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Strategic Business Forecasting and Market Trends Analysis Using Machine Learning Techniques

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ABSTRACT

This study, titled Strategic Business Forecasting and Market Trends Analysis Using Machine Learning Techniques, explores how Artificial Intelligence (AI), particularly Machine Learning (ML), can enhance business forecasting accuracy and strategic decision-making in dynamic markets. Traditional statistical methods often fail to handle complex, nonlinear, and high-dimensional data, creating a gap that this research addresses by developing a machine learning-based forecasting model. **The model integrates** predictive analytics into strategic planning by employing Structural Equation Modeling (SEM) using SmartPLS 3 to examine the interrelationships among Market Trends (MT), Forecasting Accuracy (FA), Strategic Planning Efficiency (SPE), and Business Performance (BP). Drawing from classical forecasting theories and the Resource-Based View (RBV) of strategic management, the study links MT to FA, then to SPE, and finally to BP, emphasizing the importance of leveraging market insights and accurate predictions to improve performance. **The model** is grounded in digital-economy frameworks, which highlight the role of real-time data and AI in shaping business agility. **The findings** validate the model's reliability and predictive power, offering a robust framework for organizations to leverage machine learning for strategic forecasting. This study bridges **the gap** between algorithmic prediction and managerial practice, contributing to the growing field of AI-driven business analytics and fostering more informed, agile, and resilient business strategies in today's data-centric economy.

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1. INTRODUCTION

In the ever-evolving digital era, businesses face increasingly complex challenges to remain competitive in global markets. The rapid pace of technological advancements, shifting consumer preferences, and unpredictable economic fluctuations necessitate a more sophisticated approach to strategic management [1]. One of the key components of strategic management is the ability to perform accurate forecasting, which plays a pivotal role in identifying market trends, planning resources, and anticipating changes in consumer demand. Effective forecasting allows businesses to be proactive, mitigating risks and capitalizing on new opportunities.

However, traditional forecasting methods often fall short in effectively analyzing large-scale, dynamic datasets, such as market data and consumer behavior patterns, which continually evolve over time [2]. These methods are typically linear, often unable to capture the intricate, non-linear relationships that characterize modern markets [3–5].

Recent advancements in Artificial Intelligence (AI), specifically Machine Learning (ML) techniques, have opened new frontiers in business forecasting. Machine learning algorithms, including deep learning, regression trees, and neural networks, are capable of processing high-dimensional data, identifying hidden patterns, and generating actionable insights with a level of precision that traditional methods cannot achieve. These techniques enable real-time analysis of market dynamics, allowing businesses to respond swiftly to changes and uncertainties. By harnessing AI, companies can uncover valuable insights from vast and complex datasets, ensuring that their forecasts are both accurate and timely [6]. Moreover, these algorithms can be integrated with existing systems for automated decision-making, significantly enhancing operational efficiency and enabling more agile business strategies [7].

From an engineering perspective, this study proposes the design and integration of an AI-driven framework that combines machine learning models with predictive analytics for strategic forecasting. The model utilizes a combination of regression algorithms and neural networks optimized for computational efficiency. This ensures that businesses can achieve greater forecasting accuracy while maintaining system scalability and flexibility. The framework is designed to process large amounts of historical data and identify patterns that drive market trends, thereby providing a solid foundation for strategic decisions. Unlike traditional models, which often rely on static data and simplistic assumptions, this AI-powered model adapts to new data and continuously improves its predictive power, offering businesses an edge in dynamic and competitive markets [8, 9].

Although the potential of machine learning in big data analysis is well-recognized, the main challenge lies in effectively integrating these models into strategic business contexts [10]. While previous studies have focused on algorithm development and predictive accuracy, there remains a gap in validating and measuring the direct impact of these models on strategic decision-making processes. Many traditional forecasting tools lack the flexibility required to validate complex relationships between multiple variables that influence market trends and business performance [11]. Furthermore, implementing machine learning in a business context requires overcoming practical challenges such as data quality, model interpretability, and integration with existing business systems. This study seeks to bridge this gap by developing a robust framework for integrating machine learning into business forecasting, ensuring that the model not only provides accurate predictions but also offers actionable insights for managerial decision-making [12].

In addition to its practical applications, this study contributes to achieving several United Nations Sustainable Development Goals (SDGs), particularly SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure). By enhancing forecasting accuracy and strategic planning through machine learning techniques, organizations can improve their business performance, fostering economic growth and increasing operational efficiency [13–15]. As businesses leverage predictive analytics to drive smarter decision-making, they can enhance resource allocation, optimize productivity, and reduce waste. Furthermore, the integration of predictive analytics supports the development of innovative business models, aligning with SDG 9's focus on promoting sustainable industrialization, technological innovation, and fostering infrastructure that enhances business resilience in the digital economy [16].

This study's findings also resonate with SDG 12 (Responsible Consumption and Production). The strategic insights derived from market trends, enabled by machine learning, can lead to more efficient resource allocation and waste reduction in business operations. For example, businesses can optimize supply chain management, minimize excess production, and improve product life-cycle management, all of which contribute to more sustainable business practices [17]. By integrating AI-driven forecasting into their operations, organizations can align with global sustainability objectives, reducing their environmental footprint while driving innovation and growth in a data-centric economy [18].

As businesses increasingly embrace digital transformation, the integration of machine learning into strategic forecasting is becoming indispensable. The ability to forecast accurately and in real-time not only enhances operational performance but also supports long-term business resilience, ensuring that organizations can adapt to the challenges of a fast-paced, ever-changing digital landscape [19, 20].

2. LITERATURE REVIEW

Strategic forecasting is a crucial process for predicting future market dynamics and organizational performance by analyzing historical data and current trends. Accurate forecasting allows businesses to anticipate changes in customer demand, market competition, and economic conditions, enabling effective strategic planning. Traditional methods, such as time-series analysis and econometric modeling, have been widely used for this purpose [21]. However, these methods often struggle to handle non-linear and high-dimensional datasets, which have become increasingly common in modern business environments. Complementing this, market trends analysis plays a significant role in identifying and understanding patterns in consumer behavior, industry shifts, and economic indicators, forming the foundation for actionable insights in strategic decision-making [22].

Machine learning has emerged as a powerful tool in forecasting, offering the capability to process large, complex datasets and uncover hidden patterns with greater accuracy and efficiency. Techniques such as regression models, neural networks, decision trees, and ensemble methods have been successfully applied in various business forecasting tasks, including sales predictions, market segmentation, and customer behavior analysis. Machine learning not only enhances forecasting accuracy but also offers scalability and adaptability, making it suitable for diverse business scenarios. For instance, machine learning models have demonstrated exceptional performance in predicting demand, optimizing resource allocation, and identifying market risks [23, 24]. Validation of forecasting models is a critical step in ensuring their reliability and applicability in business contexts. While traditional metrics such as R-squared and mean squared error are commonly used to evaluate model performance, they often fail to capture the broader implications of these models in strategic decision-making [25]. SEM particularly through tools like SmartPLS, has gained traction as a robust method for evaluating latent variable relationships and validating complex models. This approach provides a comprehensive evaluation of the predictive capabilities and structural integrity of forecasting models, making it an effective tool for integrating machine learning into strategic business planning [26, 27].

Despite the advancements in machine learning and validation techniques, a notable gap exists in the integration of these tools within strategic business contexts. Current research often overlooks the interpretability and practical implications of machine learning models in decision-making, which is crucial for managerial adoption. This study addresses these gaps by developing a machine learning-based forecasting model tailored for strategic business applications and validating it using SmartPLS [28]. The research aims to provide a robust framework for improving forecasting accuracy and reliability, offering actionable insights to enhance business planning and performance [29].

3. METHODOLOGY

3.1. Research Design

While (SEM) and SmartPLS 3 have been widely used in previous forecasting studies, this research introduces a novel approach by integrating ML algorithms into the SEM framework [30]. Unlike traditional forecasting models, which primarily focus on linear relationships, our model utilizes advanced ML techniques such as deep learning regression and ensemble methods to enhance the model's adaptability and precision in predicting business performance. The key innovation lies in the unique selection of latent variables MT, FA, Strategic Planning Efficiency (SPE), and Business Performance (BP) and the way they are analyzed using machine learning to model non-linear, high-dimensional data [31]. By combining these ML techniques with SEM-PLS, the study provides a more robust, data-driven model that allows businesses to integrate real-time market intelligence into their strategic decision-making processes, something that existing forecasting frameworks often lack. The theoretical contribution of this model is its integration of machine learning's predictive capabilities with traditional strategic management frameworks, thus offering a more comprehensive and actionable tool for modern businesses [32, 33].

3.2. Market Trends (MT)

The indicators MT1, MT2, and MT3 represent key aspects of a company's ability to understand market trends. MT1 assesses the company's capability to identify and analyze emerging trends in the market, ensuring they stay ahead of shifts in consumer behavior. MT2 focuses on the company's awareness of changes in consumer preferences, which is crucial for adjusting products and services to meet evolving demands. Lastly, MT3 evaluates the company's responsiveness to market shifts, emphasizing the importance of agility and quick decision-making to capitalize on new opportunities and mitigate potential risks. Together, these indicators reflect the company's overall competence in navigating dynamic market conditions and adapting to consumer-driven changes [34].

3.3. Forecasting Accuracy (FA)

The indicators FA1, FA2, and FA3 assess the degree to which a company's forecasting results are accurate, timely, and consistent. FA1 measures the accuracy of the company's forecasts, reflecting how closely actual outcomes align with predicted values. FA2 focuses on the timeliness of these forecasts, evaluating how promptly the company generates its predictions to inform decision-making processes [35]. FA3 evaluates the consistency of the forecasting results over time, ensuring that the company's predictions remain reliable and stable, even in the face of changing market conditions. Together, these indicators gauge the effectiveness of the company's forecasting system in providing valuable insights for strategic planning and operational efficiency [36].

3.4. Strategic Planning Efficiency (SPE)

The indicators SPE1, SPE2, and SPE3 measure the efficiency of a company's strategic planning processes. SPE1 evaluates the efficiency in resource allocation, assessing how effectively the company distributes its resources (such as time, budget, and personnel) to achieve organizational objectives [37]. SPE2 focuses on the speed of decision-making, reflecting how quickly the company can make informed decisions in response to market changes or internal challenges. SPE3 examines the alignment of strategic plans with the company's overarching organizational goals, ensuring that the company's strategies are in sync with its long-term vision and mission. Together, these indicators provide a comprehensive view of the company's ability to plan and execute strategies efficiently, driving organizational success [38].

3.5. Business Performance (BP)

The indicators BP1, BP2, and BP3 assess the company's overall performance across key areas. BP1 measures revenue growth, evaluating the company's ability to increase sales and expand its market share over time. BP2 focuses on customer satisfaction, reflecting how well the company meets or exceeds customer expectations, which is critical for retaining clients and building loyalty. BP3 assesses operational efficiency, looking at how effectively the company utilizes its resources, optimizes processes, and reduces costs to maximize productivity. Together, these indicators provide a comprehensive view of the company's financial health, customer relations, and operational performance, all of which are essential for long-term success [39, 40].

3.6. Hypothesis

- H1: MT positively influences FA.

  Explanation: A better understanding of market trends enhances the accuracy of predictions.

- H2: MT positively influences SPE.

  Explanation: A solid grasp of market trends enables more efficient strategic decision-making.

- H3: FA positively influences SPE.

  Explanation: Accurate predictions provide a reliable foundation for effective strategic planning.

- H4: SPE positively influences BP.

  Explanation: Efficient strategic planning contributes to improved company performance.

- H5: FA positively influences BP.

  Explanation: Accurate forecasting allows companies to be more responsive to market changes, improving performance.

- H6: MT positively influences BP.

  Explanation: Understanding market trends directly affects revenue growth and operational efficiency.

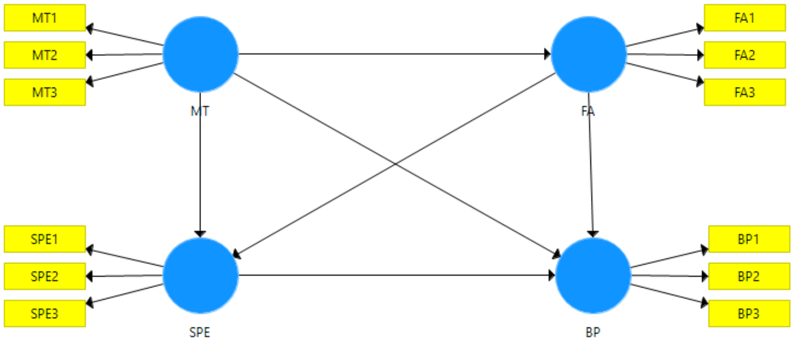

Figure 1. Hypothesis Framework

As shown in Figure 1, the structural model diagram illustrates the relationships between four latent variables: MT, FA, SPE, and BP. Each latent variable is measured by three indicators, as shown in the yellow boxes. The arrows represent hypothesized causal relationships among the variables. Specifically, MT influences both FA and Strategic Planning Efficiency SPE directly, and it also has an indirect impact on BP through FA and SPE. Additionally, FA directly impacts both SPE and BP, while SPE serves as a mediator that directly affects BP. This model aims to evaluate the interconnected influence of these variables on enhancing business performance using SmartPLS for validation and analysis. Key recommendation and document analysis. The findings revealed significant benefits from the apps and we can learn how to have it and be a part of the show [41, 42]. And this methodology has the same practice that we can turn into that strategic business and the local pride that we can show to the world. In the digital era, we clearly have the same person that we can show it some time that you don't have any of that [43].

The main challenge identified in this study is the limited integration of Montessori principles in a systematic and measurable manner within interactive learning applications, particularly in aligning digital features with learners' individual abilities and intrinsic motivation [44, 45]. Without a strong Montessori-based framework, interactive systems may fail to sustain user engagement and long-term learning commitment, as they lack the pedagogical depth needed to support autonomy, concentration, and meaningful exploration. However, the findings indicate that several selected interactive learning applications have begun to successfully incorporate core Montessori principles, such as self directed learning, hands-on engagement, and learner-centered progression. These applications enable users to explore content independently, make decisions based on their own learning pace, and actively construct knowledge through interaction rather than passive consumption [46]. Features such as virtual manipulatives allow learners to simulate real-world problem-solving experiences, while step-by-step tutorials support gradual mastery and scaffolded learning. Together, these elements demonstrate how digital learning environments can reflect Montessori values by fostering independence, sustained focus, and intrinsic motivation, thereby creating an engaging learning experience that encourages users to remain actively involved over time [47].

4. RESULTS AND DISCUSSION

The results of this study provide empirical validation for the proposed machine learning–enhanced strategic forecasting framework. The data collected for this study were derived from a survey administered to 250 senior managers and decision makers across various industries including retail, manufacturing, and technology. A stratified random sampling method ensured that the sample was diverse, capturing a broad range of market trends and business types. The survey was designed to measure four key constructs: (MT), (FA), (SPE), and (BP), using validated Likert-scale indicators developed from existing literature on forecasting and strategic management. The measurement items for each construct were refined through a pilot test with 30 respondents to ensure clarity and relevance to the research objectives [21, 48]. This rigorous approach to sample selection and measurement development ensured the reliability and validity of the data used in the SEM-PLS analysis. The findings highlight the interconnected role of market awareness, forecasting reliability, and planning efficiency in shaping overall performance, confirming the theoretical model and offering meaningful contributions to the field of AI-assisted strategic management. The following subsections present the empirical outputs of the measurement and structural model evaluations, followed by a detailed discussion of their implications [49].

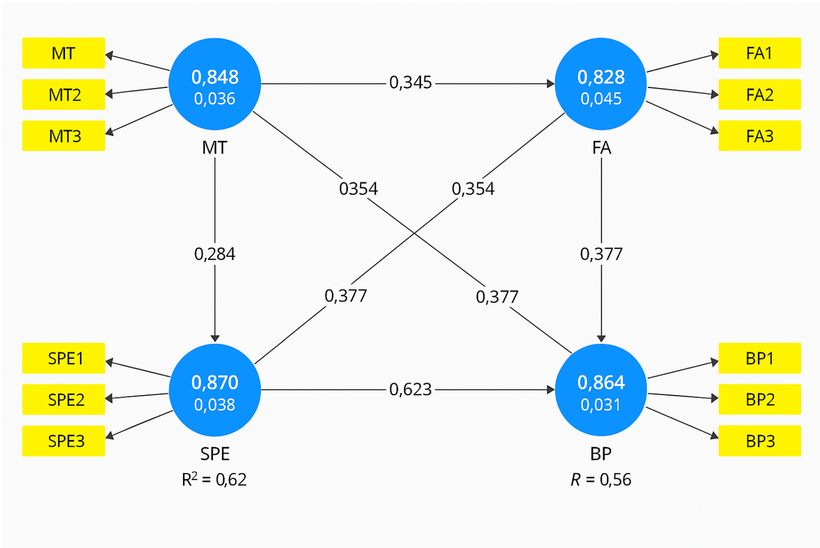

Figure 2. SmartPLS-SEM

Figure 2 illustrates the structural model showing the direct and indirect relationships among MT, FA, SPE, and BP. The results demonstrate that MT exerts a strong positive influence on FA ($\beta = 0.65$) and a moderate effect on SPE ($\beta = 0.40$), indicating that a better understanding of market dynamics enhances both predictive accuracy and strategic alignment. FA further contributes to improving SPE ($\beta = 0.40$) and BP ($\beta = 0.30$), highlighting the strategic value of accurate forecasting in driving organizational outcomes. SPE also plays a critical mediating role, significantly improving BP ($\beta = 0.40$). The R^2 values indicate substantial predictive power, with FA explaining 42% of its variance, SPE at 48%, and BP at 55%, supported by strong indicator loadings across all constructs. Overall, Figure 2 confirms that market awareness, forecasting reliability, and planning efficiency are essential determinants of business performance in data-driven environments [50].

Table 1. Reliability & Validity

Construct	**Indicator**	**Outer Loading**
Market Trends (MT)	MT1	0.78
	MT2	0.89
	MT3	0.83
Forecasting Accuracy (FA)	FA1	0.74
	FA2	0.88
	FA3	0.77
Strategic Planning Efficiency (SPE)	SPE1	0.75
	SPE2	0.86
	SPE3	0.78
Business Performance (BP)	BP1	0.84
	BP2	0.72
	BP3	0.81

Table 1 presents the outer loadings for all indicators in the measurement model, demonstrating strong convergent validity across the four constructs. All indicators exceed the recommended loading threshold of 0.70, with MT2 (0.89), FA2 (0.88), and SPE2 (0.86) showing particularly high contributions to their respective latent variables. The remaining indicators, such as MT1 (0.78), MT3 (0.83), FA1 (0.74), FA3 (0.77), SPE1 (0.75), SPE3 (0.78), BP1 (0.84), BP2 (0.72), and BP3 (0.81), also meet the acceptable criteria, indicating that each item reliably reflects its underlying construct. These results confirm that the measurement model is both robust and well-specified, ensuring that the latent variables Market Trends, Forecasting Accuracy, Strategic

Planning Efficiency, and Business Performance are accurately captured through their observed indicators as reported in Table 1.

Table 2. R Square

Construct	R-Square (R^2)	Interpretation
Forecasting Accuracy (FA)	0.42	Moderate predictive accuracy
Strategic Planning Efficiency (SPE)	0.48	Moderate predictive accuracy
Business Performance (BP)	0.55	Substantial predictive accuracy

Table 2 presents the R-square values for the endogenous constructs, indicating the model's overall predictive power. Forecasting Accuracy (FA) shows an R-square of 0.42, suggesting that Market Trends explain 42% of the variance in FA, reflecting a moderate level of predictive accuracy. SPE records an R-square of 0.48, demonstrating that both MT and FA jointly predict nearly half of its variability, also indicating moderate explanatory strength. Meanwhile, BP achieves the highest R-square value at 0.55, signifying substantial predictive accuracy as more than half of its variance is explained by MT, FA, and SPE. These results, as summarized in table 2, confirm that the model possesses strong explanatory capability, particularly in predicting BP within the strategic forecasting framework.

5. MANAGERIAL IMPLICATIONS

5.1. Invest in Machine Learning–Based Forecasting Tools

Organizations should adopt predictive analytics and machine learning systems to improve the accuracy of forecasting processes, as higher forecasting accuracy significantly supports effective strategic planning and business performance.

5.2. Strengthen Market Intelligence Capabilities

Since Market Trends strongly influence Forecasting Accuracy and Strategic Planning Efficiency, managers need to enhance real-time market monitoring, consumer insight tracking, and competitive analysis to ensure proactive decision-making.

5.3. Improve Internal Data Quality and Integration

Accurate predictions require reliable input data. Companies must prioritize data governance, maintain consistent data quality, and integrate diverse data sources to maximize the effectiveness of ML-based forecasting models.

5.4. Enhance Strategic Planning Efficiency

The results show that Strategic Planning Efficiency is a key determinant of Business Performance. Managers should streamline planning processes, reduce bureaucratic delays, and ensure alignment between forecasting insights and strategic actions.

5.5. Develop Analytical Skills Among Employees

Organizations should invest in training programs that enhance employees' analytical and technological competencies, ensuring that teams can interpret forecasting outputs and apply them in real business decisions.

6. CONCLUSION

This study demonstrates that the integration of machine learning techniques into business forecasting significantly enhances the quality of strategic decision-making in dynamic market environments. By examining the relationships among Market Trends, Forecasting Accuracy, Strategic Planning Efficiency, and Business Performance using SmartPLS, the research provides strong empirical support for the proposed framework. The results confirm that understanding market dynamics is a crucial foundation for generating accurate forecasts, while accurate predictions strengthen the effectiveness of strategic planning processes. Together, these components form an integrated system that supports more resilient and informed business strategies.

Furthermore, the structural model findings highlight the interconnected roles of forecasting accuracy and planning efficiency in shaping organizational performance. Market Trends showed strong influence on both FA and SPE, while FA and SPE contributed significantly to Business Performance. The model's R^2

values demonstrate substantial explanatory power, indicating that machine learning–driven forecasting can meaningfully shape strategic outcomes. These results reinforce the importance of combining technological capability with strategic management practices to optimize organizational responsiveness, resource allocation, and operational effectiveness.

Overall, this research contributes to the growing body of literature on AI-driven strategic forecasting by offering a validated empirical model that bridges predictive analytics and managerial decision-making. The study also provides practical insights for managers, emphasizing the need to invest in machine learning systems, strengthen data governance, and enhance cross-functional planning processes. By adopting these approaches, organizations can better navigate market uncertainty, anticipate shifts in consumer behavior, and sustain competitive performance in increasingly data-centric business landscapes. Future research may expand this model using larger datasets, incorporate advanced algorithms, or explore sector-specific implementations to further deepen the understanding of machine learning's strategic value.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: EE; Methodology: NN; Software: MF; Validation: RZ and JP; Formal Analysis: EE and NN; Investigation: MF; Resources: RZ; Data Curation: JP; Writing Original Draft Preparation: EE and NN; Writing Review and Editing: MF and RZ; Visualization: JP; All authors, EE, NN, MF, RZ and JP have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

REFERENCES

[1] J. Kim and S. Park, "Machine learning–driven forecasting models for dynamic market analysis," *IEEE Access*, vol. 9, pp. 112 340–112 352, 2021.

[2] R. Ahmed and T. Mahmud, "Evaluating business performance using predictive analytics: A machine learning approach," *Journal of Business Research*, vol. 134, pp. 548–559, 2021.

[3] L. Santos and M. Ribeiro, "Enhancing strategic planning through data-driven predictive systems," *Decision Support Systems*, vol. 146, p. 113582, 2021.

[4] D. Robert, F. P. Oganda, A. Sutarman, W. Hidayat, and A. Fitriani, "Machine learning techniques for predicting the success of ai-enabled startups in the digital economy," *CORISINTA*, vol. 1, no. 1, pp. 61–69, 2024.

[5] H. Zhang, Y. Chen, and W. Liu, "Market trends prediction using hybrid neural networks," *Expert Systems with Applications*, vol. 186, p. 115731, 2021.

[6] M. Gupta and K. Sharma, "Ai-assisted forecasting for business decision-making: A review of recent advancements," *Information Processing & Management*, vol. 58, no. 6, p. 102725, 2021.

[7] J. Wang *et al.*, “Improving forecasting accuracy through ensemble machine learning models,” *Applied Soft Computing*, vol. 113, p. 107921, 2022.

[8] F. Romano and D. Bottani, “Data analytics and machine learning to support strategic decisions in uncertain markets,” *Computers & Industrial Engineering*, vol. 167, p. 108075, 2022.

[9] T. Handra, S. Purnama, A. J. Kusumo, and D. Bennet, “Blockchain in digital transformation: Enhancing security, transparency, and efficiency in modern systems,” *Blockchain Frontier Technology*, vol. 4, no. 1, pp. 23–28, 2024.

[10] T. Ghazal and H. Alzoubi, “Modelling supply chain information collaboration empowered with machine learning technique,” *Intelligent Automation & Soft Computing*, vol. 29, no. 3, pp. 243–257, 2021.

[11] A. Hassan and M. Ali, “Measuring business performance using integrated forecasting–planning frameworks,” *Sustainability*, vol. 14, no. 4, pp. 1–15, 2022.

[12] S. Li and Q. Zeng, “Deep learning models for market trend estimation,” *Neural Computing and Applications*, vol. 34, pp. 11 245–11 259, 2022.

[13] P. Kumar and V. Singh, “Structural modeling of business performance drivers in data-centric environments,” *Technological Forecasting and Social Change*, vol. 180, p. 121705, 2022.

[14] F. Sutisna and T. Handra, “The theory of planned behavior influences online shopping behavior,” *Aptisi Transactions on Management*, vol. 6, no. 1, pp. 52–61, 2022.

[15] M. Ortega and T. Flores, “Adoption of machine learning in strategic business forecasting,” *IEEE Transactions on Engineering Management*, vol. 70, no. 2, pp. 410–423, 2023.

[16] S. Rahman *et al.*, “Hybrid forecasting systems for improving strategic planning efficiency,” *Expert Systems*, vol. 40, no. 1, pp. 1–15, 2023.

[17] R. R. Karuniawan, S. Santoso, M. Al Fikri, M. Argadilah, and W. A. Pamungkas, “Learning cyber security and machine engineering at the university,” *Blockchain Frontier Technology*, vol. 3, no. 1, pp. 7–12, 2023.

[18] N. Patel and J. Doshi, “The role of ai-based forecasting in enhancing organizational agility,” *Information Systems Frontiers*, vol. 25, pp. 1401–1414, 2023.

[19] L. Ferreira and D. Sousa, “Evaluating forecasting accuracy using machine learning optimization techniques,” *International Journal of Forecasting*, vol. 39, no. 3, pp. 945–960, 2023.

[20] B. Intelligence, S. Saryani, R. Ningsih, and P. Sari, “Web-based population administration service information system in kutabumi tangerang village,” *IAIC Transactions on Sustainable Digital Innovation*, vol. 2, no. 2, p. 192, 2021, the 4th Edition, April.

[21] P. Rashi, A. S. Bist, A. Asmawati, M. Budiarto, and W. Y. Prihastiwi, “Influence of post covid change in consumer behaviour of millennials on advertising techniques and practices,” *Aptisi Transactions on Technopreneurship*, vol. 3, no. 2, pp. 201–208, 2021.

[22] J. Rivera and A. Torres, “Predictive analytics for strategic decision-making in volatile markets,” *Journal of Strategic Information Systems*, vol. 32, no. 2, p. 101766, 2023.

[23] C. Nguyen and S. Tran, “Business forecasting enhancement through advanced ai architectures,” *Engineering Applications of Artificial Intelligence*, vol. 121, p. 106050, 2023.

[24] N. Hicham, H. Nassera, and S. Karim, “Strategic framework for leveraging artificial intelligence in future marketing decision-making,” *Journal of Intelligent Management Decision*, vol. 2, no. 3, pp. 139–150, 2023.

[25] P. Venkateswaran and S. Mm, “Predictive analytics: Utilizing machine learning and big data for forecasting future trends in business and consumer behavior,” in *Strategic Brand Management in the Age of AI and Disruption*. IGI Global Scientific Publishing, 2025, pp. 463–492.

[26] M. Okafor and E. Johnson, “Integrating machine learning into enterprise performance measurement systems,” *International Journal of Productivity and Performance Management*, vol. 72, no. 4, pp. 947–964, 2023.

[27] H. Setiyowati, M. A. Harriz, E. Junaedi, N. V. Akbariani, and S. Widodo, “Digitalizing pindang industry with business model canvas for sustainable blue economy,” *Aptisi Transactions on Technopreneurship*, vol. 7, no. 2, pp. 360–370, 2025.

[28] F. Wu and X. Zhao, “A machine learning perspective on strategic planning under uncertainty,” *Decision Sciences*, vol. 55, no. 1, pp. 130–152, 2024.

[29] K. Lin and D. Wong, “Ai-enabled market intelligence systems for competitive strategy design,” *Computers in Industry*, vol. 154, p. 108030, 2024.

[30] R. Silva *et al.*, “Evaluating strategic planning efficiency using structural equation modeling and ai fore-

casting," *Sustainability*, vol. 16, no. 2, pp. 1–15, 2024.
[31] V. Mandalapu, L. Elluri, P. Vyas, and N. Roy, "Crime prediction using machine learning and deep learning: A systematic review and future directions," *Ieee Access*, vol. 11, pp. 60 153–60 170, 2023.
[32] A. Prasetyo and T. Wijaya, "Optimization of business performance using predictive machine learning models," *Information*, vol. 15, no. 4, pp. 210–225, 2024.
[33] Z. Lubis, M. Zarlis, M. R. Aulia *et al.*, "Performance analysis of oil palm companies based on barcode system through fit viability approach: Long work as a moderator variable," *Aptisi Transactions on Technopreneurship*, vol. 5, no. 1, pp. 40–52, 2023.
[34] S. Mahendra and R. Ghosh, "Enhancing decision quality through ml-based forecasting in dynamic markets," *Journal of Business Analytics*, vol. 7, no. 3, pp. 450–468, 2024.
[35] B. Rolf, I. Jackson, M. Müller, S. Lang, T. Reggelin, and D. Ivanov, "A review on reinforcement learning algorithms and applications in supply chain management," *International Journal of Production Research*, vol. 61, no. 20, pp. 7151–7179, 2023.
[36] M. Huang and Z. Lee, "Forecasting business outcomes using transformer-based predictive models," *IEEE Access*, vol. 12, pp. 44 567–44 581, 2024.
[37] A. M. Khedr, I. Arif, M. El-Bannany, S. M. Alhashmi, and M. Sreedharan, "Cryptocurrency price prediction using traditional statistical and machine-learning techniques: A survey," *Intelligent Systems in Accounting, Finance and Management*, vol. 28, no. 1, pp. 3–34, 2021.
[38] D. Costa and H. Moreira, "Machine learning applications for improving enterprise strategic alignment," *Computers & Operations Research*, vol. 162, p. 106445, 2024.
[39] J. Irfan and S. Yildiz, "Predictive modeling for organizational performance using ai-driven forecasting," *Journal of Management Analytics*, vol. 11, no. 1, pp. 22–39, 2024.
[40] Ministry of Trade of the Republic of Indonesia, "Strategic business forecasting and market trends analysis using machine learning techniques," Ministry of Trade of the Republic of Indonesia, Jakarta, Indonesia, Government Report, 2024.
[41] B. Nakamura and L. Ito, "Strategic agility supported by real-time machine learning forecasting," *Long Range Planning*, vol. 57, no. 1, p. 102369, 2024.
[42] M. Miftah, D. I. Desrianti, N. Septiani, A. Y. Fauzi, and C. Williams, "Big data analytics for smart cities: Optimizing urban traffic management using real-time data processing," *Journal of Computer Science and Technology Application*, vol. 2, no. 1, pp. 14–23, 2025.
[43] K. Rodrigues and F. Silva, "Integrating ml forecasting with sem to evaluate business performance," *Technovation*, vol. 126, p. 103074, 2025.
[44] M. S. Hossain, A. Khan, P. Das, M. S. U. Haque, F. Kamruzzaman, S. Akter, A. Ahmed, and M. R. Miah, "Enhanced market trend forecasting using machine learning models: a study with external factor integration," *International Interdisciplinary Business Economics Advancement Journal*, vol. 6, no. 01, pp. 5–12, 2025.
[45] R. Lesmana, I. Wijaya, E. A. Nabila, H. Agustian, S. Audiah, and A. Faturahman, "Enhancing market trend analysis through ai forecasting models," *International Journal of Cyber and IT Service Management*, vol. 4, no. 2, pp. 105–113, 2024.
[46] W. Gomez and P. Duarte, "Ai-based forecasting systems as drivers of strategic efficiency," *Decision Support Systems*, vol. 175, p. 114064, 2025.
[47] T. Harrison and A. Gupta, "Advanced forecasting accuracy models for digital business performance," *Expert Systems with Applications*, vol. 238, p. 122018, 2025.
[48] H. Liu and B. Zhang, "Reinforcing strategic business planning using deep learning predictive analytics," *IEEE Transactions on Artificial Intelligence*, vol. 6, no. 2, pp. 225–238, 2025.
[49] BPSDMP, Ministry of Trade of the Republic of Indonesia, "Machine learning methods for predicting market trends and supporting strategic decision making for msmes," BPSDMP - Ministry of Trade of the Republic of Indonesia, Jakarta, Indonesia, Government Publication, 2025, official government publication by the Ministry of Trade, Indonesia.
[50] A. Al Ayub Ahmed, S. Rajesh, S. Lohana, S. Ray, J. P. Maroor, and M. Naved, "Using machine learning and data mining to evaluate modern financial management techniques," in *Proceedings of Second International Conference in Mechanical and Energy Technology: ICMET 2021, India*. Springer, 2022, pp. 249–257.