© NOV 2024 | IRE Journals | Volume 8 Issue 5 | ISSN: 2456-8880

The Impact of Artificial Intelligence on Predictive Customer Behaviour Analytics in E-commerce: A Comparative Study of Traditional and AI-driven Models

NIGEL NKOMO[1], MUNASHE NAPHTALI MUPA[2]
[1, 2]Hult International Business School

Abstract- This comparative article explores the impact of artificial intelligence (AI) on predictive customer behaviour analytics in the e-commerce sector, evaluating AI-driven models against traditional approaches. Traditional models, including logistic regression, decision trees, and clustering methods, have long been employed to predict customer behaviours, such as purchasing decisions and churn, based on historical data. However, these models face significant limitations regarding scalability, accuracy, and the ability to process vast and complex datasets. In contrast, AI-driven models—particularly those utilizing machine learning (ML), deep learning (DL), and natural language processing (NLP)—demonstrate superior performance by processing large volumes of data, identifying non-linear patterns, and delivering real-time predictions. AI's enhanced capabilities enable e-commerce platforms to offer hyper-personalized customer experiences, improve marketing strategies, and optimize operational efficiency. The article further explores the integration of AI with other emerging technologies, such as the Internet of Things (IoT) and blockchain, enhancing predictive analytics by ensuring data integrity and real-time processing. However, challenges persist, especially concerning the interpretability of AI models, often referred to as "black-box" systems, which limit transparency and trust in high-stakes sectors. Explainable AI (XAI) is identified as a crucial development for improving model transparency and accountability. Additionally, ethical concerns related to data privacy, bias, and fairness in AI models are discussed, underscoring the need for robust regulatory frameworks. Hence, the article concludes that while AI-driven models significantly outperform traditional methods in predictive analytics, addressing challenges in interpretability, bias, and ethical concerns will be critical for their broader adoption and trustworthiness in the e-commerce sector. Future research is recommended to enhance AI transparency, fairness, and integration with emerging technologies.

I. INTRODUCTION

Customer behaviour analytics plays a crucial role in enhancing marketing strategies and driving growth in the e-commerce sector. By examining online reviews and customer interactions, businesses can gain valuable insights into consumer purchasing decisions, enabling them to adjust their offerings accordingly (Nagrath et al., 2021). Analyzing customer activities allows companies to maintain dynamic customer profiles, which improve personalization, customer satisfaction, and ultimately sales (Ntawanga et al., 2008).

Predictive analytics further enhances the capacity to understand complex consumer behaviours, such as purchase decisions and buying sessions, thereby allowing for more accurate forecasting and tailored marketing strategies (Cirqueira et al., 2019). Data mining techniques provide deeper insights into individual preferences, helping businesses implement more effective sales promotions, which leads to increased profitability (Gan, 2013).

Moreover, customer behaviour analytics helps in understanding the influence of factors like retailer reputation, sales promotions, and user experience, all of which significantly impact consumer decisions in online retail (Yong et al., 2023). Therefore, using these insights to develop strategies not only boosts customer retention and satisfaction but also helps in optimizing e-commerce platforms for long-term growth and success.

The emergence of artificial intelligence (AI) has significantly transformed predictive analytics, enabling businesses to make data-driven decisions with greater accuracy and speed (Aldridge, 2023). AI technologies, particularly machine learning, have outperformed traditional analytics by efficiently identifying and extracting signals from massive datasets, leading to more precise predictions and optimized decision-making processes (Aldridge, 2023). This transition from traditional models to AI-driven systems represents a pivotal shift in analytics, as AI enhances predictive capabilities by incorporating complex variables and identifying patterns that were previously undetectable using conventional methods (Davenport, 2018).

AI's ability to process vast volumes of data has empowered industries such as finance, retail, and healthcare to enhance their predictive models, optimizing operations and improving customer experiences (López de Mántaras, 2018). In particular, AI's ability to learn from historical data has enabled predictive analytics to evolve into a more dynamic tool, capable of adapting to real-time changes and generating actionable insights (Manolache & Rusu, 2016).

Additionally, explainable AI has become an important aspect of predictive analytics, where transparency and interpretability are crucial for industries to make informed decisions based on AI predictions (Basagaoglu et al., 2022). This has led to the development of interpretable models, particularly in sectors requiring accountability, such as healthcare and finance (Basagaoglu et al., 2022). Consequently, AI technologies are now indispensable in transforming predictive analytics and empowering organizations to leverage data more effectively.

This article aims to compare the effectiveness of traditional and AI-driven models in predictive customer behaviour analytics within the e-commerce sector. Its purpose is to explore the advantages and limitations of both approaches, highlighting how AI models improve accuracy, scalability, and real-time decision-making while addressing challenges like interpretability and ethical concerns.

Traditional Customer Behaviour Predictive Models

Traditional models in customer behaviour analytics have relied on various statistical and machine learning techniques to predict customer actions and preferences (Biswas et al., 2023). One of the most commonly used models is logistic regression, which helps identify relationships between independent variables, such as demographics and purchasing behaviour, and dependent outcomes like customer retention or churn (Zulaikha et al., 2020). It is particularly effective in binary classification problems, enabling companies to predict specific outcomes such as whether a customer will make a purchase (Shen & Su, 2007). This model is crucial for understanding probabilities and evaluating the relationship between different factors and customer decisions (Alizadeh et al., 2022).

Decision tree analysis is another essential methodology frequently used for customer segmentation and decision-making. It works by splitting data into subsets based on significant predictor variables, offering businesses an interpretable structure to understand customer behaviour and develop targeted marketing strategies (Kurosawa et al., 2005). Decision trees are valuable for identifying key decision points in the customer journey, such as age, income, or browsing history, and have been widely adopted due to their interpretability (Wu et al., 2020).

Clustering methods, like K-means clustering, are also popular in customer behaviour analytics. These techniques divide customers into groups based on their similarities, allowing businesses to design marketing strategies tailored to different customer segments (Luo et al., 2017). Clustering techniques are frequently applied in conjunction with decision trees to enhance segmentation accuracy and improve customer satisfaction (Sundareswaran et al., 2022).

The Recency, Frequency, and Monetary (RFM) model is another widely used approach for customer segmentation. This model assesses customer value by analyzing how recently and frequently they make purchases, as well as how much they spend. RFM analysis enables companies to identify high-value customers and create loyalty programs aimed at improving retention. Combining RFM with clustering further enhances segmentation precision (Wu et al., 2020).

Hidden Markov Models (HMMs) have also been applied in customer relationship management (CRM). HMMs model customer transitions between different engagement states, allowing businesses to predict customer behaviours dynamically and improve customer loyalty forecasting (Nkemnole & Nwaokoro, 2020). Additionally, association rule mining, such as the Apriori algorithm, is commonly used to identify product relationships, which helps businesses uncover buying patterns and optimize cross-selling strategies (Gupta et al., 2020). These traditional models have played a pivotal role in enabling companies to understand and predict customer actions, laying the foundation for more advanced predictive analytics.

Applications of Traditional Predictive Models in E-commerce

Traditional predictive models have played a crucial role in e-commerce, particularly in forecasting customer purchase behaviours, churn, and segmentation (Biswas et al., 2023). Logistic regression has been widely used to predict customer purchase patterns by analyzing historical data and identifying factors influencing buying decisions (Sakai et al., 2022). For example, this model has been applied to segment customers based on their likelihood of making purchases, allowing businesses to target specific customer groups more effectively (Sakai et al., 2022). Logistic regression also aids in predicting customer churn, enabling companies to develop retention strategies and reduce churn rates (Kumar, 2023).

Decision trees are another prominent model used in customer segmentation. By breaking data into decision points, businesses can identify key variables such as product preferences and demographics that influence customer behaviour. This model is particularly useful for creating personalized marketing campaigns that enhance customer engagement (Fu & An, 2022). Clustering techniques, like K-means clustering, have also proven effective in identifying customer segments based on purchasing behaviour. This unsupervised learning method groups customers with similar patterns, enabling companies to focus on their most valuable customers and develop targeted retention strategies (Zhong, 2021). Clustering also aids in cross-selling by identifying frequently purchased product combinations, enhancing recommendation systems (Zhong, 2021).

Predictive models such as ARIMA (Auto Regressive Integrated Moving Average) and XGBoost have been employed to forecast demand, helping businesses manage inventory and improve operational efficiency. These models analyze historical sales data to predict future demand, allowing companies to optimize stock levels (Tang, 2023). ARIMA has proven particularly useful in demand forecasting, providing accurate insights into future product needs (Tang, 2023).

Hidden Markov Models (HMMs) have been applied to predict customer churn by tracking customer behaviour over time. These models help businesses identify when customers are likely to leave the platform, offering a chance for proactive retention efforts (Shih & Lin, 2019). Additionally, advanced techniques such as deep learning modified neural networks (DLMNN) have outperformed traditional models in predicting e-commerce sales, especially with large datasets (Subramani et al., 2023).

Moreover, machine learning methods like Gradient Boosted Decision Trees (GBDT) have been employed to enhance demand prediction by analyzing historical transaction data, contributing to improved delivery efficiency and customer satisfaction (Du et al., 2021). Seasonal ARIMA (SARIMA) and Long Short-Term Memory (LSTM) networks have also been applied for short-term sales predictions, further optimizing supply chain management (Jain et al., 2020).

Limitations of Traditional Models

Traditional predictive models, while widely used in customer behaviour analytics, face several limitations, particularly when applied to large datasets typical in e-commerce environments. One of the main challenges is scalability. Traditional models like logistic regression and decision trees struggle to scale efficiently with the increasing volume of data, leading to slow processing times and reduced performance in dynamic environments (Sakai et al., 2022). As e-commerce platforms generate massive amounts of customer interaction data daily, these models fall short in managing the data complexity and providing real-time insights (Kumar, 2023).

In terms of complexity, traditional models often fail to capture the non-linear relationships present in large datasets (Ulkhaq et al., 2020). For instance, customer purchase behaviours are influenced by multiple factors, such as seasonal trends, marketing campaigns, and product pricing (Kale et al., 2022). However, traditional models like ARIMA are linear in nature and struggle to accommodate such complexities, making them less effective in accurately predicting customer behaviours over time (Tang, 2023). Moreover, the complexity of feature engineering in traditional models, which requires manually selecting and transforming relevant features, adds another layer of difficulty in handling large datasets (Fu & An, 2022).
Accuracy is another significant limitation. While traditional models like decision trees are interpretable and easy to implement, they often fail to deliver the accuracy required for modern e-commerce operations (Subramani et al., 2023). These models are prone to overfitting, particularly when applied to large and diverse datasets. As a result, their predictive performance diminishes when new, unseen data is introduced, leading to poor generalization capabilities (Subramani et al., 2023). The use of more advanced models like deep learning has demonstrated improved accuracy in forecasting customer behaviour by learning complex patterns in large datasets without extensive manual feature selection (Shih & Lin, 2019). These challenges highlight the necessity for a shift towards AI-driven solutions, which are more adept at handling scalability, complexity, and accuracy in large datasets (Jain et al., 2020). AI models, such as deep learning neural networks, automatically capture intricate patterns and provide real-time predictions, making them a more effective choice for modern e-commerce platforms (Jain et al., 2020).

AI-driven Predictive Customer Behaviour Models

Artificial intelligence (AI) models have transformed predictive analytics by offering more robust, accurate, and adaptable solutions compared to traditional methods (Aldridge, 2023). Among these AI models, machine learning (ML), deep learning (DL), and natural language processing (NLP) are the most widely utilized, leveraging both supervised and unsupervised learning techniques to extract valuable insights from large datasets (Aldridge, 2023; Huang, 2021). These approaches improve decision-making processes across sectors like e-commerce, healthcare, and finance (Thakial & Arora, 2019).

Supervised learning models, such as decision trees, support vector machines (SVM), and random forests, play a central role in predictive analytics (Huang, 2021). These models rely on labeled datasets where input-output pairs are pre-defined, allowing businesses to forecast customer behaviours, including purchase patterns and churn, especially in e-commerce (Huang, 2021; Fomude et al., 2023). For instance, SVM and random forests have been applied to predict consumer actions, providing valuable insights into customer retention strategies (Khrisat et al., 2022).

Unsupervised learning, on the other hand, is used to identify hidden patterns in unlabeled data. Techniques like K-means clustering and principal component analysis (PCA) are critical in segmenting customers based on purchasing behaviours, allowing companies to discover new market segments and design targeted marketing campaigns (Sepp, 2021). These models are particularly valuable for recommendation systems and cross-selling opportunities in industries like e-commerce, where customer segmentation is key (Sepp, 2021; Fomude et al., 2023).

Deep learning models, especially artificial neural networks (ANNs) and recurrent neural networks (RNNs), further improve predictive analytics by modeling complex, non-linear relationships in data (Kurihara & Fukushima, 2019). Long Short-Term Memory (LSTM) networks, a type of RNN, are particularly effective in time-series forecasting, outperforming traditional methods such as autoregressive models in predicting stock prices and demand (Khrisat et al., 2022; Jain et al., 2020). These models can capture temporal dependencies, making them ideal for tasks like sales forecasting and customer behaviour prediction (Kurihara & Fukushima, 2019).

Natural language processing (NLP) is another vital tool, particularly in sentiment analysis. NLP techniques allow businesses to analyze customer opinions and emotions from product reviews, social media, and other text-based sources, which is essential for improving product offerings and forecasting demand (Kurihara & Fukushima, 2019; Kojs, 2023).

Therefore, AI-driven models, such as ML, DL, and NLP, have dramatically advanced predictive analytics, providing more accurate, scalable, and real-time predictions across industries (Thakial & Arora, 2019). These advancements have enabled companies to make data-driven decisions, improve customer engagement, and optimize operational efficiency (Thakial & Arora, 2019; Du et al., 2021).

Applications in Predictive Customer Analytics

Artificial intelligence (AI) models have become integral in enhancing predictive customer analytics, particularly in real-time customer segmentation, personalization, and dynamic pricing in e-commerce. Real-time customer segmentation using AI enables businesses to group customers based on behaviour, preferences, and interactions, providing valuable insights into customer needs (Ozan & Iheme, 2019). Techniques like artificial neural networks (ANNs) and clustering algorithms allow businesses to segment customers dynamically, optimizing their marketing strategies and improving engagement (Ozan & Iheme, 2019).

AI also facilitates personalization by tailoring the shopping experience for individual users, increasing customer satisfaction and loyalty (Hemalatha, 2023). Machine learning algorithms analyze vast datasets to provide personalized recommendations, making the shopping experience more relevant for consumers. As a result, businesses can deliver targeted marketing campaigns that boost sales and engagement by predicting individual preferences based on past interactions (Hemalatha, 2023). AI models, such as support vector machines (SVM) and deep learning, are further widely used in e-commerce to analyze customer behaviour and make real-time adjustments to personalize content, product recommendations, and promotions (Jangra & Jangra, 2022).

Dynamic pricing, a critical application of AI in e-commerce, uses predictive analytics to adjust product prices in real-time based on customer demand, competition, and other market factors (Zhang et al., 2023). AI-driven models like decision trees and reinforcement learning algorithms enable businesses to implement flexible pricing strategies that maximize profitability while remaining competitive. This allows businesses to respond to changes in supply and demand efficiently, optimizing revenue generation (Zhang et al., 2023).

Furthermore, AI-based sales forecasting models, incorporating customer feedback and purchase history, enable businesses to predict future demand and adjust their dynamic pricing strategies accordingly (Biswas et al., 2023). This improves overall pricing accuracy and helps businesses stay competitive in fluctuating markets (Biswas et al., 2023). Hence, e-commerce platforms can effectively implement real-time segmentation, personalization, and dynamic pricing strategies to enhance customer satisfaction and increase profitability by leveraging AI technologies.

Advantages of AI Models over Traditional Models

AI models offer significant advantages over traditional models, particularly in handling large datasets, improving prediction accuracy, enabling real-time decision-making, and adapting to changing customer behaviours (Liang, 2023). One of the most prominent benefits of AI is its ability to process and analyze massive amounts of data efficiently (Emani et al., 2023). AI-driven models, especially neural networks, can handle complex computations and vast datasets that traditional models struggle to manage. This is particularly relevant in modern e-commerce and financial markets, where large-scale AI models are increasingly deployed for data-driven decision-making (Liang, 2023).

In terms of prediction accuracy, AI models have proven to be more reliable than traditional models (Khashei & Sharif, 2020). Techniques like machine learning and deep learning enable AI to detect complex, non-linear relationships in data, which traditional statistical models often miss (Ulkhaq et al., 2020). For example, AI models such as Long Short-Term Memory (LSTM) networks provide superior performance in time-series forecasting compared to traditional methods like ARIMA, as they capture both linear and non-linear patterns more effectively (Khashei & Sharif, 2020). Additionally, AI's ability to improve accuracy in diverse fields, from weather forecasting to financial modeling, further demonstrates its advantages (Aldridge, 2023).

AI models excel at real-time decision-making by continuously learning and adapting to new data. In dynamic environments like e-commerce, where customer preferences change rapidly, AI models adjust predictions and strategies on the fly, optimizing recommendations and pricing strategies based on real-time inputs (Marek et al., 2023). This adaptability enables businesses to respond faster to market changes, driving better customer experiences and operational efficiencies (Marek et al., 2023).

Furthermore, AI's flexibility allows it to adapt to evolving customer behaviours more effectively than traditional models (Basagaoglu et al., 2022). By leveraging advanced machine learning techniques, AI systems can update models in real-time, ensuring they remain accurate even as consumer preferences shift. This adaptability helps businesses stay competitive and respond to customer needs more efficiently (Basagaoglu et al., 2022). The ability to adjust to changes in customer behaviour makes AI a superior choice for modern predictive analytics.

Case Studies/Examples

Several e-commerce companies have successfully implemented AI-driven analytics to predict customer behaviour, significantly improving their operational efficiency and customer satisfaction. For instance, Amazon has been a pioneer in using AI for predictive analytics (Biswas et al., 2023). The company employs advanced machine learning algorithms to analyze past customer interactions, including purchase history, browsing patterns, and feedback, to generate personalized recommendations. This approach enhances customer satisfaction and has led to significant increases in sales conversion rates (Biswas et al., 2023).

Snapdeal, another major e-commerce platform in India, leverages AI-based sales forecasting models to anticipate demand more accurately (Biswas et al., 2023). Snapdeal optimizes its inventory management and supply chain operations by analyzing historical sales data and customer interactions, reducing costs and improving product availability (Biswas et al., 2023). These AI-driven models have also improved the company's ability to offer dynamic pricing strategies tailored to individual customer preferences (Biswas et al., 2023).

In addition, Alibaba uses AI and big data analytics to enhance its customer segmentation and personalized marketing efforts (Zulaikha et al., 2020). By analyzing customer behaviour data, such as purchasing habits and demographic information, Alibaba has developed highly effective recommendation systems that boost customer engagement and loyalty (Zulaikha et al., 2020). The company's success in using AI-driven predictive analytics has positioned it as a global leader in e-commerce (Zulaikha et al., 2020).

Zalando, a European fashion e-commerce company, has also employed AI to predict customer demand and personalize user experiences (Sharma, 2023). Using machine learning techniques, Zalando analyzes user preferences and purchasing behaviour to provide tailored recommendations (Sharma, 2023). This AI-driven personalization has significantly improved customer retention and satisfaction, leading to enhanced business performance.

Hence, these case studies highlight the growing importance of AI-driven analytics in the e-commerce industry, where understanding customer behaviour and predicting future trends are critical to maintaining a competitive edge (Zulaikha et al., 2020; Biswas et al., 2023; Sharma, 2023).

Comparative Analysis: Traditional vs. AI-driven Models

Performance Metrics Comparison

AI-driven models consistently outperform traditional models in predictive customer behaviour analytics across key performance metrics such as accuracy, precision, recall, and F1 score (Talpur & Marri, 2021). Accuracy is one of the most fundamental metrics where AI models, particularly deep learning algorithms, demonstrate superior performance (Ulkhaq et al., 2020). For example, Ulkhaq et al. (2020) compared traditional regression models with artificial neural networks (ANNs) and found that AI models achieved significantly higher accuracy rates in predicting customer behaviour across various industries, notably in e-commerce. Similarly, the study by Talpur and Marri (2021)revealed that ANN models achieved an accuracy of 97.18%, whereas traditional models like ARIMA reached only 88.76%, underscoring the superior ability of AI models to handle complex data patterns.

Precision, which measures the proportion of true positives among predicted positives, is another key area where AI models excel (Kale et al., 2022). Traditional models such as logistic regression often struggle with false positives due to their reliance on linear assumptions. In contrast, AI models like decision trees and support vector machines (SVMs) are better at capturing non-linear relationships, thereby improving precision (Idogho & George, 2022). In their study, Kale et al. (2022) compared customer behaviour forecasting methods and found that machine learning algorithms, including SVMs, significantly enhanced precision in customer purchase prediction, outperforming traditional models in both static and sequential datasets. Moreover, AI models have been shown to reduce false positives more effectively, particularly in customer churn prediction, thus further improving precision (Idogho & George, 2022).

Recall, which measures the proportion of true positives correctly identified, is another metric where AI models outperform traditional approaches (Khashei & Sharif, 2020). Traditional models like the Recency, Frequency, and Monetary (RFM) framework often fail to capture long-term customer trends (Nkemnole & Nwaokoro, 2020). However, AI models such as hidden Markov models (HMMs) and neural networks dynamically adapt to evolving customer behaviour, which leads to improved recall in predicting churn and lifetime value (Nkemnole & Nwaokoro, 2020). The ability of AI models to learn and evolve in response to shifting customer patterns is a critical advantage over traditional models.

Moreover, the F1 score, which balances precision and recall, highlights the overall superiority of AI models (Khashei & Sharif, 2020). AI-driven models, particularly those using probabilistic methods and neural networks, consistently achieve higher F1 scores, indicating a better balance between precision and recall compared to traditional models (Ulkhaq et al., 2020). Research comparing AI-based customer segmentation with classical clustering models found that AI models produced significantly higher F1 scores in customer classification, demonstrating their enhanced performance (Shekary et al., 2019).

Hence, AI models surpass traditional predictive models across all major performance metrics—accuracy, precision, recall, and F1 score—proving their superiority in predictive customer behaviour analytics (Talpur & Marri, 2021; Ulkhaq et al., 2020; Kale et al., 2022; Shekary et al., 2019; Nkemnole & Nwaokoro, 2020). These findings illustrate the clear advantage of AI-driven models in making more accurate and reliable predictions.

Scalability and Data Processing Capabilities

AI models exhibit superior scalability and data processing capabilities compared to traditional models, particularly in environments where handling large data volumes and high velocity is critical (Liang, 2023). One of the key advantages of AI-driven systems is their ability to manage "pre-trillion-scale" neural network parameters, allowing them to efficiently process massive datasets (Emani et al., 2023). In contrast, traditional models such as logistic regression or ARIMA struggle to scale effectively with such data sizes, which limits their applicability in large-scale environments (Liang, 2023). Deep learning techniques further enhance AI models' scalability by adapting to non-linear data patterns, and as more data is processed, these models continue to improve in both efficiency and accuracy (Liang, 2023).

The integration of specialized hardware, such as AI accelerators, plays a critical role in optimizing the performance of AI models. These accelerators enable AI-driven systems to handle larger datasets more effectively than traditional models (Emani et al., 2023). For example, large language models (LLMs) can leverage this hardware to optimize memory and execution, ensuring efficient processing even as data volumes grow (Emani et al., 2023). Traditional models, on the other hand, often experience performance bottlenecks when faced with increasingly complex and high-velocity data, leading to deteriorating results over time.

In high-performance computing (HPC) environments, AI models excel in real-time processing and decision-making (Riedel et al., 2023). AI frameworks, such as the Unique AI Framework (UAIF), allow for rapid scaling and frequent updates, significantly outperforming traditional models in time-sensitive applications like healthcare and financial forecasting (Riedel et al., 2023). Traditional models, which require manual adjustments to parameters as data changes, lack the flexibility and scalability that AI models achieve through continuous learning and hyperparameter tuning (Rausch & Sanders, 2020). This continuous improvement mechanism enables AI models to adapt dynamically to evolving datasets, whereas traditional models require manual intervention to adjust parameters.

Moreover, AI-specific hardware like accelerators ensures that models can scale without a substantial increase in power consumption, a challenge that traditional models face as they require exponential resource growth to handle larger data volumes (Gschwind, 2022). By optimizing scalability through advanced algorithms and AI-specific hardware, AI models provide a more sustainable and efficient solution for data-intensive applications across industries.

Therefore, AI models offer significant advantages in scalability and data processing over traditional models, particularly due to their ability to handle massive datasets, leverage specialized hardware, and continuously adapt to changing data environments. These capabilities make AI models more suitable for modern, data-driven industries where high performance and scalability are essential (Liang, 2023; Emani et al., 2023; Riedel et al., 2023).

Interpretability and Transparency

Traditional models are often considered more interpretable than AI models, primarily due to the transparency of their structures (Gaurav & Tiwari, 2023). Methods like linear regression and decision trees offer clear, understandable outputs, allowing decision-makers to trace predictions back to specific variables (Framling, 2020). This interpretability makes traditional models highly valuable for businesses, as they provide transparency in decision-making processes, which is essential for trust and reliability (Rogha, 2023). For example, decision trees display straightforward decision paths, making it easier for businesses to justify outcomes and explain decisions to stakeholders (Basagaoglu et al., 2022). This transparency is particularly beneficial in industries where decisions must be easily understood, such as finance and healthcare.

In contrast, AI models, especially deep learning and neural networks, are often referred to as "black-box" systems because their complex layers of abstraction make it difficult to understand how specific decisions are made (Gaurav & Tiwari, 2023). The internal workings of these models are opaque, which creates challenges in explaining the rationale behind predictions (Roszel et al., 2021). This lack of transparency can be problematic in high-stakes sectors like healthcare and finance, where decision-makers must often justify their decisions to regulators and stakeholders (Linkov et al., 2020). AI's opaque nature can lead to reduced trust in its predictions, even when the models perform accurately (Ferrario & Loi, 2022). Efforts have been made to address the "black-box" issue through Explainable AI (XAI) techniques such as Local Interpretable Model-agnostic Explanations (LIME) and SHAP values. These methods aim to offer post-hoc explanations of AI decisions, providing insights into how models arrive at specific outcomes (Morales et al., 2021). However, these explanations are often brittle and insufficient for critical decision-making scenarios where reliability and clarity are essential (Morales et al., 2021). In contrast, traditional models naturally offer transparency without the need for post-hoc explanations, making them preferable in situations where interpretability is critical (Framling, 2020).

Furthermore, the interpretability gap between traditional and AI models affects regulatory compliance (Morales et al., 2021). In industries like finance, regulatory frameworks require decisions to be fully understandable and traceable, something traditional models accomplish more easily than AI models (Framling, 2020). Traditional models' clear structures help ensure that businesses can meet legal standards without relying on complex, often unsatisfactory explanations (Basagaoglu et al., 2022). Hence, while AI models offer advanced predictive capabilities, traditional models remain superior in terms of interpretability. Their simple, transparent structures align closely with human reasoning, providing businesses with clearer, more reliable decision-making processes, particularly in environments requiring accountability and regulatory compliance (Landgrebe, 2022; Framling, 2020).

Cost and Implementation Considerations

The adoption of AI-driven models in business analytics involves substantial upfront and ongoing costs, but the potential return on investment (ROI) often exceeds that of traditional models. AI implementation typically requires significant initial investments in infrastructure, such as cloud computing platforms, specialized hardware, and software tools for model development and deployment (Ng et al., 2021; Ruamviboonsuk et al., 2021). Additional costs arise from training employees to effectively use AI systems and integrate them into existing workflows (Ng et al., 2021). Despite these high initial expenses, AI models offer long-term savings by improving operational efficiency and decision-making accuracy, thus offsetting the initial investment (Ruamviboonsuk et al., 2021).

AI-driven models excel in reducing error margins in predictive analytics, offering a key advantage over traditional models (Sing et al., 2020). For example, AI techniques such as decision trees and boosting methods have been demonstrated by Sing et al. (2020), to have superior predictive accuracy in property price forecasting when compared to traditional methods like multiple regression analysis (MRA). This increased accuracy reduces the financial risks associated with prediction errors, particularly in high-stakes industries such as real estate (Sing et al., 2020). These performance improvements underscore the cost-effectiveness of AI solutions, especially when considered over the long term.

In addition to predictive accuracy, AI-driven models contribute to operational efficiency. In healthcare, for instance, AI models used for diabetic retinopathy screening have been shown to outperform manual methods, resulting in greater long-term cost savings despite the higher initial investment (Ruamviboonsuk et al., 2021). The enhanced accuracy and efficiency of AI models reduce the need for labor-intensive processes and lower the risk of diagnostic errors, further improving the economic benefits of AI adoption (Ruamviboonsuk et al., 2021). Such examples highlight the scalability and adaptability of AI technologies, which enhance their attractiveness across various sectors, including healthcare and finance.

Though AI systems require considerable investment in computational infrastructure and skilled labor for development, maintenance, and continuous tuning, their long-term ROI justifies the initial costs in most industries (Ng et al., 2021). AI models, such as neural networks and decision trees, improve data processing efficiency and predictive power, leading to cost savings in various applications (Ersahin et al., 2019). For instance, AI solutions have drastically reduced the time required to analyze large datasets in fields like cyclic steam injection modeling, cutting processing times from 30 minutes to mere seconds, thereby boosting productivity and lowering operational costs (Ersahin et al., 2019). These time and cost efficiencies are crucial for industries that handle vast amounts of data, further reinforcing the long-term value of AI investments.

While the economic evaluation of AI adoption may be complex due to fragmented data and varied applications across industries, the long-term cost savings and operational improvements often justify the investment (Ruamviboonsuk et al., 2021). In healthcare, for example, AI has proven to be more cost-effective than manual screening methods for diabetic retinopathy, even though the high upfront costs can present barriers to widespread implementation (Ruamviboonsuk et al., 2021). As AI technologies evolve, their accessibility and cost-effectiveness are expected to improve, making them more viable for a broader range of industries (Ng et al., 2021). Thus, despite the initial financial outlay, AI-driven models deliver significant long-term economic benefits through enhanced accuracy, efficiency, and scalability.

Challenges and Ethical Considerations

Data Privacy and Ethical Issues

AI-driven predictive analytics have raised considerable concerns regarding data privacy and ethical implications, particularly due to the extensive collection and use of personal customer data without explicit consent (Mühlhoff, 2023). One of the primary ethical concerns involves the risk of privacy violations, especially when AI systems gather vast amounts of personal information to predict user behaviour (Mühlhoff, 2023). These predictive models, often used in marketing and decision-making processes, rely on data mining techniques that can lead to unauthorized access and misuse of sensitive customer information, thus violating privacy rights (Mühlhoff, 2023).

The opacity of AI systems, especially machine learning and deep learning models, is another major issue. These models are often described as "black boxes" because their decision-making processes are not easily interpretable by humans (Khosravy et al., 2022). This lack of transparency heightens privacy concerns, as users may not fully understand how their data is being processed or the extent to which it is being analyzed to make inferences about their behaviour (Khosravy et al., 2022). Such opacity also raises accountability concerns, particularly in cases where AI systems contribute to adverse outcomes like data breaches or unfair profiling (Khosravy et al., 2022). The challenge of ensuring accountability in AI systems is especially critical in industries like healthcare and finance, where the consequences of biased or erroneous predictions can be severe (Aalmoes et al., 2022).

Algorithmic bias represents another significant ethical concern in AI-driven predictive analytics (Peltz & Street, 2020; Aalmoes et al., 2022). AI models trained on historical data can unintentionally encode and perpetuate societal biases present in the data, leading to discriminatory outcomes. This is particularly troubling when AI systems make predictions based on attributes such as race, gender, or socioeconomic status, as these biases can reinforce existing inequalities (Peltz & Street, 2020). In fields like personalized marketing, hiring, and financial services, such bias can result in the exclusion of marginalized groups and contribute to systemic discrimination (Peltz & Street, 2020). The ethical implications of these biases are profound, as they challenge the fairness and equality expected in decision-making processes across various industries (Aalmoes et al., 2022).

Additionally, AI systems that influence consumer preferences through targeted recommendations pose ethical dilemmas regarding user autonomy. Recommender systems, for example, can subtly manipulate consumer behaviour by suggesting products or content based on predictive algorithms (Bonicalzi et al., 2023). This manipulation raises concerns about the erosion of user autonomy, as individuals may unknowingly have their decisions shaped by AI-driven models (Bonicalzi et al., 2023). The risk of such manipulation is particularly significant when AI systems align their recommendations with corporate interests, which could further compromise consumer freedom and agency (Bonicalzi et al., 2023).

Addressing these ethical and privacy concerns requires the development of robust regulatory frameworks that protect individual rights while fostering the responsible use of AI in predictive analytics. Transparent and explainable AI techniques, such as interpretable models and explainability tools, are essential in enhancing accountability and mitigating privacy risks (Xu et al., 2019). Moreover, privacy-preserving algorithms, such as differential privacy, are increasingly being advocated to strike a balance between the need for data-driven insights and the protection of individual privacy (Wang et al., 2019). The integration of these approaches into AI systems will be critical in ensuring that technological innovation does not come at the expense of ethical standards and consumer trust.

Model Bias and Fairness

Bias in AI models is a significant issue, particularly in areas like customer profiling and decision-making, where these systems may reinforce historical inequalities embedded in the training data. AI models, especially those trained on large datasets that reflect societal biases, can unintentionally perpetuate discrimination, resulting in unfair outcomes in areas such as hiring, lending, and marketing (Kartal Karatas, 2022; Kim et al., 2023). For instance, if training data contains biases based on race, gender, or socioeconomic status, the AI models may replicate these patterns, leading to skewed predictions and decisions that disproportionately affect marginalized groups (Kartal Karatas, 2022).

The opacity of AI models, commonly referred to as the "black box" problem, exacerbates these issues. In many cases, the complex nature of AI systems, particularly deep learning models, makes it difficult to trace how specific inputs lead to particular outcomes (Laclau et al., 2020; Martin & Waldman, 2022). This lack of transparency hinders efforts to detect and mitigate bias, as it is not always clear how certain decisions are made or why certain groups are disadvantaged. For example, in systems like predictive policing or credit scoring, biased inputs can result in discriminatory actions, such as increased surveillance in certain neighborhoods or reduced access to financial services for minority communities (Martin & Waldman, 2022). The inability to clearly explain the decision-making process further complicates efforts to hold AI systems accountable and rectify biased outcomes.

Efforts to address bias in AI have led to the development of fairness-enhancing algorithms, but these solutions often involve difficult trade-offs. For example, fairness metrics like equal opportunity or demographic parity aim to reduce bias across different demographic groups (Ma et al., 2023). However, optimizing for one fairness metric can sometimes worsen performance in another area, such as predictive accuracy or individual fairness (Zhang et al., 2020). This creates a balancing act in which achieving fairness for one group may inadvertently introduce biases or inaccuracies for others, complicating efforts to create truly unbiased AI models.

The ethical implications of biased AI systems are profound, as they can erode public trust in AI-driven decision-making processes. In sectors like healthcare and criminal justice, biased algorithms can lead to life-altering consequences for individuals, further underscoring the importance of addressing these issues (Shimao et al., 2019). For instance, biased algorithms in healthcare may result in unequal access to treatment or misdiagnoses, disproportionately affecting certain racial or ethnic groups (Vyas et al., 2020). In criminal justice, biased AI models can perpetuate discriminatory practices, such as over-policing in minority communities or biased sentencing decisions (Richardson et al., 2019).

One proposed solution to mitigate the ethical risks posed by biased AI is the development of explainable AI (XAI) systems, which aim to provide more transparency in decision-making processes (Gaurav & Tiwari, 2023). XAI offers stakeholders the ability to better understand how decisions are made, ensuring that biases can be identified and corrected. Transparent models also allow for greater accountability, as businesses and regulators can audit AI systems more effectively to ensure fairness and mitigate discriminatory outcomes (Shimao et al., 2019). Ultimately, addressing bias in AI models requires a combination of technical solutions, such as fairness metrics and XAI, alongside regulatory frameworks that promote accountability and protect against discrimination.

Technical Challenges in AI Implementation

AI implementation presents several technical challenges, primarily related to the need for high-quality data, substantial infrastructure, and the complexity of model deployment in dynamic business environments. One of the critical challenges is data quality. AI models rely heavily on vast amounts of accurate and well-structured data to deliver reliable predictions (Bérubé et al., 2021). However, many organizations face difficulties in ensuring that their datasets are free from bias, inconsistencies, or incomplete information. Poor data quality significantly impacts the performance and outcomes of AI systems, leading to inaccurate predictions and flawed decision-making (Bérubé et al., 2021).

Infrastructure requirements for AI implementation are another significant obstacle. AI models, particularly deep learning algorithms, demand considerable computational power and storage capacity (Radhakrishnan et al., 2022). This necessitates investments in advanced hardware, such as GPUs and cloud computing platforms, which may be cost-prohibitive for some organizations. Additionally, businesses must ensure that their existing IT infrastructure is capable of integrating AI technologies seamlessly, which can be challenging without the proper expertise or resources (Radhakrishnan et al., 2022).

Deploying AI models in real-time, dynamic business environments adds to the complexity. AI systems must be continuously updated and adapted to evolving data streams and changing business conditions (Nguyen-Duc et al., 2020). This requires robust monitoring and management tools to ensure that the models are functioning correctly and delivering accurate predictions (Sandkuhl, 2019). Model drift, where an AI model's performance degrades over time due to changes in data patterns, is a persistent issue that organizations must manage effectively to maintain optimal performance (Nguyen-Duc et al., 2020).

In addition to these technical challenges, AI implementation often encounters barriers related to organizational readiness. A lack of skilled personnel capable of developing, deploying, and maintaining AI systems is a common issue (Nigmatov & Pradeep, 2023). This skills gap can delay AI adoption and limit its effectiveness, especially in industries where AI is expected to be a critical driver of competitive advantage (Nigmatov & Pradeep, 2023).

In terms of infrastructure, AI models, particularly deep learning algorithms, demand substantial computational power and specialized hardware, such as GPUs or TPUs, to function effectively. The cost of such infrastructure can be prohibitive, especially for smaller organizations (Nguyen-Duc et al., 2020; Radhakrishnan et al., 2022). Moreover, maintaining the computational resources to handle large-scale data processing requires continuous investment in both hardware and cloud-based platforms (Nguyen-Duc et al., 2020). Many businesses face challenges integrating AI into their existing IT infrastructure, which is often not designed to support the intensive computational demands of AI technologies.

The deployment of AI models in dynamic business environments also presents significant challenges. AI systems must be adaptable, capable of continuous learning, and able to cope with rapidly changing data streams (Sandkuhl, 2019). In business settings where data patterns frequently evolve, the phenomenon of model drift—where an AI model's accuracy deteriorates over time—can present ongoing operational challenges (Sandkuhl, 2019). Regular model updates and retraining are required to maintain performance, which increases both the complexity and cost of AI system management.

Additionally, AI deployment requires robust integration with business processes and systems, which can be difficult to achieve in environments where operations are continually shifting (Reim et al., 2020). Many organizations lack the skilled workforce necessary to manage the complexities of AI model development and deployment, further slowing adoption and effectiveness (Reim et al., 2020).

Future Trends in Multi-Touch Attribution and Marketing ROI Optimization

Real-time Analytics and Hyper-personalization

AI-driven real-time analytics is transforming customer experiences by delivering hyper-personalized interactions based on dynamic data processing (Amosu et al., 2024). Real-time analytics enables businesses to gather insights into customer behaviours as they happen, allowing for immediate adjustments in marketing strategies to optimize customer engagement (Desai, 2022). This capacity to provide timely and relevant interactions helps improve customer retention and conversion rates, making it a key component of modern business strategies (Amosu et al., 2024).

Hyper-personalization takes this a step further by tailoring experiences to individual customer preferences, needs, and behaviours (Desai, 2022). Businesses can deliver personalized content and product recommendations in real-time by leveraging AI models, adjusting these offerings based on continuous data inputs (Tammana, 2022). This dynamic learning process allows for segmentation and targeting to become more precise over time, enhancing the effectiveness of personalized marketing campaigns (Desai, 2022).

For instance, systems like Pega’s Customer Decision Hub enable hyper-personalized experiences by processing real-time customer data across multiple channels (Tammana, 2022). This omnichannel approach ensures that customers receive tailored interactions, regardless of where they engage with the brand, improving overall satisfaction and loyalty (Tammana, 2022). As AI continues to evolve, its role in hyper-personalization will likely expand, with innovations such as AI-as-a-Service (AIaaS) enabling more businesses to adopt real-time analytics without the need for extensive infrastructure investments (Liu et al., 2020). This evolution will further improve the ability to deliver highly customized and immediate customer experiences.

Integration of AI with Other Technologies

The integration of AI with other emerging technologies such as IoT and blockchain has the potential to significantly enhance predictive analytics by leveraging the strengths of each technology (Mahalakshmi, 2019). IoT generates vast amounts of data through connected devices, and when combined with AI's machine learning algorithms, it enables the processing of this data in real-time to produce actionable insights (Priya et al., 2023). For instance, AI-driven predictive models can analyze IoT data to improve efficiency and decision-making across various industries, particularly in healthcare and logistics (Mahalakshmi, 2019).

Blockchain, on the other hand, brings security and trust to the integration. By using blockchain technology, AI systems can ensure the integrity and privacy of data, which is crucial for maintaining the reliability of predictive analytics (Dutta et al., 2022). Blockchain's decentralized nature enhances the transparency of data exchanges, enabling more accurate and secure analytics processes, particularly in industries that require robust data security, such as finance and healthcare (Dutta et al., 2022).

Moreover, the integration of AI, IoT, and blockchain supports advanced applications such as smart cities and autonomous vehicles by enabling real-time monitoring, decentralized decision-making, and secure data sharing (Chavali et al., 2020). This integrated system can provide hyper-personalized services and optimize urban infrastructure management (Chavali et al., 2020).

As AI continues to evolve alongside these technologies, its role in enhancing predictive analytics will expand, improving accuracy, security, and scalability across various applications (Priya et al., 2023).

The Role of Explainable AI (XAI)

Explainable AI (XAI) plays a critical role in enhancing trust and adoption in predictive analytics by providing transparency and interpretability in decision-making processes (Linkov et al., 2020). One of the primary concerns with AI systems is their "black box" nature, where users are often unable to understand how AI models arrive at certain predictions (Roszel et al., 2021). This opacity hinders trust, particularly in high-stakes applications such as healthcare or finance (Ha & Kim, 2023). Developing explainable AI models allows users to gain insights into how and why certain decisions are made, which is essential for fostering trust in AI systems (Linkov et al., 2020).

Incorporating explainability in AI models also helps address concerns about accountability, fairness, and ethical issues in predictive analytics (Roszel et al., 2021). Businesses and stakeholders can better assess whether the models are biased or discriminatory by making AI models more transparent (Ha & Kim, 2023). This, in turn, supports ethical AI deployment by ensuring that AI systems operate in a manner consistent with societal values and legal regulations (Roszel et al., 2021).

Moreover, explainable AI can mitigate cognitive biases, as research has shown that clear and interpretable AI explanations improve user trust, especially in decision-making scenarios (Ha & Kim, 2023). Explanations that highlight feature importance or provide textual reasoning are particularly effective in promoting user confidence and ensuring more reliable adoption of AI-driven systems in predictive analytics (Ha & Kim, 2023). Thus, explainable AI is essential not only for improving individual user trust but also for enhancing public trust in AI systems. It provides users with the tools to evaluate and validate the reliability of AI models, making AI adoption more feasible across diverse sectors (Ferrario & Loi, 2022).

CONCLUSION

The comparative analysis reveals that AI-driven models significantly outperform traditional models in terms of scalability, accuracy, and adaptability. While traditional models like logistic regression and decision trees offer more interpretability, they struggle with large datasets and fail to capture complex patterns in data. AI models, especially those utilizing machine learning and deep learning, excel in handling vast data volumes and delivering more precise predictions. However, AI models present challenges related to their "black box" nature, raising concerns about trust and accountability.

The integration of AI with technologies like IoT and blockchain enhances predictive analytics by enabling real-time data processing and ensuring data integrity. Additionally, Explainable AI (XAI) is crucial for improving trust and adoption, as it provides transparency and allows users to understand the decision-making process of AI models. Although AI implementation involves high costs and infrastructure requirements, its long-term benefits, such as operational efficiency and enhanced customer personalization, offer significant returns on investment. Addressing ethical concerns, such as bias and fairness in AI models, remains a priority to ensure responsible and equitable AI use across industries. Overall, AI-driven models provide more dynamic, scalable, and accurate solutions for predictive analytics compared to traditional approaches.

For e-commerce practitioners, the rise of AI-driven models presents significant opportunities for improving customer engagement, operational efficiency, and revenue growth. Marketers can leverage AI to deliver hyper-personalized experiences, tailoring recommendations, promotions, and content to individual customer preferences in real-time. This ability to offer personalized shopping experiences increases customer satisfaction and loyalty, directly impacting sales.

For data scientists, AI models offer advanced tools for analyzing vast amounts of customer data and identifying patterns that traditional models may miss. The integration of AI with other emerging technologies like IoT allows for real-time data collection and insights, enabling more proactive and informed decision-making. However, both marketers and data scientists must be aware of the challenges posed by AI, particularly in ensuring data quality and managing infrastructure requirements.

Furthermore, explainability and transparency in AI are crucial for maintaining trust with consumers and regulatory bodies. E-commerce businesses must ensure that AI models are interpretable and free from biases that could result in unfair customer profiling. Addressing ethical concerns and implementing explainable AI systems will be essential for maintaining consumer trust and complying with privacy regulations, ultimately supporting sustainable business growth in the AI-powered future of e-commerce.

Recommendation for Future Research

Future research should focus on enhancing the interpretability of AI models, particularly in high-stakes sectors like e-commerce, where transparency in decision-making is crucial for gaining consumer trust. Developing more effective explainable AI (XAI) frameworks will be essential for providing clearer insights into how AI systems make predictions, ensuring that both practitioners and end-users can understand and trust the outcomes.

Additionally, there is a need for deeper investigation into addressing ethical challenges related to AI, particularly concerning bias and fairness. As AI models continue to evolve, ensuring that they do not perpetuate or amplify societal biases will be critical. Research should explore new methods for debiasing AI models and establishing more robust fairness metrics that work across various applications and datasets.

The integration of AI with emerging technologies such as blockchain and IoT also presents exciting research opportunities. Exploring how these integrations can improve data security, scalability, and real-time decision-making could offer new ways to enhance predictive analytics in e-commerce. Finally, research into AI model governance, particularly in the context of regulatory compliance, will be necessary to ensure that AI systems meet legal standards and ethical guidelines. This will support the broader adoption of AI in e-commerce while safeguarding consumer rights.

REFERENCES

[1] Aalmoes, J., Duddu, V., & Boutet, A. (2022). Dikaios: Privacy Auditing of Algorithmic Fairness via Attribute Inference Attacks. *arXiv Preprints*, https://arxiv.org/abs/2202.02242.

[2] Aldridge, I. E. (2023). The AI Revolution: From Linear Regression to ChatGPT and beyond and How It All Connects to Finance. *Journal of Portfolio Management*, 49(4), 65-75. https://dx.doi.org/10.3905/jpm.2023.1.519.

[3] Alizadeh, M., Soleymannejad, M., & Moshiri, B. (2022). An OWA-Powered Dynamic Customer Churn Modeling in the Banking Industry Based on Customer Behavioural Vectors. *Proceedings*

of the International Conference on Information and Knowledge Technology, 1(1), 94-101. https://dx.doi.org/10.1109/IKT57960.2022.10039012.

[4] Amosu, O. R., Kumar, P., Fadina, A., Ogunsuji, Y. M., Oni, S., & Adetula, K. (2024). Harnessing real-time data analytics for strategic customer insights in e-commerce and retail. *World Journal of Advanced Research and Reviews*, 23(2), 2407. https://dx.doi.org/10.30574/wjarr.2024.23.2.2407.

[5] Basagaoglu, H., Chakraborty, D., Lago, C. D., Gutierrez, L., Şahinli, M. A., Giacomoni, M., Furl, C. V., Mirchi, A., Moriasi, D., & Şengör, S. S. (2022). A Review on Interpretable and Explainable Artificial Intelligence in Hydroclimatic Applications. *Water*, 14(8), 1230. https://dx.doi.org/10.3390/w14081230.

[6] Bérubé, M., Giannelia, T., & Vial, G. (2021). Barriers to the Implementation of AI in Organizations: Findings from a Delphi Study. *Proceedings of the Hawaii International Conference on System Sciences*, 805, 1-15. https://dx.doi.org/10.24251/HICSS.2021.805.

[7] Biswas, B., Sanyal, M., & Mukherjee, T. (2023). AI-Based Sales Forecasting Model for Digital Marketing. *International Journal of E-Business Research*, 317888, 89-99. https://dx.doi.org/10.4018/ijebr.317888.

[8] Bonicalzi, S., De Caro, M., & Giovanola, B. (2023). Artificial Intelligence and Autonomy: On the Ethical Dimension of Recommender Systems. *Topoi*, 10(1007), 09922-5. https://dx.doi.org/10.1007/s11245-023-09922-5.

[9] Chavali, B., Khatri, S., & Hossain, S. A. (2020). AI and Blockchain Integration. *Proceedings of the International Conference on Information Technology*, 48877, 7847. https://dx.doi.org/10.1109/ICRITO48877.2020.9197847.

[10] Cho, S., Kim, I., Kim, J.-H., Woo, H., & Shin, W.-S. (2023). A Maturity Model for Trustworthy AI Software Development. *Applied Sciences*, 13(8), 4771. https://dx.doi.org/10.3390/app13084771.

[11] Cirqueira, D., Hofer, M., Nedbal, D., Helfert, M., & Bezbradica, M. (2019). Customer Purchase Behaviour Prediction in E-commerce: A Conceptual Framework and Research Agenda. *Lecture Notes in Business Information Processing*, 8, 144-161. https://dx.doi.org/10.1007/978-3-030-48861-1_8.

[12] Davenport, T. (2018). From analytics to artificial intelligence. *Journal of Information Technology Teaching Cases*, 8(2), 107-113. https://dx.doi.org/10.1080/2573234X.2018.1543535.

[13] Desai, D. (2022). Hyper-Personalization. In *Data-Driven Marketing Strategies for E-Commerce*. IGI Global. https://dx.doi.org/10.4018/978-1-7998-7959-6.ch003.

[14] Du, J., Wang, X., & Liu, X. (2021). Demand Prediction for E-Commerce Multi-Warehouse Based on Machine Learning. *Proceedings of the International Conference on Business Intelligence*, 5, 98-107. https://dx.doi.org/10.1201/9781003144977-5.

[15] Dutta, J., Puthal, D., & Damiani, E. (2022). AI-based Block Identification and Classification in the Blockchain Integrated IoT. *Proceedings of the International Conference on IoT*, 56763, 84. https://dx.doi.org/10.1109/OCIT56763.2022.00084.

[16] Emani, M., Foreman, S., Sastry, V. K., Xie, Z., Raskar, S., Arnold, W., Thakur, R., Vishwanath, V., & Papka, M. (2023). A Comprehensive Performance Study of Large Language Models on Novel AI Accelerators. *arXiv*, 2310.04607, 1-20. https://dx.doi.org/10.48550/arXiv.2310.04607.

[17] Ersahin, A., Gul, S., Ertekin, T., & Temizel, C. (2019). Artificial Neural Network Modeling of Cyclic Steam Injection Process in Naturally Fractured Reservoirs. *Society of Petroleum Engineers*, 195307-MS. https://dx.doi.org/10.2118/195307-MS.

[18] Ferrario, A., & Loi, M. (2022). How Explainability Contributes to Trust in AI. *Proceedings of the ACM Conference on Fairness, Accountability, and Transparency*, 12(1), 134-142. https://dx.doi.org/10.1145/3531146.3533202.

[19] Fomude, A. H., Yang, C., Agordzo, G. K., Serwah, A. V., & Abangbila, L. (2023). AI Model to Improve HR Decision-Making with Machine Learning Predictions Algorithm.

Proceedings of the International Conference on Advanced Communication Technology, 56868, 10079282. https://dx.doi.org/10.23919/ICACT56868.2023.10079282.

[20] Framling, K. (2020). Explainable AI without Interpretable Model. *arXiv*, 2009.13996. https://arxiv.org/abs/2009.13996.

[21] Fu, C., & An, R. (2022). Research on E-commerce Mathematical Forecasting Model based on Hybrid Neural Network. *IEEE International Conference on Emerging Technologies and Intelligent Systems*, 23(4), 98-107. https://dx.doi.org/10.1109/icetci55101.2022.9832316.

[22] Gan, P. (2013). Users Shopping Behaviour Mining of B2C E-Commerce. *Applied Mechanics and Materials*, 765-767, 1568-1571. https://dx.doi.org/10.4028/www.scientific.net/AMR.765-767.1568.

[23] Gaurav, D., & Tiwari, S. (2023). Interpretability Vs Explainability: The Black Box of Machine Learning. *Proceedings of the International Conference on Computing, Communication, and Intelligent Systems (ICCoSITE)*, 57641, 10127717. https://dx.doi.org/10.1109/ICCoSITE57641.2023.10127717.

[24] Gschwind, M. (2022). ScaDL 2022 Invited Talk 4: Sustainable AI @ Scale: Accelerating AI models for billions of users. *Proceedings of the International Conference on Parallel and Distributed Processing Symposium Workshops (IPDPSW)*, 55747, 00169. https://dx.doi.org/10.1109/IPDPSW55747.2022.00169.

[25] Gupta, R., Kamble, P., Negandhi, V., & Hutke, A. (2020). Customer Behaviour Analysis and Revenue Prediction System. *International Journal of Engineering Research and Technology*, 9(4), 243-250. https://dx.doi.org/10.35291/2454-9150.2020.0245.

[26] Ha, T., & Kim, S. (2023). Improving Trust in AI with Mitigating Confirmation Bias: Effects of Explanation Type and Debiasing Strategy for Decision-Making with Explainable AI. *International Journal of Human-Computer Interaction*, 39(11), 897-910. https://dx.doi.org/10.1080/10447318.2023.2285640.

[27] Hemalatha, A. (2023). AI-Driven Marketing: Leveraging Artificial Intelligence for Enhanced Customer Engagement. *Journal of Consumer Behaviour and E-Commerce*, 978-93-91303-61-7, 45-62. https://dx.doi.org/10.47715/jpc.b.978-93-91303-61-7.

[28] Huang, S. (2021). AI-based Repeat Buyers Prediction System using Deep Learning. *Proceedings of the International Conference on Signal Processing (ICSP)*, 51882, 9408760. https://dx.doi.org/10.1109/ICSP51882.2021.9408760.

[29] Idogho, J., & George, G. (2022). Path Loss Prediction Based on Machine Learning Techniques: Support Vector Machine, Artificial Neural Network, and Multilinear Regression Model. *Open Journals of Physical Science*, 3(2), 14-23. https://dx.doi.org/10.52417/ojps.v3i2.393.

[30] Jain, A., Karthikeyan, V., S. B., Shambhavi, B. R., S. K., & Balaji, S. (2020). Demand Forecasting for E-Commerce Platforms. *Proceedings of the International Conference on Computing and Networking (INOCON)*, 9298395. https://dx.doi.org/10.1109/INOCON50539.2020.9298395.

[31] Jangra, G., & Jangra, M. (2022). Role of Artificial Intelligence in Online Shopping and its Impact on Consumer purchasing behaviour and Decision. *Proceedings of the International Conference on Computational Intelligence and Security (ICCSEA)*, 54677, 9936374. https://dx.doi.org/10.1109/ICCSEA54677.2022.9936374.

[32] Kale, R., Bidwai, K., Maske, M., Bansode, R., & Gurav, P. (2022). Prediction of Customer Purchase Intention using Social Media Data. *International Journal of Advanced Research in Science, Communication and Technology*, 4003, 23-35. https://dx.doi.org/10.48175/ijarsct-4003.

[33] Kartal Karatas, E. (2022). A Comprehensive Study on Bias in Artificial Intelligence Systems: Biased or Unbiased AI, That's the Question! *International Journal of Information*

Technology, 11(1), 23-33. https://dx.doi.org/10.4018/ijiit.309582.

[34] Khashei, M., & Sharif, B. M. (2020). A Kalman filter-based hybridization model of statistical and intelligent approaches for exchange rate forecasting. *Journal of Modelling in Management*, 15(4), 845-861. https://dx.doi.org/10.1108/jm2-12-2019-0277.

[35] Khosravy, M., Nakamura, K., Pasquali, A., Witkowski, O., Nitta, N., & Babaguchi, N. (2022). When AI Facilitates Trust Violation: An Ethical Report on Deep Model Inversion Privacy Attack. *Proceedings of the International Conference on Computational Science and Computational Intelligence (CSCI)*, 58124, 00166. https://dx.doi.org/10.1109/CSCI58124.2022.00166.

[36] Khrisat, M. S., Alabadi, A., Khawatreh, S., Al-Dwairi, M., & Alqadi, Z. (2022). Autoregressive Prediction Analysis Using Machine Deep Learning. *Indonesian Journal of Electrical Engineering and Computer Science*, 27(3), 1509-1516. https://dx.doi.org/10.11591/ijeecs.v27.i3.pp1509-1516.

[37] Kim, S., Kim, S., Kim, K., & Kim, Y. (2023). Lq regularization for fair artificial intelligence robust to covariate shift. *Statistical Analysis and Data Mining: The ASA Data Science Journal*, 16(1), 51-66. https://dx.doi.org/10.1002/sam.11616.

[38] Kojs, K. (2023). A Survey of Serverless Machine Learning Model Inference. *arXiv*, 2311.13587, 1-12. https://dx.doi.org/10.48550/arXiv.2311.13587.

[39] Kumar, R. (2023). Hybrid Machine Learning Method for Product Sales Forecasting in E-Commerce. *Proceedings of the International Conference on Smart Engineering*, 102(1), 235-241. https://dx.doi.org/10.1109/ICOSEC58147.2023.10276171.

[40] Kurihara, Y., & Fukushima, A. (2019). AR Model or Machine Learning for Forecasting GDP and Consumer Price for G7 Countries. *Applied Economics and Finance*, 6(3), 86-98. https://dx.doi.org/10.11114/AEF.V6I3.4126.

[41] Kurosawa, T., Inoue, A., & Nishimatsu, K. (2005). Service demand analysis using customer-choice behaviour modeling, with consideration of awareness and perception. *EEE International Conference*, 4(1), 74-79. https://dx.doi.org/10.1109/EEE.2005.119.

[42] Laclau, C., Redko, I., Choudhary, M., & Largeron, C. (2020). All of the fairness for edge prediction with optimal transport. *arXiv Preprints*, https://arxiv.org/abs/2010.16326.

[43] Landgrebe, J. (2022). Certifiable AI. *Applied Sciences*, 12(3), 1050. https://dx.doi.org/10.3390/app12031050.

[44] Liang, B. (2023). AI Computing in Large-Scale Era: Pre-trillion-scale Neural Network Models and Exa-scale Supercomputing. *Proceedings of the International Conference on VLSI-TSA and VLSI-DAT*, 57221, 10134466. https://dx.doi.org/10.1109/VLSI-TSA/VLSI-DAT57221.2023.10134466.

[45] Linkov, I., Galaitsi, S., Trump, B. D., Keisler, J., & Kott, A. (2020). Cybertrust: From Explainable to Actionable and Interpretable Artificial Intelligence. *IEEE Computer*, 53(9), 102-106. https://dx.doi.org/10.1109/MC.2020.2993623.

[46] Liu, X., Wang, J., Zhang, W., Zheng, Q., & Li, X. (2020). EmotionTracker: A Mobile Real-time Facial Expression Tracking System with the Assistant of Public AI-as-a-Service. *Proceedings of the ACM Conference on Mobile Computing and Networking*, 2020, 441-447. https://dx.doi.org/10.1145/3394171.3414447.

[47] López de Mántaras, R. (2018). Progressos, reptes i riscos de la Intel·ligència Artificial. *Mètode Science Studies Journal*, 9, 45-55. https://dx.doi.org/10.7203/metode.9.11145.

[48] Luo, L., Li, B., Koprinska, I., Berkovsky, S., & Chen, F. (2017). Tracking the Evolution of Customer Purchase Behaviour Segmentation via a Fragmentation-Coagulation Process. *Proceedings of the International Joint Conference on Artificial Intelligence*, 336, 56-64. https://dx.doi.org/10.24963/ijcai.2017/336.

[49] Ma, S.-C., Ermakova, T., & Fabian, B. (2023). FairGridSearch: A framework to compare fairness-enhancing models. *Proceedings of the IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*, 64-72.

https://dx.doi.org/10.1109/WI-IAT59888.2023.00064.

[50] Mahalakshmi, S. (2019). Artificial Intelligence with the Internet of Things on Healthcare systems: A Survey. *International Journal of Advanced Trends in Computer Science and Engineering*, 2786, 15 December. https://dx.doi.org/10.30534/ijatcse/2019/27862019.

[51] Manolache, F. B., & Rusu, O. (2016). General valuation framework for artificial intelligence models. *Proceedings of the International Conference on Telecommunications and Signal Processing*, 1(3), 236-240. https://dx.doi.org/10.1109/ROEDUNET.2016.7753204.

[52] Marek, A., Rampp, M., Reuter, K., & Laure, E. (2023). Beyond the Fourth Paradigm — the Rise of AI. *Proceedings of the International Conference on e-Science*, 58273, 10254904. https://dx.doi.org/10.1109/e-Science58273.2023.10254904.

[53] Martin, K. E., & Waldman, A. (2022). Are Algorithmic Decisions Legitimate? The Effect of Process and Outcomes on Perceptions of Legitimacy of AI Decisions. *Journal of Business Ethics*, 175(1), 57-75. https://dx.doi.org/10.1007/s10551-021-05032-7.

[54] Morales, C. G., Gisolfi, N., Edman, R., Miller, J. K., & Dubrawski, A. (2021). Provably Robust Model-Centric Explanations for Critical Decision-Making. *arXiv*, 2110.13937. https://arxiv.org/abs/2110.13937.

[55] Mühlhoff, R. (2023). Predictive privacy: Collective data protection in the context of artificial intelligence and big data. *Big Data & Society*, 10(1), 20539517231166886. https://dx.doi.org/10.1177/20539517231166886.

[56] Nagrath, P., Nguyen, T. N., Aggarwal, S., & Hemanth, D. (2021). A comprehensive E-commerce customer behaviour analysis using convolutional methods. *Computers & Electrical Engineering*, 96, 107541. https://dx.doi.org/10.1016/j.compeleceng.2021.107541.

[57] Ng, P., Khoo, M., Yeong, W. C., Saha, S., & Chew, X. (2021). Economic and Economic-Statistical Designs of the Side Sensitive Group Runs Chart with Auxiliary Information. *Quality and Reliability Engineering International*, 37(2), 941-960. https://dx.doi.org/10.1002/QRE.2841.

[58] Nguyen-Duc, A., Sundbø, I., Nascimento, E., Conte, T., & Abrahamsson, P. (2020). A Multiple Case Study of Artificial Intelligent System Development in Industry. *Proceedings of the ACM/IEEE International Conference on Software Engineering*, 12(3), 222-231. https://dx.doi.org/10.1145/3383219.3383220.

[59] Nigmatov, A., & Pradeep, A. (2023). The Impact of AI on Business: Opportunities, Risks, and Challenges. *Proceedings of the International Conference on Advanced Communications and Information Technologies (ACIT)*, 58437, 10275510. https://dx.doi.org/10.1109/ACIT58437.2023.10275510.

[60] Nkemnole, E., & Nwaokoro, E. (2020). Modelling Customer Relationships as Hidden Markov Chains. *Path of Science*, 6(4), 23-30. https://dx.doi.org/10.22178/pos.64-9.

[61] Ntawanga, F., Calitz, A., & Barnard, L. (2008). Maintaining customer profiles in an e-commerce environment. *Proceedings of the Annual Conference of the South African Institute of Computer Scientists and Information Technologists on IT Research in Developing Countries*, 39-46. https://dx.doi.org/10.1145/1456659.1456679.

[62] Ozan, Ş., & Iheme, L. O. (2019). Artificial Neural Networks in Customer Segmentation. *Proceedings of the Signal Processing and Communication Applications Conference (SIU)*, 8806558, 112-121. https://dx.doi.org/10.1109/SIU.2019.8806558.

[63] Peltz, J. J., & Street, A. (2020). Artificial Intelligence and Ethical Dilemmas Involving Privacy. *Emerald Publishing*, 1(1), 20. https://dx.doi.org/10.1108/978-1-78973-811-720201006.

[64] Priya, S. J., Aruna, S., Tasneem Firdhosh A., U. L., Malavikka S., & Monika S. (2023). Revolutionizing Industries Through IoT, Blockchain and AI Integration. *Proceedings of the International Conference on Pervasive Computing and Social Networking*, 58827, 166. https://dx.doi.org/10.1109/ICPCSN58827.2023.00166.

[65] Radhakrishnan, J., Gupta, S., & Prashar, S. (2022). Understanding Organizations' Artificial Intelligence Journey: A Qualitative Approach. *Pacific Asia Journal of the Association for Information Systems*, 14(1), 31-51. https://dx.doi.org/10.17705/1pais.14602.

[66] Rausch, M., & Sanders, W. (2020). Stacked Metamodels for Sensitivity Analysis and Uncertainty Quantification of AMI Models. *Proceedings of the International Conference on Smart Grid Communications (SmartGridComm)*, 47815, 9302957. https://dx.doi.org/10.1109/SmartGridComm47815.2020.9302957.

[67] Reim, W., Åström, J., & Eriksson, O. (2020). Implementation of Artificial Intelligence (AI): A Roadmap for Business Model Innovation. *AI*, 1(2), 180-191. https://dx.doi.org/10.3390/ai1020011.

[68] Richardson, R., Schultz, J. M., & Crawford, K. (2019). Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice. *New York University Law Review*, 94(1), 192-233. https://www.nyulawreview.org/wp-content/uploads/2019/04/NYULawReview-94-Richardson-Schultz-Crawford.pdf.

[69] Riedel, M., Barakat, C., Fritsch, S., Aach, M., Busch, J., Lintermann, A., Schuppert, A., Brynjólfsson, S., Neukirchen, H., & Book, M. (2023). Enabling Hyperparameter-Tuning of AI Models for Healthcare using the CoE RAISE Unique AI Framework for HPC. *Proceedings of the International Conference on Information Technology and Electrical Engineering (MIPRO)*, 57284, 10159755. https://dx.doi.org/10.23919/MIPRO57284.2023.10159755.

[70] Rogha, M. (2023). Explain To Decide: A Human-Centric Review on the Role of Explainable Artificial Intelligence in AI-assisted Decision Making. *arXiv*, 2312.11507. https://dx.doi.org/10.48550/arXiv.2312.11507.

[71] Roszel, M., Norvill, R., Hilger, J., & State, R. (2021). Know Your Model (KYM): Increasing Trust in AI and Machine Learning. *arXiv Preprints*. https://arxiv.org/abs/2106.11036.

[72] Ruamviboonsuk, P., Chantra, S., Seresirikachorn, K., Ruamviboonsuk, V., & Sangroongruangsri, S. (2021). Economic Evaluations of Artificial Intelligence in Ophthalmology. *Asia-Pacific Journal of Ophthalmology*, 10(3), 256-263. https://dx.doi.org/10.1097/APO.0000000000000403.

[73] Sakai, T., Hara, Y., Seshadri, R., Alho, A., Hasnine, M. S., Jing, P., Chua, Z. Y., & Ben-Akiva, M. (2022). Household-based E-commerce demand modeling for an agent-based urban transportation simulation platform. *Applied Mathematical Modelling*, 46(2), 785-804. https://dx.doi.org/10.1080/03081060.2022.2084397.

[74] Sandkuhl, K. (2019). Putting AI into Context - Method Support for the Introduction of Artificial Intelligence into Organizations. *Proceedings of the Conference on Business Informatics (CBI)*, 25, 1-10. https://dx.doi.org/10.1109/CBI.2019.00025.

[75] Sepp, A. (2021). State of the Art of Predictive Modeling for Real-life Applications. *OSF Preprints*, 1(1), 2-17. https://dx.doi.org/10.31219/osf.io/m3y4v.

[76] Sharma, A. (2023). Product design and development using Artificial Intelligence (AI) techniques: A review. *Engrxiv* https://doi.org/10.31224/2958

[77] Shekary Ashkezary, M., Albadavi, A., & Shekari Ashkezari, M. (2019). Presenting a Model for Calculating ISACO Customers Lifetime Value by Markov Chain using data mining techniques. *International Journal of Industrial Engineering & Production Research*, 30(4), 429-441. https://dx.doi.org/10.22068/IJIEPR.30.4.429.

[78] Shen, Z., & Su, X. (2007). Customer Behaviour Modeling in Revenue Management and Auctions: A Review and New Research Opportunities. *Production and Operations Management*, 16(6), 713-728. https://dx.doi.org/10.1111/j.1937-5956.2007.tb00291.x.

[79] Shih, Y., & Lin, M. (2019). A LSTM Approach for Sales Forecasting of Goods with Short-Term Demands in E-Commerce. *Lecture Notes in Business Information Processing*, 21(1), 203-213. https://dx.doi.org/10.1007/978-3-030-14799-0_21.

[80] Shimao, H., Komiyama, J., Khern-am-nuai, W., & Kannan, K. N. (2019). Strategic Best Response Fairness in Fair Machine Learning. *SSRN*, https://dx.doi.org/10.2139/ssrn.3389631.

[81] Sing, T., Yang, J., & Yu, S. (2020). Decision Tree and Boosting Techniques in Artificial Intelligence-Based Automated Valuation Models (AI-AVM). *SSRN*. https://dx.doi.org/10.2139/ssrn.3605798.

[82] Subramani, N., Prakash, V., PranavKumar, M. S., & Balasubramaniam, R. (2023). Forecasting of E-Commerce System for Sale Prediction Using Deep Learning Modified Neural Networks. *Proceedings of the International Conference on Artificial Intelligence and Smart Cities (ICAISC)*, 10199817. https://dx.doi.org/10.1109/ICAISC58445.2023.10199817.

[83] Sundareswaran, G., Kamaraj, H., Sanjay, S., Devi, A., Elangovan, P., & Kruthikkha, P. (2022). Consumer Behaviour Analysis. *Injuratech*, 2(1), 45-58. https://dx.doi.org/10.34010/injuratech.v2i1.6536.

[84] Talpur, M. G. H., & Marri, A. (2021). Forecasting Using Neural Networks and Stochastic Models on Day of the Week Effect: A Case Study of KSE 100 Index. *Journal of Contemporary Issues in Business and Government*, 27(5), 116-122. https://dx.doi.org/10.47750/CIBG.2021.27.05.116.

[85] Tammana, P. K. (2022). Real-Time Decision Making with Pega Customer Decision Hub: Transforming Customer Experience in the Digital Age. *Journal of Artificial Intelligence and Computational Computing*, 1(202), 1-8. https://dx.doi.org/10.47363/jaicc/2022(1)202.

[86] Tang, T. (2023). Analysis and Demand Forecasting Based On e-Commerce Data. *International Conference on Artificial Intelligence and Big Data (ICAIBD)*, 571-576. https://dx.doi.org/10.1109/ICAIBD57115.2023.10206072.

[87] Thakial, S., & Arora, B. (2019). Neural Network Based Prediction Model for Job Applicants. *Journal of Computational and Theoretical Nanoscience*, 16(8), 3297-3301. https://dx.doi.org/10.1166/jctn.2019.8263.

[88] Ulkhaq, M., Adyatama, A., Fidiyanti, F., Rozaq, R., & Raharjo, M. (2020). An Artificial Neural Network Approach for Predicting Customer Loyalty: A Case Study in an Online Travel Agency. *International Journal of Machine Learning and Computing*, 10(2), 133-137. https://dx.doi.org/10.18178/ijmlc.2020.10.2.933.

[89] Vyas, D. A., Eisenstein, L. G., & Jones, D. S. (2020). Hidden in Plain Sight—Reconsidering the Use of Race Correction in Clinical Algorithms. *The New England Journal of Medicine*, 383, 874-882. https://dx.doi.org/10.1056/NEJMms2004740

[90] Wang, T., Zhao, J., Yu, H., Liu, J., Yang, X., Ren, X., & Shi, S. (2019). Privacy-preserving Crowd-guided AI Decision-making in Ethical Dilemmas. *Proceedings of the International Conference on World Wide Web (WWW)*, 3357384, 3357954. https://dx.doi.org/10.1145/3357384.3357954.

[91] Wu, J., Shi, L. N., Lin, W. P., Tsai, S., Li, Y., Yang, L., & Xu, G. (2020). An Empirical Study on Customer Segmentation by Purchase Behaviours Using a RFM Model and K-Means Algorithm. *Mathematical Problems in Engineering*, 2020, 8884227. https://dx.doi.org/10.1155/2020/8884227.

[92] Xu, D., Yuan, S., & Wu, X. (2019). Achieving Differential Privacy and Fairness in Logistic Regression. *Proceedings of the 28th International Conference on World Wide Web (WWW)*, 3308560, 3317584. https://dx.doi.org/10.1145/3308560.3317584.

[93] Yong, S. C. S., Huan, R. T., Poh, W. S., Osman, M., & Ng, D. C. W. (2023). Assessing the Factors Influencing Consumer Behaviour in E-Commerce Platforms. *International Journal of Management, Business, and Economics Research*, 4(10), 456-478. https://dx.doi.org/10.11594/ijmaber.04.10.25.

[94] Zhang, C., Liu, B., Mohammed, B., & Jumani, A. (2023). Big Data Assisted Empirical Study for Business Value Identification Using Smart Technologies: An Empirical Study for Business Value Identification of Big Data Adaption in E-Commerce. *International Journal of E-Commerce Research*, 316882, 111-125. https://dx.doi.org/10.4018/ijec.316882.

[95] Zhang, Y., Bellamy, R. K., & Varshney, K. R. (2020). Joint Optimization of AI Fairness and Utility: A Human-Centered Approach. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(1), 784-791. https://dx.doi.org/10.1145/3375627.3375862.

[96] Zhong, W. (2021). E-commerce Service Equilibrium Prediction Simulation Based on Ontology. *2021 21st International Conference on Data, Communication & Computer Networks*, 89-98. https://dx.doi.org/10.1109/DCABES52998.2021.00009.

[97] Zulaikha, S., Mohamed, H. M. H. H. M., Kurniawati, M., Rusgianto, S., & Rusmita, S. (2020). Customer Predictive Analytics Using Artificial Intelligence. *Asia-Pacific Journal of Operational Research*, 48(2), 1-13. https://dx.doi.org/10.1142/s0217590820480021