sources and scalable analytics infrastructure enables SMEs to transition from descriptive reporting to predictive and prescriptive intelligence. Nevertheless, persistent challenges related to data sparsity, integration complexity, and skills shortages continue to shape the practical impact of AI-enabled market forecasting in small business contexts (Jarrahi, 2018; Dwivedi et al., 2021).

6. Future Research Agenda and Emerging Trends

Despite rapid advances in artificial intelligence (AI) for market risk and opportunity forecasting, the literature reveals several unresolved gaps and emerging research directions, particularly in the context of small and medium-sized enterprises (SMEs). One critical area for future research is the development of explainable and transparent AI models tailored to SME decision-making environments. While deep learning and ensemble models demonstrate superior predictive performance, their limited interpretability constrains managerial trust and adoption (Doshi-Velez & Kim, 2017; Ribeiro et al., 2016). Future studies should explore hybrid frameworks that integrate explainable AI (XAI) techniques with high-performing models to balance accuracy and usability.

Another emerging trend is the integration of alternative and real-time data sources, including social media sentiment, web search behavior, platform-based transactions, and Internet of Things (IoT) data, into SME forecasting systems. Research is needed to assess how these data streams enhance early opportunity detection and risk anticipation, particularly in volatile and emerging markets (Gandomi & Haider, 2015; Liu et al., 2022). In addition, longitudinal studies examining the long-term economic impact of AI-driven forecasting on SME growth, resilience, and survival remain scarce and warrant further investigation. From a methodological perspective, future research should focus on transfer learning, federated learning, and lightweight AI models that reduce data and computational requirements. These approaches are particularly relevant for SMEs with limited historical data and restricted infrastructure (Pan & Yang, 2010; Kairouz et al., 2021). Ethical AI, data governance, and regulatory compliance also represent underexplored areas, especially as SMEs increasingly rely on automated decision-support systems (Dwivedi et al., 2021). Interdisciplinary research combining insights from information systems, strategic management, and entrepreneurship can deepen understanding of organizational readiness, human–AI collaboration, and capability development in SMEs. Such work will be essential for translating technical advancements into sustainable competitive advantage.

7. Conclusion and Managerial Implications

This review provides a comprehensive synthesis of artificial intelligence–driven market risk and opportunity forecasting models in small and medium-sized enterprises. The findings demonstrate that AI-based predictive analytics significantly enhance SMEs' ability to anticipate market volatility, identify growth opportunities, and support data-driven strategic decisions. Machine learning, deep learning, and hybrid AI frameworks consistently outperform traditional forecasting methods, particularly in complex and dynamic market environments. From a managerial perspective, the review highlights the importance of strategic alignment between AI initiatives and business objectives. SME managers should prioritize analytics solutions that not only deliver predictive accuracy but also provide interpretable insights that support timely and actionable decisions. Investment in cloud-based analytics infrastructure, data integration capabilities, and employee data literacy is essential to fully realize the value of AI-driven forecasting. The review also underscores the need for a phased and scalable approach to AI adoption. Rather than pursuing highly complex models from the outset, SMEs can achieve substantial benefits by incrementally integrating AI tools into existing decision processes, starting with supervised learning and progressing toward more advanced models as organizational capabilities mature.

To conclude, artificial intelligence represents a transformative force in SME market forecasting, offering pathways to enhanced resilience, competitiveness, and sustainable growth. By addressing existing limitations and embracing emerging trends, researchers and practitioners can collaboratively advance AI-enabled decision-making frameworks that are both technically robust and practically relevant for small and medium-sized enterprises.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Aggarwal, C. C. (2018). *Machine learning for data mining*. Springer. https://doi.org/10.1007/978-3-319-73531-3

[2] Ahmad, F., Khan, M. S., & Ahmed, S. (2015). Forecasting stock prices using machine learning techniques. International Journal of Computer Applications, 114(1), 1–5. https://doi.org/10.5120/19992-2025

[3] Armbrust, M., et al. (2010). A view of cloud computing. Communications of the ACM, 53(4), 50–58. https://doi.org/10.1145/1721654.1721672

[4] Armstrong, J. S. (2001). Principles of forecasting: A handbook for researchers and practitioners. Springer. https://doi.org/10.1007/978-0-306-47630-3

[5] Atsalakis, G. S., & Valavanis, K. P. (2009). Surveying stock market forecasting techniques. Expert Systems with Applications, 36(3), 5932–5941. https://doi.org/10.1016/j.eswa.2008.07.006

[6] Ayyagari, M., Demirgüç-Kunt, A., & Maksimovic, V. (2011). Small vs. young firms across the world. World Bank Economic Review, 25(3), 415–440. https://doi.org/10.1093/wber/lhr009

[7] Bandara, K., Bergmeir, C., & Smyl, S. (2020). Forecasting across time series databases using recurrent neural networks. International Journal of Forecasting, 36(3), 803–821. https://doi.org/10.1016/j.ijforecast.2019.09.004

[8] Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

[9] Beck, T., & Demirgüç-Kunt, A. (2006). Small and medium-size enterprises: Access to finance. Journal of Banking & Finance, 30(11), 2931–2943. https://doi.org/10.1016/j.jbankfin.2006.05.009

[10] Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

[11] Brynjolfsson, E., & McElheran, K. (2016). The rapid adoption of data-driven decision-making. American Economic Review, 106(5), 133–139. https://doi.org/10.1257/aer.p20161016

[12] Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). Notes from the AI frontier. McKinsey Global Institute Discussion Paper, 1–72.

[13] Cao, G., Duan, Y., & El Banna, A. (2021). A dynamic capability view of marketing analytics. Industrial Marketing Management, 93, 77–90. https://doi.org/10.1016/j.indmarman.2020.12.005

[14] Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2021). AI-driven strategic decision-making in SMEs. Technological Forecasting and Social Change, 172, 121009. https://doi.org/10.1016/j.techfore.2021.121009

[15] Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the ACM SIGKDD, 785–794. https://doi.org/10.1145/2939672.2939785

[16] Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine Learning, 20(3), 273–297. https://doi.org/10.1007/BF00994018

[17] Davenport, T. H., & Harris, J. G. (2017). Competing on analytics. Harvard Business Review Press.

[18] Dietterich, T. G. (2000). Ensemble methods in machine learning. Multiple Classifier Systems, 1857, 1–15. https://doi.org/10.1007/3-540-45014-9_1

[19] Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. arXiv preprint, arXiv:1702.08608. https://doi.org/10.48550/arXiv.1702.08608

[20] Dubey, R., Gunasekaran, A., Childe, S. J., et al. (2019). Big data analytics and firm performance. International Journal of Production Economics, 209, 263–276. https://doi.org/10.1016/j.ijpe.2018.12.015

[21] Dwivedi, Y. K., et al. (2021). Artificial intelligence (AI): Multidisciplinary perspectives. International Journal of Information Management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.004

[22] Fan, S., Lau, R. Y., & Zhao, J. L. (2019). Demystifying big data analytics for SMEs. Information & Management, 56(6), 103–115. https://doi.org/10.1016/j.im.2018.12.005

[23] Fildes, R., & Goodwin, P. (2007). Against your better judgment? Interfaces, 37(6), 570–576. https://doi.org/10.1287/inte.1070.0306

[24] Fischer, T., & Krauss, C. (2018). Deep learning with LSTM networks for financial market predictions. European Journal of Operational Research, 270(2), 654–669. https://doi.org/10.1016/j.ejor.2017.11.054

[25] Gandomi, A., & Haider, M. (2015). Beyond the hype. International Journal of Information Management, 35(2), 137–144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007

[26] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

[27] Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning. Springer. https://doi.org/10.1007/978-0-387-84858-7

[28] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

[29] Huang, G., Zhu, Q., & Siew, C. (2018). Machine learning for sales forecasting. Decision Support Systems, 111, 33–46. https://doi.org/10.1016/j.dss.2018.04.005

[30] Jain, A. K., Murty, M. N., & Flynn, P. J. (1999). Data clustering. ACM Computing Surveys, 31(3), 264–323. https://doi.org/10.1145/331499.331504

[31] Jarrahi, M. H. (2018). Artificial intelligence and the future of work. Business Horizons, 61(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

[32] Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends and prospects. Science, 349(6245), 255–260. https://doi.org/10.1126/science.aaa8415

[33] Kim, K. J. (2003). Financial time series forecasting using support vector machines. *Neurocomputing, 55*(1–2), 307–319. https://doi.org/10.1016/S0925-2312(03)00372-2

[34] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539

[35] Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and ML forecasting methods. Journal of Forecasting, 37(1), 3–20. https://doi.org/10.1002/for.2518

[36] Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2020). The M4 competition. International Journal of Forecasting, 36(1), 54–74. https://doi.org/10.1016/j.ijforecast.2019.04.014

[37] Margherita, A., Elia, G., & Passiante, G. (2021). Digital technologies and SME business models. Technological Forecasting and Social Change, 166, 120613. https://doi.org/10.1016/j.techfore.2021.120613

[38] Mitchell, T. M. (1997). Machine learning. McGraw-Hill.

[39] OECD. (2019). OECD SME and entrepreneurship outlook. OECD Publishing. https://doi.org/10.1787/34907e9c-en

[40] Provost, F., & Fawcett, T. (2013). Data science for business. O'Reilly Media.

[41] Rai, A., Constantinides, P., & Sarker, S. (2019). Next-generation digital platforms. MIS Quarterly, 43(1), iii–ix. https://doi.org/10.25300/MISQ/2019/14120

[42] Rialti, R., Zollo, L., Ferraris, A., & Alon, I. (2019). Big data analytics capabilities. Journal of Business Research, 98, 241–252. https://doi.org/10.1016/j.jbusres.2019.01.055

[43] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). “Why should I trust you?”. Proceedings of the ACM SIGKDD, 1135–1144. https://doi.org/10.1145/2939672.2939778

[44] Russell, S., & Norvig, P. (2016). Artificial intelligence: A modern approach. Pearson.

[45] Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial forecasting with deep learning. Applied Soft Computing, 90, 106181. https://doi.org/10.1016/j.asoc.2020.106181

[46] Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems. MIS Quarterly, 35(3), 553–572. https://doi.org/10.2307/23042796

[47] Teece, D. J., Peteraf, M., & Leih, S. (2016). Dynamic capabilities and organizational agility. California Management Review, 58(4), 13–35. https://doi.org/10.1525/cmr.2016.58.4.13

[48] Vapnik, V. (1998). Statistical learning theory. Wiley.

[49] Verma, S., Sharma, R., & Deb, S. (2022). AI adoption in SMEs. Journal of Small Business Management, 60(3), 514–541. https://doi.org/10.1080/00472778.2020.1846992

[50] Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2017). Big data analytics and firm performance. Journal of Business Research, 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

[51] Wedel, M., & Kamakura, W. A. (2012). Market segmentation. International Journal of Research in Marketing, 19(3), 181–201. https://doi.org/10.1016/S0167-8116(02)00076-6

[52] Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. Journal of Marketing, 80(6), 97–121. https://doi.org/10.1509/jm.15.0413

[53] Witten, I. H., Frank, E., & Hall, M. A. (2016). Data mining: Practical machine learning tools. Morgan Kaufmann.

[54] World Bank. (2020). Small and medium enterprises finance. World Bank Publications.

[55] Zhou, Z.-H. (2012). Ensemble methods. CRC Press.