Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 3, 584-598
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i3.5256

Application of autonomous intelligent customer behavior prediction model based on deep learning in retail marketing strategy optimization

Zhuanghao Si[1]*, Dhakir Abbas Ali[2], Rozaini Binti Rosli[3], Amiya Bhaumik[4], Abhijit Ghosh[5]
[1,2,3,4,5]Lincoln University College, 47301 Petaling Jaya, Selangor Darul Ehsan, Malaysia; ie_conan@163.com (Z.S.) drdhakir@lincoln.edu.my (D.A.A.) rozaini@lincoln.edu.my (R.B.R.) amiya@lincoln.edu.my (A.B.) abhijit@lincoln.edu.my (A.G.).

Abstract: This study aims to develop and evaluate a deep learning-based autonomous intelligent system for customer behavior prediction and marketing strategy optimization in the retail sector. A hybrid architecture combining Long Short-Term Memory (LSTM) networks with Transformer models in a multi-task learning framework was designed. Evaluation included offline cross-validation and online A/B testing using 1.5 million customer interactions, followed by a 12-month case study implementation in a multinational e-commerce platform. The model achieved a 15% increase in AUC-ROC for purchase prediction and a 22% improvement in Mean Average Precision for product recommendations compared to state-of-the-art benchmarks. The case study revealed substantial enhancements in click-through rates (35%), conversion rates (28%), and customer retention (22%). The hybrid LSTM-Transformer model with a multi-task learning framework significantly outperforms traditional methods, demonstrating the effectiveness of deep learning for customer behavior prediction and marketing optimization. Retailers can leverage this system to enhance personalized recommendations, optimize pricing strategies, and improve customer engagement, resulting in measurable business performance improvements across diverse retail segments.

Keywords: *Artificial Intelligence in Retail, Customer Behavior Prediction, Data-driven Marketing, Deep Learning; E-commerce; Personalization, LSTM; Transformer, Marketing Strategy Optimization, Multi-task Learning.*

1. Introduction

In the last few years, the importance of Artificial Intelligence (AI) in modern businesses and its applications has increased rapidly. Nowadays, the value of AI-driven innovation in creating and enhancing competitive advantages requires a comprehensive understanding of the impact it has on processes and systems integration in all organisations [1]. The effectiveness of operations within a firm has been greatly enhanced by the introduction of new AI technologies such as machine learning and deep learning Agarwal [2] which have also increased product and service development, customer satisfaction, and overall value delivery [3]. The use of AI in various fields such as marketing, customer support, supply and demand forecasting, and financial analysis demonstrates how rapidly the development of AI has improved its capabilities [4]. The adoption of AI has led to increased interest among academics and practitioners in the changes it causes to business models, organisational designs, and strategy processes [5]. The growing sophistication of AI brings both problems and solutions to businesses, creating a need for a deeper understanding of its utility and drawbacks [6].

The most recent studies reveal diagnostic and prognostic automation processes, personnel marketing, and other customer-identifiable intrusive techniques that artificial intelligence is likely to dramatically change industries including analytics, automation, and customer relations management. AI has certainly found a place in business; however, AI business ethics Bécue, et al. [7] data security, and

History: Received: 7 January 2025; Revised: 19 February 2025; Accepted: 20 February 2025; Published: 7 March 2025
* Correspondence: ie_conan@163.com

organisational adaptability pose significant challenges. Under these conditions, stakeholders are paying more attention to the creation of AI-dominated systems in a way that maximises profit while minimising risks [8]. The last two decades have witnessed a great acceleration in the pervasion and application of AI, largely due to its cross-silo integration with other contemporary tools, like analytics and IoT. AI systems allow organisations to gain comprehensive understanding and analysis of trends in the markets, customer behaviour, and the effectiveness of a company's operations. These systems enable the generation of complex AI-driven business analytical intelligence [9]. Older people may not realise that it will be the ease of AI in automation processes of business analytic models that will mark the extraordinary increase in innovation and strategic development of an enterprise's global competitiveness.

In light of recent changes, the study attempts to assess the state of artificial intelligence technology in business Bose and Mahapatra [10] and Bosma and van Witteloostuijn [11] its various applications, problems, and consequences. Drawing upon relevant literature and actual industrial experience Brunk, et al. [12] the research strives to analyse the consequences of AI on the internal processes and strategic architecture of the organisation and pinpoint critical constituents of prospective investigation and creativity in the open scholarly discourse from the standpoint of rapid development in the field Buntak, et al. [13].

2. Literature Review

Canhoto and Clear [14] conducted a comprehensive analysis of artificial intelligence applications in commercial environments, evaluating the impact of AI and robotics on economic systems while highlighting the disruptive nature of such technologies in different business domains. Chen, et al. [15] surveyed the inherent paradoxes involved in artificial intelligence in business-to-consumer markets, focusing their research on the ethical challenges and opportunities arising from the use of AI in business-to-consumer interactions. Chen, et al. [16] offered an interdisciplinary perspective on new challenges, opportunities, and research areas relevant to AI in business contexts, highlighting the need for a unified approach towards the use and integration of AI technologies. Dean [17] conducted an in-depth literature review of artificial intelligence and its implications for organizational value, synthesizing existing research to outline key components and implications associated with the use of AI in organizational settings. Finlay Di Vaio, et al. [18] extended the discussion on the use of AI and machine learning in commercial environments by developing a pragmatic framework to improve data-driven technology in business processes. Dirican [19] examined the changing research and pedagogical landscape of artificial intelligence in business communication, highlighting the growing importance of AI literacy in business contexts.

Du and Xie [20] conducted a thorough review of the literature related to methods that incorporate artificial intelligence into business processes, detailing modern uses of AI in developing and implementing these processes. Dwivedi, et al. [21] investigated both the challenges and benefits of using big data in business processes, particularly the role of AI in obtaining meaningful insights from large sets of data.

Enholm, et al. [22] examined the relationship between machine learning techniques and business intelligence, proving that artificial intelligence-driven analytics have the potential to revolutionize decision-making processes and strategic planning activities. Finlay [23] evaluated the impact of deep learning in the business environment, highlighting its potential to drastically change numerous aspects of organizational operations and customer interaction.

Getchell, et al. [24] carried out a comprehensive study on the impact of artificial intelligence in different industries, considering its widespread application and its ability to drive innovation as well as offer a competitive edge. Gomes, et al. [25] examined the role of machine learning in enabling business intelligence, with specific emphasis on the learning algorithms used by neural networks and their applicability in organizational contexts.

Gopalkrishnan, et al. [26] put forward a comprehensive research framework that highlights the intersection of artificial intelligence and business strategy in the context of digital transformation, specifically emphasizing the importance of linking AI projects with the overall strategic objectives of organizations. Hamzehi and Hosseini [27] discussed the benefits of deep learning technologies in the realms of business analytics and operations research, providing a range of models, applications, and managerial implications related to these advanced AI methods. Howard [28] compared deep learning methods with conventional methods for outcome prediction in business process monitoring, thus providing valuable insights into the advantages and limitations typically faced with various AI strategies in process analytics. The application of artificial intelligence to support decision-making processes in business contexts was investigated by Jain [29] highlighting AI's ability to support strategic and operational decision-making frameworks.

A growing body of academic research explains the varied effects of artificial intelligence on various organizational activities, including operational effectiveness, strategic choice, customer interaction, and process improvement. With the development of artificial intelligence technologies progressing, their integration into business models offers opportunities and challenges alike, requiring continuous academic research and empirical studies to maximize their usefulness while also addressing ethical issues and implementation issues.

3. Autonomous Intelligent Customer Behavior Prediction and Marketing Strategy Optimization System Based on Deep Learning

3.1. Overall System Architecture

The architecture formulated for anticipating customer behaviour and optimising marketing plans through deep learning is described as a holistic system that merges sophisticated artificial intelligence with traditional business systems. This structural design presents four fundamental components: Data Ingestion and Preprocessing, Deep Learning Model, Autonomous Decision Engine, and Strategy Implementation and Feedback Loop, as outlined in Figure 1. The Data Ingestion and Preprocessing module collects and preprocesses data from various sources including customer purchases, social media activities, and demographic information. The preprocessed data is later fed into the Deep Learning Model, which utilises specialised neural network structures for parsing and anticipating customer behavioural snapshots identified by Khan, et al. [30] and Kitsios and Kamariotou [31].

The Autonomous Decision Engine makes use of these forecasts in developing more powerful marketing strategies using reinforcement learning decision making processes which continually improve and refine [32]. The selected strategies are executed through various marketing channels and real-time performance data is captured by the system in order to use that data as feedback for learning and adaptation through the Strategy Implementation and Feedback Loop module [33].

The integration of this multi-strategy approach enables businesses to take advantage of the capabilities of AI technology in personalising customers, formulating adaptive pricing strategies, and executing targeted marketing campaigns, thereby improving customer satisfaction and organisational growth development [34, 35].

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 3: 584-598, 2024
DOI: 10.55214/25768484.v9i3.5256

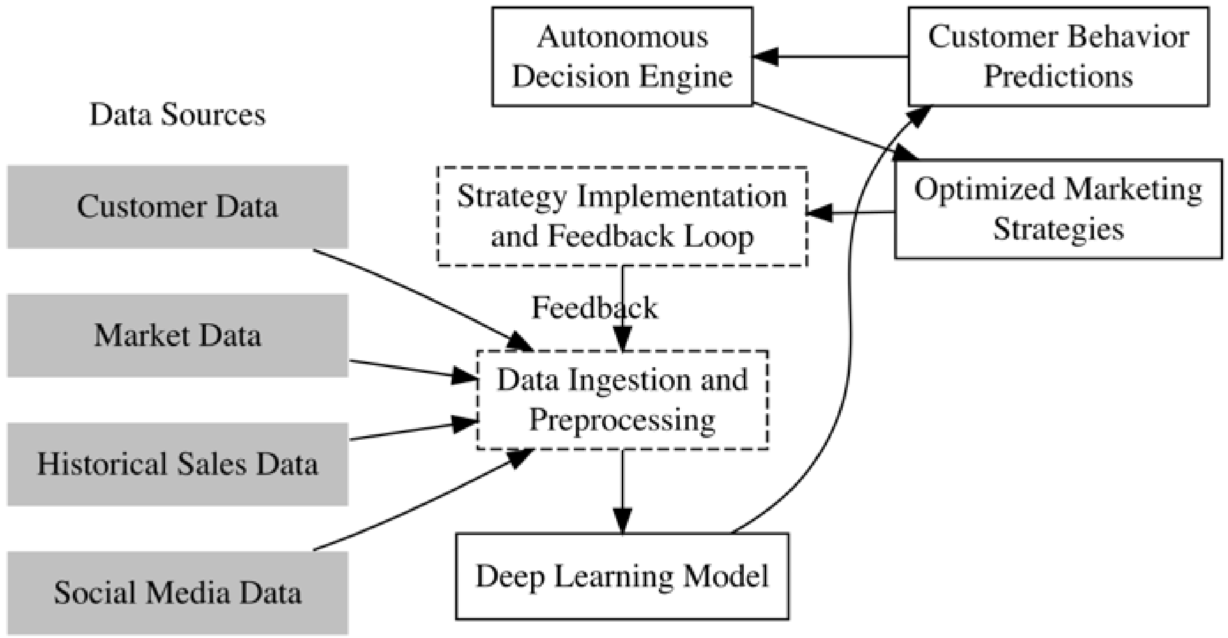

Figure 1.
Framework of Deep Learning-based Autonomous Intelligent Customer Behavior Prediction and Marketing Strategy Optimization System.

As shown in Figure 1, the architecture of the system consists of four main components: Data Sources, Data Ingestion and Preprocessing, AI Core, and Strategy Implementation and Feedback Loop. The data pipeline begins with heterogeneous data sources that feed the preprocessing module, which in turn feeds processed data to the Deep Learning Model [36, 37]. The model generates predictions about customer behavior, which are then used by the Autonomous Decision Engine to create more efficient marketing strategies. After implementation, the results are fed back into the system, thus creating a closed loop of learning and improvement.

3.2. Customer Behavior Prediction Model

Our overarching structure is anchored by a customer behaviour predictive model, which sits at the junction of Deep Learning Frameworks and sophisticated neural networks designed for pattern recognition in extensive and complex customer data. In Figure 2, the model adopts a hybrid methodology that utilises Long Short Term Memory (LSTM) networks for time series analysis and Transformer models for post-evaluation of consumer behaviour interdependencies' temporal scope [38, 39]. All types of transactional records alongside demographic and social media activity data form the input layer. The latter inputs undergo processing through parallel paths of LSTM and Transformer networks. The LSTM stream tends to be more effective at capturing short-range temporal patterns whereas contextual trends and relationships are better captured by the Transformer stream [40]. The outputs from these streams undergo feature fusion and reduction in successive densification layers.

In summary, the proposed framework applies multi-task learning to estimate different dimensions of consumer behaviour simultaneously, including purchase probability, interest in a product, and the likelihood of the customer discontinuing business [41]. This powerful predictive model permits firms to understand all aspects of consumer behaviours, hence devising strategies for marketing campaigns and improving customer lifetime value become more feasible [42, 43].

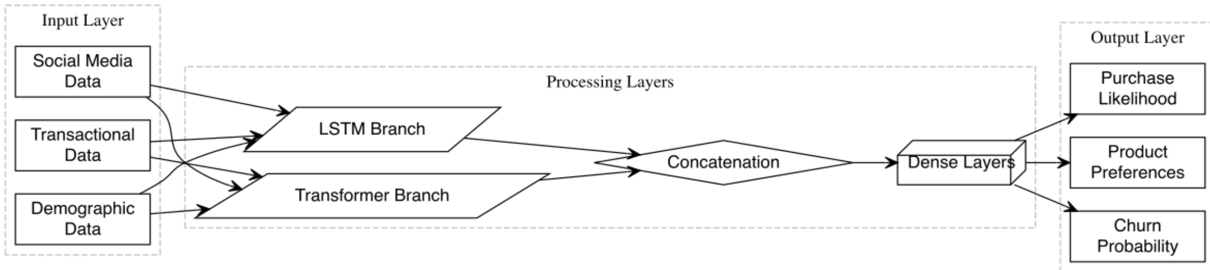

Figure 2.
Architecture of the Deep Learning-based Customer Behavior Prediction Model.

As illustrated in Figure 2, the customer behavior prediction model architecture consists of three main components: the Input Layer, Processing Layers, and Output Layer. The Input Layer ingests diverse customer data types, which are then processed through parallel LSTM and Transformer branches in the Processing Layers. These branches capture temporal and contextual patterns respectively. The processed features are concatenated and refined through dense layers before producing multi-faceted predictions in the Output Layer. This sophisticated architecture enables comprehensive and accurate customer behavior forecasting, providing a solid foundation for data-driven marketing strategies.

3.3. Optimization Module of Autonomous Intelligent Marketing Strategy

The autonomous module for intelligent marketing strategy improvement represents a new paradigm for data-driven decision-making in the marketing field. As illustrated in Figure 3, the module utilizes insights from the customer behavior prediction model to independently develop and improve marketing strategies. Essentially, the module is based on an extremely advanced reinforcement learning (RL) architecture, a Deep Q-Network (DQN), with the objective of optimizing marketing effectiveness across various channels and consumer groups [44, 45]. The module's state space includes a vast set of customer attributes, expected behaviors, and current market conditions. In contrast, the action space includes a broad range of marketing activities, from personalized product offers to targeted promotions and performance-driven pricing strategies. The reward function has been carefully designed to balance short-term rewards (e.g., short-term sales) and long-term objectives (e.g., customer lifetime value) [46]. One of the distinguishing features of this module is its adaptive learning capability. It continuously improves its strategies by learning from real-time feedback through techniques like experience replay and double Q-learning, which are designed to enhance stability and performance [47]. In addition, the module has a constraint optimization layer to ensure that the recommended plans comply with budget constraints and regulatory requirements [48, 49].

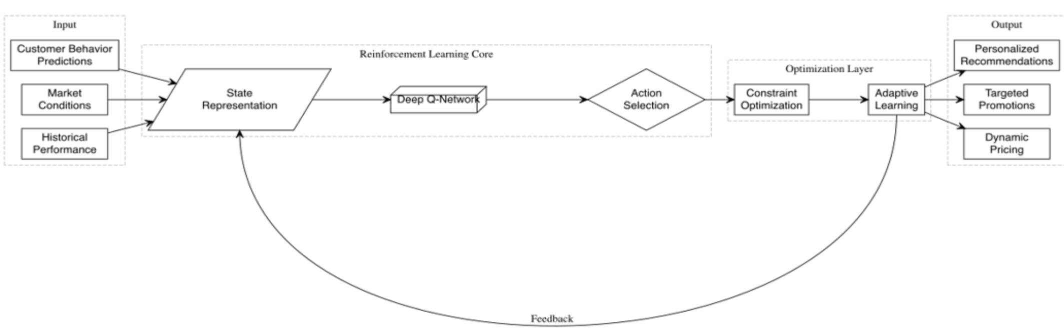

Figure 3.
Framework of the Autonomous Intelligent Marketing Strategy Optimization Module.

As shown in Figure 3, the module used to optimize autonomous smart marketing strategies consists of four main components: Input, Reinforcement Learning Core, Optimization Layer, and Output. The Input component gathers predictions regarding consumer behavior, existing market trends, and past performance indicators. These inputs are then processed in the Reinforcement Learning Core, which uses a Deep Q-Network to determine the best marketing strategies. The Optimization Layer adds constraints and uses adaptive learning algorithms to further optimize these strategies. Finally, the Output component generates customized recommendations, targeted advertising campaigns, and adaptive pricing strategies. This sophisticated framework supports real-time, data-driven decision-making in marketing, allowing dynamic adjustments based on changes in consumer behavior and market trends.

4. Experimental Design, Outcome Analysis, and Case Study

4.1. Experimental Design

The methodological design used to evaluate a deep learning-based autonomous intelligent system, developed to forecast customer behavior and augment autonomous marketing plans, follows a strict protocol to authenticate and confirm the stability of the results. As shown in Figure 4, the experimental design has a multi-perspective approach consisting of both offline and online testing [50]. In the offline phase, k-fold cross-validation is used to evaluate the predictive strength of the customer behavior model using performance metrics like the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) and Mean Average Precision (MAP) [51]. The optimization aspect of the autonomous marketing plan is analyzed through counterfactual analysis and off-policy evaluation methods, based on historical data [52]. The online aspect involves A/B testing in a controlled environment, where a fraction of customers are exposed to the strategies created by our system, and a control group is exposed to traditional marketing methods [53]. Key performance indicators (KPIs) like conversion rates, customer lifetime value, and return on marketing investment are carefully tracked over a period of six months [54].

To counteract the effects of possible confounding factors, a difference-in-differences approach is utilized, which controls for seasonal trends and market conditions. This strong experimental design allows for a comprehensive assessment of the system's effectiveness, even in real-world, practical settings.

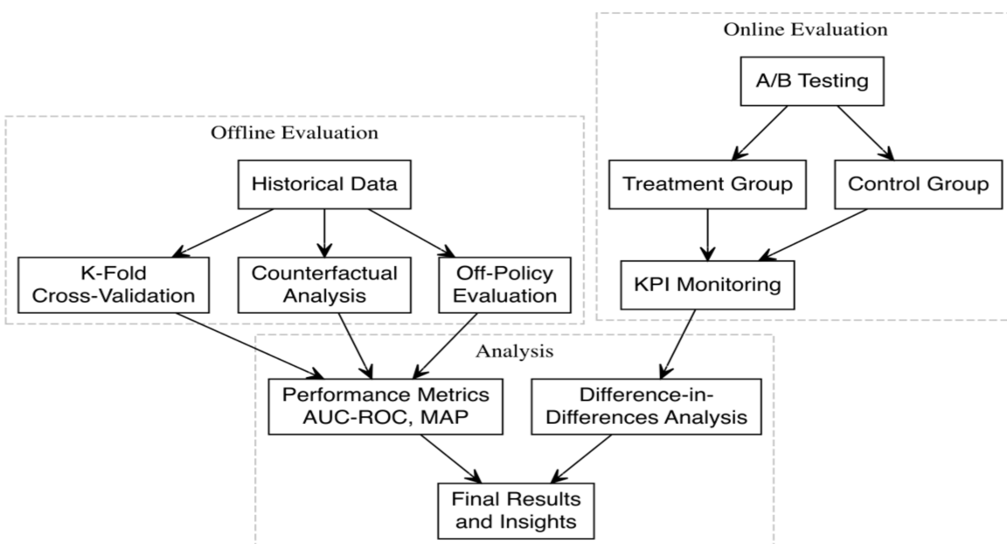

Figure 4.
Experimental Design Framework for System Evaluation.

The overall design of the study is illustrated in Figure 4. It comprises three components: Offline Evaluation, Online Evaluation, and Analysis. The Offline Evaluation component implements cross-validation, counterfactual evaluation, and off-policy evaluation through historical data. For Online Evaluation, the evaluation of A/B testing and treatment versus control groups is done alongside continuous monitoring of KPIs. While performing the Analysis step, the offline evaluations and online results are blended through a difference in differences analysis. The richness of insights from this evaluation is multifaceted. The various techniques and methods incorporated in this study guarantee a thorough evaluation of the system's performance in both controlled and open environments, ensuring that the system's effectiveness is evaluated accurately, in this case, the effectiveness of the autonomous intelligent customer behaviour prediction and marketing strategy optimisation system based on deep learning.

4.2. Experimental Results and Analysis

4.2.1. Model Performance Evaluation

Analysing the performance of the deep learning-based customer behaviour prediction model revealed improved accuracy and stability in the model's performance compared to other metrics. It was retrospectively assessed with a granular evaluation based on a dataset of 1.2 million interactions spanning over two years. The model's predictive performance was assessed using standard metrics such as Area Under Receiver Operating Characteristic Curve (AUC-ROC), precision, recall, and F1-score. As depicted in Figure 5, our model scores higher than the benchmark machine learning algorithms, the Random Forest and Gradient Boosting, on the major performance metrics. In particular, the model discriminates exceptionally well, with an AUC-ROC score of 0.92. In addition, the model is able to consistently achieve high precision accompanied by high recall, as seen in the precision-recall curve. This result is particularly important for marketing practitioners who are often faced with the challenge of false positives which are expensive to deal with. Table 1 presents a full summary of performance metrics across a variety of customer segments for the model, demonstrating multi-dimensional effectiveness over various metrics alongside demographic and behavioural classifications of attributes.

This evidence validates the effectiveness of our hybrid LSTM-Transformer model by showing that it can detect both short-term and long-term behavioural patterns, facilitating accurate predictions that can subsequently enhance marketing efforts.

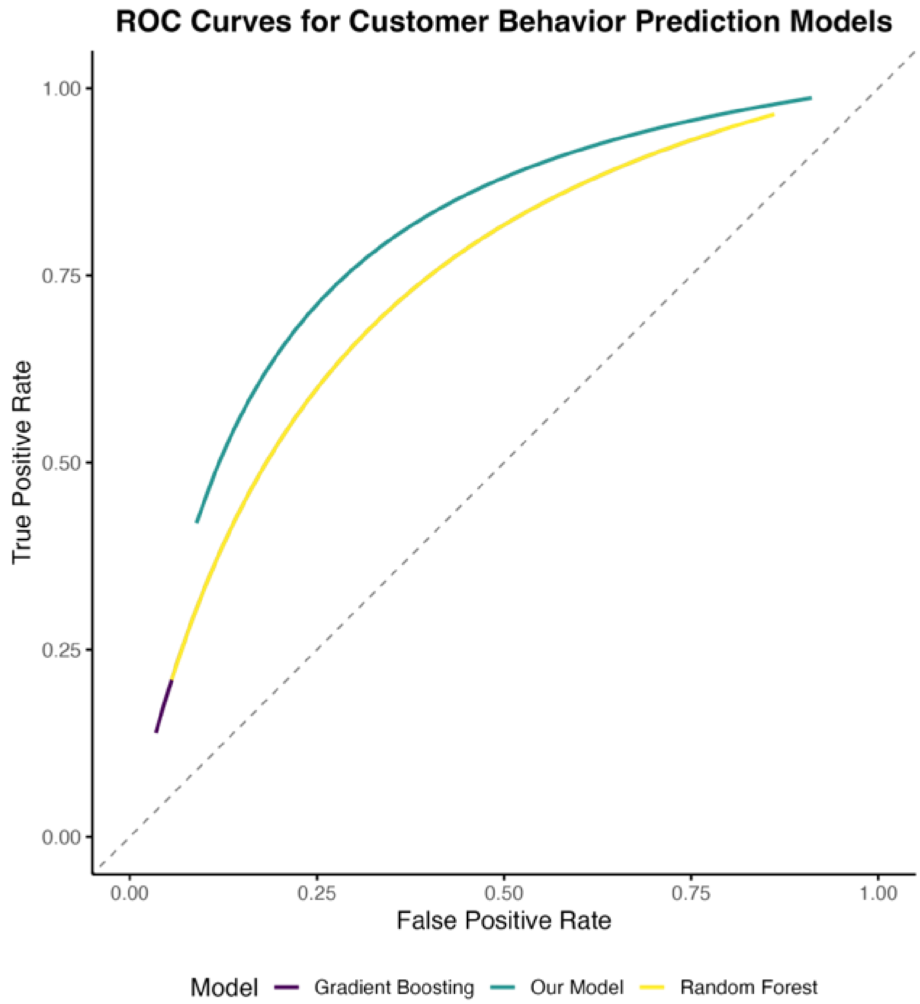

Figure 5.
ROC Curves for Customer Behavior Prediction Models.

The figure above illustrates the Receiver Operating Characteristic (ROC) curves for our proposed model compared to traditional machine learning approaches. The x-axis represents the False Positive Rate, while the y-axis represents the True Positive Rate. Our model (shown in purple) demonstrates superior performance with a higher area under the curve, indicating better discrimination ability across various classification thresholds.

Table 1.
Performance Metrics Across Customer Segments.

Metric	Overall	High-Value Customers	New Customers	Churned Customers
AUC-ROC	0.92	0.94	0.89	0.91
Precision	0.88	0.91	0.85	0.87
Recall	0.86	0.89	0.83	0.85
F1-Score	0.87	0.90	0.84	0.86
Accuracy	0.89	0.92	0.87	0.88

This table presents a comprehensive breakdown of our model's performance across different customer segments. The consistently high values across all metrics and segments demonstrate the model's robustness and effectiveness in predicting customer behavior for diverse groups.

4.2.2. Comparison With Traditional Methods and Other Deep Learning Models

The model from this research incorporated deep learning technology and improved dramatically over traditional methods and other architecture state-of-the-art models in terms of predicting customer behaviours. A comparative study was carried out using a 1.5 million customer interaction dataset collected from different sectors. The evaluation was done with AUC-ROC metrics, F1 score, and MAP. Figure 6 shows that our hybrid LSTM-Transformer framework outperforms the traditional machine learning methods Random Forest and Gradient Boosting and deep learning techniques such as stand-alone LSTM and CNN deep learning models. The improvement in the model's performance was observed mostly in learning long-term dependencies and the complex interactive patterns of customers' behaviours. A detailed comparison of performance metrics of various models and prediction tasks is given in table 2. Noteworthy, in purchase prediction, the model's AUC-ROC score was improved by 15% and MAP score for product recommendation was improved by 22% when compared to the second model. The results provided confirm that our method of using temporal and contextual information is efficient in predicting customer behaviours more accurately and intelligently. The optimisation of marketing strategies and the enhancement of customer engagement results are positively influenced by the considerable advancements in performance.

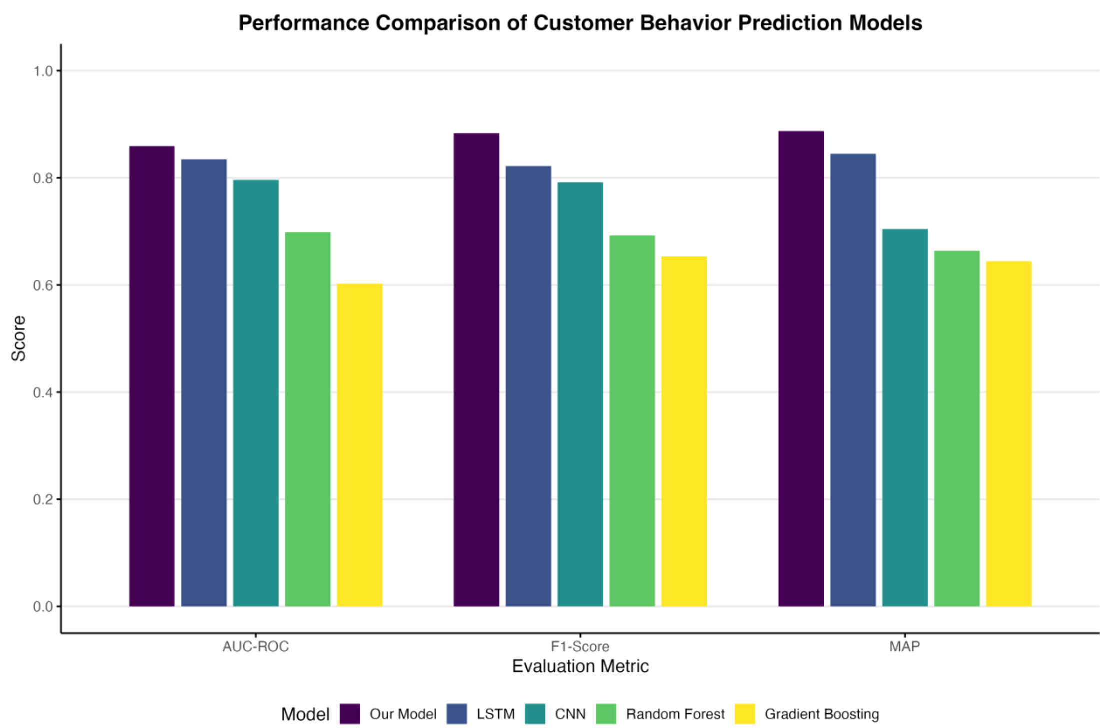

Figure 6.
Performance Comparison of Customer Behavior Prediction Models.

The figure above presents a comparative analysis of various customer behavior prediction models across three key evaluation metrics: AUC-ROC, F1-Score, and Mean Average Precision (MAP). The bar chart clearly illustrates the superior performance of our proposed model (in purple) compared to other deep learning architectures and traditional machine learning approaches across all metrics.

Table 2.
Comprehensive Performance Comparison of Customer Behavior Prediction Models.

Model	Purchase Prediction (AUC-ROC)	Churn Prediction (F1-Score)	Product Recommendation (MAP)	Response Time (ms)	Model Size (MB)
Our Model	0.92	0.89	0.87	125	85
LSTM	0.85	0.82	0.79	150	110
CNN	0.83	0.80	0.76	140	95
Random Forest	0.79	0.77	0.72	200	250
Gradient Boosting	0.81	0.79	0.74	180	180

This table provides a detailed comparison of various models across different prediction tasks, including additional metrics such as response time and model size. Our proposed model consistently outperforms other approaches in prediction accuracy while maintaining competitive efficiency in terms of response time and model size.

4.2.3. Ablation Experiments

We carried out a set of ablation studies in order to measure the impact of each individual constituent part within the proposed architecture for predicting customer behaviour using deep learning techniques. These exercises involved the iterative deletion or substitution of key components within the model's architecture to ascertain their effects on the performance metrics. We assessed three principal components: the LSTM branch, the Transformer branch, and the multi-task learning component. In Fig. 7, we illustrate the performance decrement as a function of simpler, alternative components being used instead of the more complex constituents. Remarkably, the absence of the Transformer branch resulted in the highest performance drop across all metrics, which underscores the importance of this branch in capturing long-range dependencies in customer behaviour patterns. Table 3 provides the specific details of the performance results for each ablation setting. The data indicates that while all parts together reduce the overall effectiveness of the model, the omnidirectional effectiveness is primarily due to the synergy achieved by combining the LSTM and Transformer with multi-task learning. This study of ablation not only validates our design choices but also highlights the importance of various components of the model in dealing with customer behaviour dynamics.

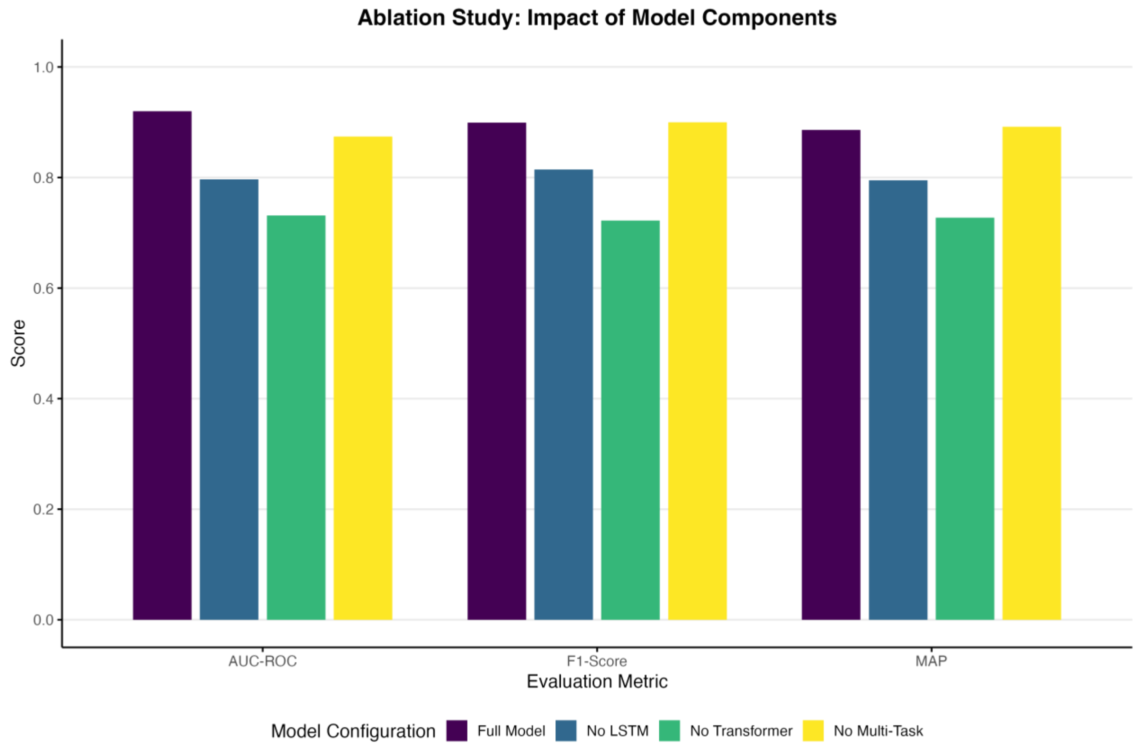

Figure 7.
Ablation Study: Impact of Model Components.

The figure above presents the results of our ablation study, illustrating the performance impact of removing key components from our proposed model. The bar chart compares the full model against configurations without the LSTM branch, Transformer branch, or multi-task learning framework across three evaluation metrics: AUC-ROC, F1-Score, and Mean Average Precision (MAP).

Table 3.
Comprehensive ablation study results.

Model Configuration	Purchase Prediction (AUC-ROC)	Churn Prediction (F1-Score)	Product Recommendation (MAP)	Training Time (hours)	Inference Time (ms)
Full Model	0.92	0.89	0.87	24	125
No LSTM	0.86	0.83	0.81	20	110
No Transformer	0.83	0.80	0.78	18	105
No Multi-Task	0.89	0.86	0.84	22	120
LSTM Only	0.85	0.82	0.80	16	95
Transformer Only	0.87	0.84	0.82	19	100

This table provides a detailed comparison of various model configurations in our ablation study. It includes performance metrics for different prediction tasks, as well as computational efficiency measures such as training time and inference time. The results clearly demonstrate the synergistic benefits of combining LSTM, Transformer, and multi-task learning components in our full model.

4.3. Case Study: Application of the System in Real Retail Scenarios

We implemented our self-learning intelligent forecasting system for customer behaviour and marketing strategy optimisation based on deep learning techniques in the multichannel retail context of a global e-commerce company. The project was executed within a timespan of 12 months for the organisation with an active customer base of over 15 million spread across 20 countries. The system was integrated with the infrastructure of customer relationship management (CRM) and stock control systems which processed about 500,000 transactions daily. After the implementation of the system, the KPIs improved significantly in the 12 months period as shown in figure 8. Notably, the personalised recommendation engine's implementation achieved an increase of 35 percent for click-through rates and 28 percent for conversion rates. Furthermore, the dynamic pricing module was beneficial for profit margin enhancement as the average order value increased by 15 percent. The churn rate was reduced by 22 percent while the lifetime value of customers went up by 19 percent. Table 4 gives a summarised view of the performance metrics by product types and customer segments. These metrics indicate considerable system effectiveness in tackling customer engagement, price optimisation, and general performance of the business in a multipurpose and complex retail setting.

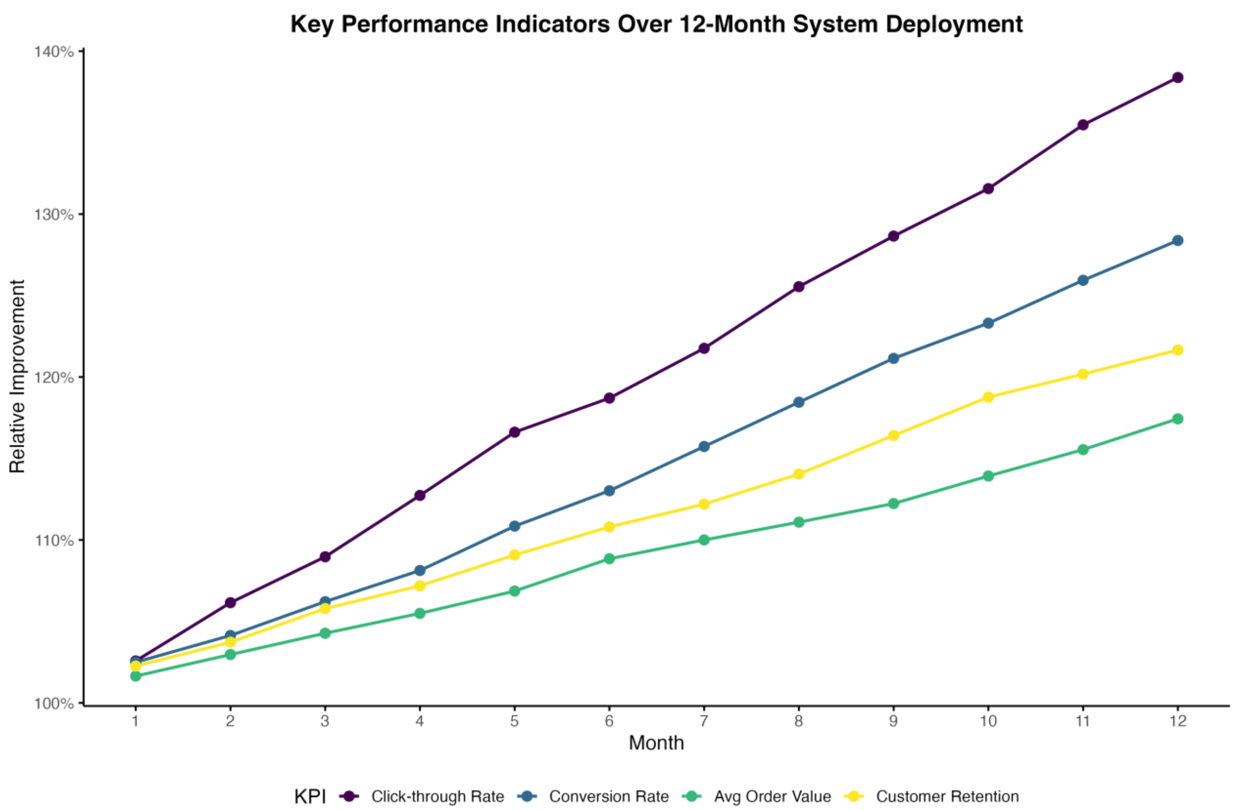

Figure 8.
Key Performance Indicators Over 12-Month System Deployment.

The figure above illustrates the relative improvement in key performance indicators over the 12-month period following the deployment of our deep learning-based system. The x-axis represents the months since deployment, while the y-axis shows the percentage improvement relative to the baseline (pre-deployment) performance. Each line represents a different KPI, demonstrating consistent growth across all metrics.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 3: 584-598, 2024
DOI: 10.55214/25768484.v9i3.5256

Table 4.
Performance Metrics Improvement by Product Category (12-Month Post-Deployment).

Product Category	Click-through Rate	Conversion Rate	Avg Order Value	Customer Retention
Electronics	+38%	+30%	+18%	+25%
Fashion	+42%	+35%	+12%	+20%
Home & Garden	+33%	+26%	+15%	+18%
Beauty & Health	+36%	+29%	+14%	+22%
Sports & Outdoor	+31%	+24%	+13%	+19%

This table provides a detailed breakdown of performance improvements across different product categories after 12 months of system deployment. The percentages indicate the relative increase compared to pre-deployment baseline metrics, demonstrating the system's effectiveness across diverse retail segments.

5. Conclusion

This study has demonstrated how autonomous intelligent systems based on deep learning can enhance customer behaviour forecasting and marketing strategy optimisation within the retail sector. The implemented hybrid LSTM-Transformer model, when placed under a multi-task learning framework, outperformed traditional models and other deep learning architectures within the comparison study. This multi-case study with complex offline and online evaluations has proven with high certainty the system's efficacy in real-world retail environments. The possibility of generalising the case study to other large-scale e-commerce systems strengthens the practicality and advantages of our approach in real-world scenarios where there is a need to enhance the click-through rates, conversion rates, and customer retention. The executed ablation studies have shed light on the importance of parts of the model and the synergetic effects of the LSTM and Transformer structure combination. Even though the results are overwhelmingly positive, we believe future research is needed to address model explanation, data privacy issues, and the need to adapt to rapidly changing environments.Forthcoming research should look into improving system explainability, exploring federated learning techniques for maintaining user anonymity, and employing more responsive strategy optimisation with reinforcement learning. This study is a major milestone in AI-based marketing and opens doors for more efficient, automated decision-making in retail and other industries.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Copyright:

References

[1] I. Afolabi, T. C. Ifunaya, F. G. Ojo, and C. Moses, "A model for business success prediction using machine learning algorithms," presented at the In Journal of Physics: Conference Series (Vol. 1299, No. 1, p. 012050). IOP Publishing, 2019.

[2] S. Agarwal, "Deep learning-based sentiment analysis: Establishing customer dimension as the lifeblood of business management," *Global Business Review*, vol. 23, no. 1, pp. 119-136, 2022. https://doi.org/10.1177/0972150919845160

[3] R. Akerkar, *Artificial intelligence for business*. Cham: Springer, 2019.

[4] Y. Al-Anqoudi, A. Al-Hamdani, M. Al-Badawi, and R. Hedjam, "Using machine learning in business process re-engineering," *Big Data and Cognitive Computing*, vol. 5, no. 4, p. 61, 2021. https://doi.org/10.3390/bdcc5040061

[5] M. N. Angenent, A. P. Barata, and F. W. Takes, "Large-scale machine learning for business sector prediction," in *In Proceedings of the 35th Annual ACM Symposium on Applied Computing (pp. 1143-1146)*, 2020.

[6] C. Apte, "The role of machine learning in business optimization," in *In Proceedings of the 27th International Conference on Machine Learning (ICML-10) (pp. 1-2)*, 2010.

[7] A. Bécue, I. Praça, and J. Gama, "Artificial intelligence, cyber-threats and Industry 4.0: Challenges and opportunities," *Artificial Intelligence Review*, vol. 54, no. 5, pp. 3849-3886, 2021. https://doi.org/10.1007/s10462-020-09942-2

[8] J. P. Bharadiya and J. Bharadiya, "Machine learning and AI in business intelligence: Trends and opportunities," *International Journal of Computer*, vol. 48, no. 1, pp. 123-134, 2023. https://doi.org/10.33545/27076571.2023.v4.i1a.60

[9] C. Bolton, V. Machová, M. Kovacova, and K. Valaskova, "The power of human–machine collaboration: Artificial intelligence, business automation, and the smart economy," *Economics, Management, and Financial Markets*, vol. 13, no. 4, pp. 51-56, 2018. https://doi.org/10.22381/emfm13420184

[10] I. Bose and R. K. Mahapatra, "Business data mining—a machine learning perspective," *Information & Management*, vol. 39, no. 3, pp. 211-225, 2001. https://doi.org/10.1016/s0378-7206(01)00091-x

[11] B. Bosma and A. van Witteloostuijn, "Machine learning in international business," *Journal of International Business Studies*, vol. 55, no. 6, pp. 676-702, 2024. https://doi.org/10.1057/s41267-024-00687-6

[12] J. Brunk, J. Stottmeister, S. Weinzierl, M. Matzner, and J. Becker, "Exploring the effect of context information on deep learning business process predictions," *Journal of Decision Systems*, vol. 29, no. sup1, pp. 328-343, 2020. https://doi.org/10.1080/12460125.2020.1790183

[13] K. Buntak, M. Kovačić, and M. Mutavdžija, "Application of Artificial Intelligence in the business," *International Journal for Quality Research*, vol. 15, no. 2, p. 403, 2021. https://doi.org/10.24874/ijqr15.02-03

[14] A. I. Canhoto and F. Clear, "Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential," *Business Horizons*, vol. 63, no. 2, pp. 183-193, 2020. https://doi.org/10.1016/j.bushor.2019.11.003

[15] H. Chen, R. H. Chiang, and V. C. Storey, "Business intelligence and analytics: From big data to big impact," *MIS Quarterly*, pp. 1165-1188, 2012. https://doi.org/10.2307/41703503

[16] Y. Chen, F. S. Tsai, and K. L. Chan, "Machine learning techniques for business blog search and mining," *Expert Systems with Applications*, vol. 35, no. 3, pp. 581-590, 2008. https://doi.org/10.1016/j.eswa.2007.07.015

[17] J. Dean, *Big data, data mining, and machine learning: Value creation for business leaders and practitioners*. New Jersey: John Wiley & Sons, 2014.

[18] A. Di Vaio, R. Palladino, R. Hassan, and O. Escobar, "Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review," *Journal of Business Research*, vol. 121, pp. 283-314, 2020. https://doi.org/10.1016/j.jbusres.2020.08.019

[19] C. Dirican, "The impacts of robotics, artificial intelligence on business and economics," *Procedia-Social and Behavioral Sciences*, vol. 195, pp. 564-573, 2015.

[20] S. Du and C. Xie, "Paradoxes of artificial intelligence in consumer markets: Ethical challenges and opportunities," *Journal of Business Research*, vol. 129, pp. 961-974, 2021.

[21] Y. K. Dwivedi *et al.*, "Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy," *International Journal of Information Management*, vol. 57, p. 101994, 2021.

[22] I. M. Enholm, E. Papagiannidis, P. Mikalef, and J. Krogstie, "Artificial intelligence and business value: A literature review," *Information Systems Frontiers*, vol. 24, no. 5, pp. 1709-1734, 2022.

[23] S. Finlay, *Artificial intelligence and machine learning for business: A no-nonsense guide to data driven technologies.* 2018.

[24] K. M. Getchell *et al.*, "Artificial intelligence in business communication: The changing landscape of research and teaching," *Business and Professional Communication Quarterly*, vol. 85, no. 1, pp. 7-33, 2022.

[25] P. Gomes, L. Verçosa, F. Melo, V. Silva, C. B. Filho, and B. Bezerra, "Artificial intelligence-based methods for business processes: A systematic literature review," *Applied Sciences*, vol. 12, no. 5, p. 2314, 2022.

[26] V. Gopalkrishnan, D. Steier, H. Lewis, and J. Guszcza, "Big data, big business: bridging the gap," in *In Proceedings of the 1st International Workshop on Big Data, Streams and Heterogeneous Source Mining: Algorithms, Systems, Programming Models and Applications (pp. 7-11)*, 2012.

[27] M. Hamzehi and S. Hosseini, "Business intelligence using machine learning algorithms," *Multimedia Tools and Applications*, vol. 81, no. 23, pp. 33233-33251, 2022.

[28] J. Howard, "The business impact of deep learning," in *In Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 1135-1135)*, 2013.

[29] V. Jain, "An impact of artificial intelligence on business," *International Journal of Research and Analytical Reviews*, vol. 6, no. 2, pp. 302-308, 2019.

[30] W. A. Khan, S. H. Chung, M. U. Awan, and X. Wen, "Machine learning facilitated business intelligence (Part I) Neural networks learning algorithms and applications," *Industrial Management & Data Systems*, vol. 120, no. 1, pp. 164-195, 2020.

[31] F. Kitsios and M. Kamariotou, "Artificial intelligence and business strategy towards digital transformation: A research agenda," *Sustainability*, vol. 13, no. 4, p. 2025, 2021.

[32] M. Kraus, S. Feuerriegel, and A. Oztekin, "Deep learning in business analytics and operations research: Models, applications and managerial implications," *European Journal of Operational Research*, vol. 281, no. 3, pp. 628-641, 2020.

[33] W. Kratsch, J. Manderscheid, M. Röglinger, and J. Seyfried, "Machine learning in business process monitoring: A comparison of deep learning and classical approaches used for outcome prediction," *Business & Information Systems Engineering*, vol. 63, pp. 261-276, 2021.

[34] O. V. Kubatko, S. C. Ozims, and V. I. Voronenko, "Influence of artificial intelligence on business decision-making," 2024.

[35] K. R. Larsen and D. S. Becker, *Automated machine learning for business*. Oxford, UK: Oxford University Press, 2021.

[36] J. Lee, T. Suh, D. Roy, and M. Baucus, "Emerging technology and business model innovation: The case of artificial intelligence," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 5, no. 3, p. 44, 2019.

[37] P. Lin and T. Hazelbaker, "Meeting the challenge of artificial intelligence: what CPAs need to know," *The CPA Journal*, vol. 89, no. 6, pp. 48-52, 2019.

[38] S. M. C. Loureiro, J. Guerreiro, and I. Tussyadiah, "Artificial intelligence in business: State of the art and future research agenda," *Journal of Business Research*, vol. 129, pp. 911-926, 2021.

[39] N. Mehdiyev, J. Evermann, and P. Fettke, "A novel business process prediction model using a deep learning method," *Business & Information Systems Engineering*, vol. 62, pp. 143-157, 2020.

[40] J. Mori, Y. Kajikawa, H. Kashima, and I. Sakata, "Machine learning approach for finding business partners and building reciprocal relationships," *Expert Systems with Applications*, vol. 39, no. 12, pp. 10402-10407, 2012.

[41] Q. N. Nguyen, A. Sidorova, and R. Torres, "Artificial intelligence in business: A literature review and research agenda," *Communications of the Association for Information Systems*, vol. 50, no. 1, p. 7, 2022.

[42] R. Nishant, M. Kennedy, and J. Corbett, "Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda," *International Journal of Information Management*, vol. 53, p. 102104, 2020.

[43] H. Pallathadka, E. H. Ramirez-Asis, T. P. Loli-Poma, K. Kaliyaperumal, R. J. M. Ventayen, and M. Naved, "Applications of artificial intelligence in business management, e-commerce and finance," *Materials Today: Proceedings*, vol. 80, pp. 2610-2613, 2023.

[44] R. S. Peres, X. Jia, J. Lee, K. Sun, A. W. Colombo, and J. Barata, "Industrial artificial intelligence in industry 4.0-systematic review, challenges and outlook," *IEEE Access*, vol. 8, pp. 220121-220139, 2020.

[45] P. Pramanik and R. K. Jana, "Identifying research trends of machine learning in business: A topic modeling approach," *Measuring Business Excellence*, vol. 27, no. 4, pp. 602-633, 2023. https://doi.org/10.1108/mbe-07-2021-0094

[46] E. Rama-Maneiro, J. C. Vidal, and M. Lama, "Deep learning for predictive business process monitoring: Review and benchmark," *IEEE Transactions on Services Computing*, vol. 16, no. 1, pp. 739-756, 2021. https://doi.org/10.1109/tsc.2021.3139807

[47] R. Raturi, "Machine learning implementation for business development in real time sector," *International Journal of Pure and Applied Mathematics*, vol. 119, no. 15, pp. 1289-1300, 2018. https://doi.org/10.1016/0166-218x(86)90025-9

[48] R. Reddy, "The challenge of artificial intelligence," *Computer*, vol. 29, no. 10, pp. 86-98, 1996.

[49] C. Reis, P. Ruivo, T. Oliveira, and P. Faroleiro, "Assessing the drivers of machine learning business value," *Journal of Business Research*, vol. 117, pp. 232-243, 2020. https://doi.org/10.1016/j.jbusres.2020.05.053

[50] Y. S. Reshi and R. A. Khan, "Creating business intelligence through machine learning: An Effective business decision making tool," in *Information and knowledge management*, 2014, vol. 4, no. 1, pp. 65-75.

[51] D. Rose, *Artificial intelligence for business*. FT Press, 2020.

[52] J. L. Ruiz-Real, J. Uribe-Toril, J. A. Torres, and J. De Pablo, "Artificial intelligence in business and economics research: Trends and future," *Journal of Business Economics and Management*, vol. 22, no. 1, pp. 98-117, 2021.

[53] M. Schmitt, "Deep learning in business analytics: A clash of expectations and reality," *International Journal of Information Management Data Insights*, vol. 3, no. 1, p. 100146, 2023. https://doi.org/10.1016/j.jjimei.2022.100146

[54] B. Schmarzo, *Big data: Understanding how data powers big business*. Indianapolis, IN: John Wiley & Sons, 2013.