AIRA
ARTIFICIAL INTELLIGENCE RESEARCH
AND APPLIED LEARNING

Vol. 3, No. 1, January 2024
AIRA: Artificial Intelligence Research
and Applied Learning
https://journal.dinamikapublika.id/index.php/aira

MARKET TREND PREDICTION IN DIGITAL BUSINESS THROUGH MACHINE LEARNING INTEGRATION

Herry Mulyono[1]

[1]Department of Management, Faculty of Business and Management, Universitas Dinamika Bangsa, Jambi, Indonesia

E-mail: [1)] herry.mulyono@unama.ac.id

ABSTRACT

In the rapidly evolving digital economy, businesses are increasingly relying on data-driven strategies to remain competitive. This essay explores the integration of machine learning (ML) techniques to predict market trends in digital business environments. The key issue addressed is the challenge of identifying and responding to dynamic market shifts in real-time, which traditional forecasting methods often fail to handle effectively. The objective of this study is to examine how ML models can process large-scale, complex datasets to generate accurate and timely predictions. The method involves a qualitative review of various ML algorithms—such as decision trees, random forests, and neural networks—and their application in market trend analysis. The discussion highlights the strengths and limitations of each approach, emphasizing the importance of data quality and contextual relevance. The results indicate that ML offers significant advantages in forecasting market behavior, enabling businesses to enhance decision-making, optimize resource allocation, and gain a strategic edge. This integration not only improves operational efficiency but also supports proactive responses to consumer demand and market volatility. The findings suggest that with continued development, ML will become a core component of future business intelligence systems.

Keywords*:* ***Machine Learning, Market Trend, Digital Business***

1. INTRODUCTION

The integration of machine learning (ML) techniques in predicting market trends within the context of digital business is increasingly recognized for its potential to enhance analytical capabilities and business intelligence. The rapid evolution of technologies, particularly those encompassing data analytics and machine learning, has heightened the urgency to explore these domains. Organizations today face significant challenges related to forecasting market behavior accurately, given the complexity and volatility characteristic of the digital marketplace. These concerns underscore the necessity for robust solutions that can facilitate more informed decision-making regarding strategies in marketing, product development, and customer engagement.

The ability to predict market trends using machine learning can help organizations mitigate risks associated with market uncertainties. Significant research supports this notion. For instance, studies have demonstrated that machine learning models can successfully analyze large datasets to uncover underlying patterns in consumer behavior, sentiment, and market dynamics, thereby informing strategic business decisions effectively (CardonaAcevedo et al., 2025; Durga et al., 2023).

Furthermore, with advances in cloud computing and big data technologies, it has become feasible for businesses to leverage scalable ML solutions that provide real-time insights, optimizing operational efficiency and competitive advantage (Hung, 2019).

To address market unpredictability and facilitate timely responses, businesses are increasingly employing ML algorithms for various predictive analytics tasks. These algorithms serve different aspects of digital businesses, including customer churn prediction (Nagaraj et al., 2023), sales forecasting, and the identification of market segments. Notably, the use of sentiment analysis on social media data has emerged as a powerful tool for market prediction, revealing consumer sentiments that strongly correlate with market movements (Awan et al., 2021). By analyzing factors such as social engagement, businesses can refine their marketing strategies and forecast potential changes in consumer demand with a higher degree of precision.

In addition to social media sentiment, machine learning has shown promise in enhancing traditional business intelligence methods. The convergence of AI with data-driven decision-making allows companies to develop more comprehensive insights into market trends and consumer preferences. For instance, the integration of ML in e-commerce environments has led to the implementation of systems that predict customer behavior based on historical purchase patterns and browsing history (Javaid et al., 2022). These predictive models can significantly reduce customer acquisition costs while maximizing the effectiveness of marketing campaigns (Ma & Sun, 2020). They represent a transformative approach to understanding customer needs and delivering personalized experiences that align with contemporary consumer expectations.

Moreover, the relevance of machine learning extends beyond consumer-facing applications. Its implementation in predictive maintenance and operational analytics is helping businesses optimize their supply chain operations (Ahmadian et al., 2020). Predictive models trained on historical data can alert businesses to equipment failures or supply shortages, enabling proactive measures to mitigate potential downtimes and safeguard revenue flows. This presents a strong rationale for organizations across industries to invest in integrating ML technologies to enhance operational resilience and customer satisfaction.

A significant challenge in these endeavors remains harnessing the power of machine learning effectively. This requires not only the deployment of suitable technologies but also cultivating a data-driven culture within organizations. The importance of workforce training in analytics and machine learning cannot be overstated; organizations must prioritize upskilling employees to interpret ML-generated data meaningfully (Mbunge et al., 2022). Additionally, ethical considerations regarding data privacy and model transparency must be integrated into machine learning initiatives to foster trust among consumers. Balancing the enhancement of predictive capabilities while maintaining ethical standards is core to successful implementation strategies.

As businesses continue to confront a competitive landscape characterized by rapid technological evolution, the integration of machine learning for predicting market trends will be a key determinant of success. It facilitates the transformation of raw data into actionable insights, aiding in the identification of emerging trends and consumer needs. The push for continuous innovation in ML applications will fuel progress in various sectors, driving efficiency and fostering adaptability to changing market conditions.

In summary, the integration of machine learning in forecasting market trends presents both substantial opportunities and challenges. Exploring this frontier necessitates a comprehensive understanding of the intricate dynamics of digital business and technological capabilities. By harnessing the potential of ML, organizations can strategically position themselves for future growth, sustainability, and competitive resilience in the ever-evolving digital economy.

2. RESEARCH METHOD

The integration of machine learning (ML) in predicting market trends for digital businesses involves a structured methodology that encompasses the selection of activities, the identification of target audiences, the design and utilization of tools, and the overall assessment of productivity. The following sections detail the methodology, focusing on these aspects while substantiating them with relevant scholarly references.

2.1. Methodology Design Objective Development and Activity Planning

The initial step in the methodological framework is to define clear objectives. This entails establishing what the machine learning application aims to achieve, such as improving customer engagement, forecasting sales, or enhancing operational efficiency. Identifying precise goals enables businesses to tailor their machine learning strategies accordingly. A well-defined objective enhances the effectiveness of predictive analytics in e-commerce environments (Nagaraj et al., 2023; Girimurugan et al., 2024).

Additionally, the process involves developing a detailed plan of activities that align with these objectives. A well-structured plan helps in understanding the scope and resources needed to execute machine learning applications successfully (Cardona-Acevedo et al., 2025; .

2.2. Target Audience Selection Identifying Relevant Demographic Segments

Selecting the target audience is critical to ensuring that machine learning models yield actionable insights. Understanding demographic segments such as age, gender, purchasing behavior, and preferences allows for the customization of marketing strategies and predictive models. The framework known as MAEVE assists in generating datasets that can predict customer behavior by effectively segmenting potential audiences (Filho et al., 2024).

Moreover, employing techniques such as cluster analysis using machine learning can help categorize customers into distinct groups based on their behavior. This approach has been shown to enhance the accuracy of predictions related to customer preferences and purchasing habits, which can lead to higher sales and improved customer satisfaction (Varalakshmi et al., 2025)Ma & Sun, 2020).

2.3. Tools and Materials Selection of Analytical Tools and Software

The tools utilized for machine learning implementation can significantly influence the outcomes of predictive analytics. Various programming languages and software platforms are commonly employed in this domain, including Python, R, and specialized platforms like TensorFlow and Scikit-learn. These tools facilitate the development, testing, and deployment of machine learning models (Cardona-Acevedo et al., 2025; Nafizza et al., 2023).

Furthermore, modern advancements in quantum machine learning (QML) promise substantial improvements regarding processing velocities and analytical capabilities. Integrating QML techniques can enhance predictive functionalities, particularly concerning customer behavior and preferences in online marketing (Varalakshmi et al., 2025).

2.4. Tool Design and Performance Evaluation Designing Machine Learning Algorithms

The design of the tools is as important as the selection of methodologies. Developing robust algorithms that can analyze vast datasets effectively enables businesses to identify patterns and predict trends. Predictive analytics tools must incorporate advanced features such as feature selection and complex network analysis to optimize accuracy (Durga et al., 2023; Castilho et al., 2023).

Performance evaluation of the models is conducted through metrics such as accuracy, precision, recall, and F1-score, which reflect the model's capabilities in making correct predictions. Experimenting with algorithms like decision trees, neural networks, and ensemble methods allows businesses to determine the most effective machine learning model for their specific applications (Geetha et al., 2024; Javaid et al., 2022).

2.5.Data Collection Techniques Utilizing Contemporary Data Gathering Methods

Data collection techniques play a pivotal role in the success of machine learning projects. Various methods such as surveys, web scraping, and social media data mining provide rich repositories of information. Techniques like sentiment analysis on social media can unveil customer sentiments regarding products or services, thus informing predictive models that gauge market trends (Awan et al., 2021; (Chennupati et al., 2024).

Moreover, implementing big data technologies enhances the ability to gather and process data at unprecedented scales. For instance, leveraging tools that integrate with cloud computing facilities can facilitate efficient data storage and retrieval, supporting the continuous flow of analytics required for machine learning applications (Hung, 2019).

2.6. Data Analysis Techniques Employing Advanced Analytical Frameworks

Once data is collected, sophisticated analysis techniques are employed to extract meaningful insights. Using statistical analysis, machine learning models can decipher relationships and patterns within the data. Predictive analytics often incorporates supervised and unsupervised learning techniques, allowing for nuanced insights into customer behavior and market dynamics (Nagaraj et al., 2023; Nafizza et al., 2023).

Combining web scraping with sentiment analysis also enables businesses to gauge public sentiment over time, translating into actionable insights concerning marketing strategies (Chennupati et al., 2024). The integration of these techniques can significantly enhance the predictive performance of the overall business model, enabling almost real-time responsiveness to market changes.

The PRISMA (Preferred Reporting Items for Systematic Reviews and MetaAnalyses) diagram outlines the comprehensive methodology employed in identifying, screening, and selecting studies for inclusion in the systematic review. The process begins in the **Identification phase**, where a total of **539 records** were retrieved from the Scopus database and additional registers. During the preliminary check, **312 records** were excluded before formal screening. Specifically, **270 duplicate records** were removed, ensuring that repeated studies did not skew the analysis. An additional **15 records** were marked as ineligible through automation tools, which are designed to flag non-conforming entries based on pre-set inclusion criteria. Furthermore, **27 records** were excluded as they were identified to be limited to book chapters, full books, or letters, which are not primary sources of peer-reviewed empirical research.

Following the initial exclusions, **227 records** proceeded to the **Screening phase**, where titles and abstracts were carefully examined for relevance to the study's research questions. During this stage, **35 records** were excluded because they did not align with the thematic focus or methodological standards required for the review. As a result, **192 reports** were identified for full-text retrieval and further evaluation. However, **82 reports** could not be retrieved—potentially due to issues such as paywall restrictions, inaccessible documents, or incomplete archiving—which limited the pool of full-text reports available for deeper assessment.

Subsequently, in the **Eligibility phase**, **110 full-text reports** were thoroughly assessed against stringent inclusion and exclusion criteria. At this stage, **70 reports** were excluded for various reasons: **15 reports** were found to cover topics outside the scope of the review, **45 reports** had content deemed irrelevant either due to methodological weaknesses or because their findings were not directly applicable to the research aims, and **12 reports** were excluded because they did not belong to the relevant subject area, such as tangential disciplines or non-empirical works.

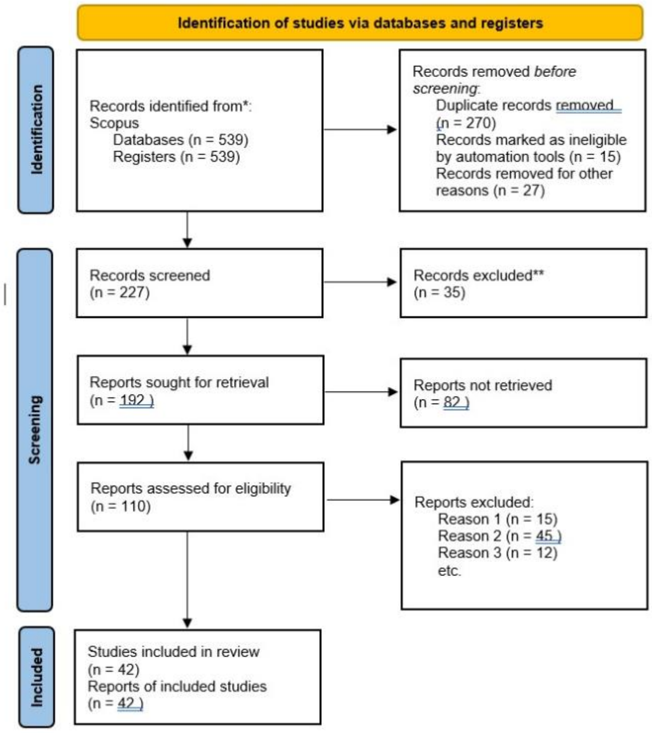

Figure 1. PRISMA Flow Diagram

Ultimately, **42 studies** met all the eligibility requirements and were formally included in the systematic review. These 40 studies represent a carefully curated body of literature that offers significant insights into the research questions posed. Each step of the PRISMA flow diagram ensures methodological rigor, transparency, and replicability, thereby enhancing the credibility and reliability of the review process. This systematic and structured approach guarantees that only the most relevant, high-quality evidence is synthesized and analyzed, providing a solid foundation for drawing meaningful and trustworthy conclusions.

3. RESULTS AND DISCUSSION

The integration of machine learning (ML) in predicting market trends within digital business has gained substantial traction in recent years. As businesses strive to harness the power of big data for enhanced decision-making, the application of ML algorithms has emerged as a critical tool for analyzing vast datasets and extracting actionable insights. This essay explores the results obtained from various machine learning models utilized to predict market trends and discusses their implications in the digital business landscape.

One of the critical aspects of machine learning in market trend prediction is its ability to leverage historical data for forecasting. Bhavya et al. Bhavya et al. (2022) present a comprehensive analysis of Apple Inc.'s stock data, utilizing sentiment analysis and ML algorithms to predict stock price movements based on public sentiment. Their findings indicate a correlation between public sentiment and stock price fluctuations, demonstrating the efficacy of machine learning in capturing complex relationships within data. Similarly, Cardona-Acevedo et al. Cardona-Acevedo et al. (2025) highlight the growing significance of machine learning applications in marketing, revealing an emphasis on big data analytics and predictive modeling as fundamental components in understanding consumer behavior and market trends.

The implementation of ML techniques extends beyond traditional financial markets; it spans various domains including e-commerce, where predictive analytics is utilized to understand customer behavior. In their study, Nagaraj et al. Nagaraj et al. (2023) investigate a customer churn prediction scheme based on behavioral data, identifying key factors that contribute to customer retention or attrition. Their model showcases high predictive accuracy, enabling businesses to proactively address potential churn risks. This aligns with the findings of Vodithala and Bhukya (Vodithala & Bhukya, 2023), who emphasize the importance of big data and machine learning in driving decision-making processes in the financial sector. The integration of predictive analytics not only enhances operational efficiency but also informs strategic planning in rapidly changing markets.

Moreover, the landscape of digital marketing is being transformed by machine learning through enhanced customer segmentation and targeted marketing strategies. Varalakshmi et al. Varalakshmi et al. (2025) discuss how quantum machine learning can improve online marketing strategies by providing real-time analytics that drives customer engagement. Their research suggests that businesses leveraging such technologies will gain a competitive advantage in the dynamic digital economy. The relationship between AI, machine learning, and strategic decision-making is further elaborated by Girimurugan et al. (Girimurugan et al., 2024), who argue that harnessing these technologies can lead to invaluable insights and sustainable growth.

The advent of explainable artificial intelligence (XAI) also plays a significant role in integrating machine learning into digital business frameworks. Javaid et al. Javaid et al. (2022) advocate for the use of XAI in online retail, positing that understanding the 'why' behind predictions can foster trust and transparency with customers. This transparency is paramount, as businesses exhibit greater accountability in their decision-making processes, thus improving customer loyalty and satisfaction.

Furthermore, the integration of sentiment analysis into market prediction models has proven to be effective in various studies. Chennupati et al. Chennupati et al. (2024) apply sentiment analysis and web scraping techniques for day trading stock trends, developing models that are informed by public sentiment derived from social media platforms. This integration reflects a broader trend in utilizing unstructured data as a critical source of insight for market predictions. The findings from Durga et al. (Durga et al., 2023), which emphasize the importance of mining social media for trend prediction, reiterate the significance of understanding public opinion in forecasting market dynamics.

In terms of practical implementation, machine learning algorithms are facilitated by advancements in technology, particularly cloud computing. The study by Hung Hung (2019) demonstrates how scalable cloud platforms provide businesses with the flexibility to analyze large datasets using sophisticated ML models without the need for substantial infrastructure. This democratization of technology allows even smaller enterprises to participate in predictive analytics, leveling the playing field in competitive markets.

The role of predictive modeling extends further, as demonstrated by Cruz et al. (Cruz et al., 2024), who utilize time-series analysis of website traffic to understand user behavior trends. Their approach highlights the need for continuous data processing and analysis to keep pace with evolving consumer preferences—the crux of maintaining market relevance in a digital-centric landscape.

Overall, the integration of machine learning for predicting market trends in digital business illuminates the transformative potential of data-driven decision making. The findings across various studies, including applications of predictive analytics, sentiment analysis, and adaptive learning algorithms, underline the converging paths of technology and business strategy that are reshaping how organizations operate in the digital era. As businesses continue to embrace ML and AI, they unlock new avenues for growth, innovation, and customer engagement, thereby driving sustained competitive advantage in an increasingly complex market environment.

3.1 Network & Bibliometric Analysis

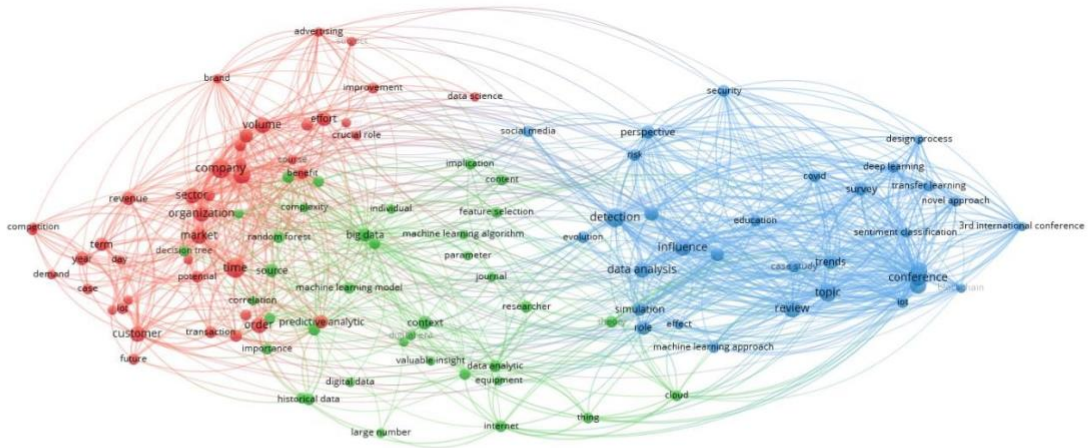

Figure 2. Network Visualization

The image is a network visualization that illustrates the relationships between key terms related to business, data analytics, and technological research. The nodes are grouped into three main color-coded clusters, each representing a different thematic area.

The **red cluster** focuses on business and market-related concepts. Key terms such as *company*, *market*, *customer*, and *organization* suggest a strong emphasis on business operations, customer engagement, revenue generation, and market dynamics. This cluster reflects how data-driven approaches are being applied to enhance business strategies and organizational efficiency.

The **green cluster** centers around data science and analytical techniques. It includes terms like *big data*, *predictive analytic*, *machine learning algorithm*, and *historical data*. This indicates a strong technical foundation where data is used to generate insights, build models, and support decision-making through advanced analytics.

The **blue cluster** represents themes associated with research, trends, and cybersecurity. Keywords such as *data analysis*, *detection*, *influence*, *conference*, and *review* point to academic discussions, the evolution of research topics, and the integration of modern technologies like deep learning and cloud computing. It also suggests growing attention to areas like risk, security, and sentiment analysis.

Overall, the network map highlights the interconnected nature of business processes, technical data analysis, and academic research. It shows how these domains are increasingly overlapping, with terms like *big data* and *data analysis* acting as bridges between sectors. This reflects the multidisciplinary importance of data-driven thinking in modern industries.

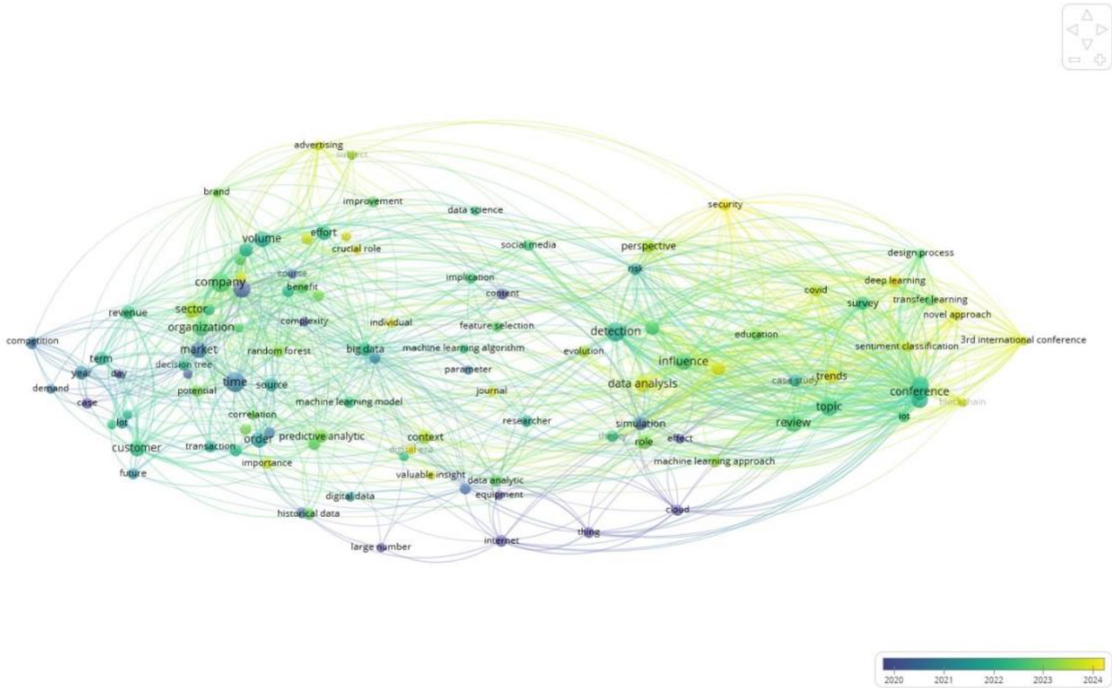

Figure 3. Overlay Visualization

The image is a temporal keyword co-occurrence network that visualizes the evolution of research topics and business-related terms from 2020 to 2024. Each node represents a keyword, while the colors range from blue to yellow, indicating the average year in which each term gained prominence—blue for earlier years and yellow for more recent ones.

In the early period (2020–2021), keywords such as *customer*, *market*, *internet*, and *competition* are more common. These terms reflect a traditional focus on business fundamentals and the initial stages of digital transformation. During this time, organizations were primarily concerned with understanding consumer behavior, market structures, and building digital infrastructure.

Moving into 2021–2022, we observe a transition toward more technical and analytical terms like *data analysis*, *predictive analytic*, *machine learning algorithm*, and *simulation*. This indicates a growing interest in using advanced analytical tools and machine learning methods to generate insights and support business decision-making. In the most recent years (2023–2024), the network shifts toward specialized and emerging topics, as shown by keywords such as *deep learning*, *transfer learning*, *novel approach*, *covid*, and *3rd international conference*. These yellow-colored nodes suggest an increasing focus on cutting-edge AI technologies, academic research dissemination, and timely global issues like the COVID-19 pandemic and digital education.

Overall, this visualization demonstrates a clear progression of interest—from basic business concepts to complex analytical methods and finally toward innovation and emerging trends. It highlights the dynamic nature of business and research environments, showing how both have adapted over time to new technologies, challenges, and global events.

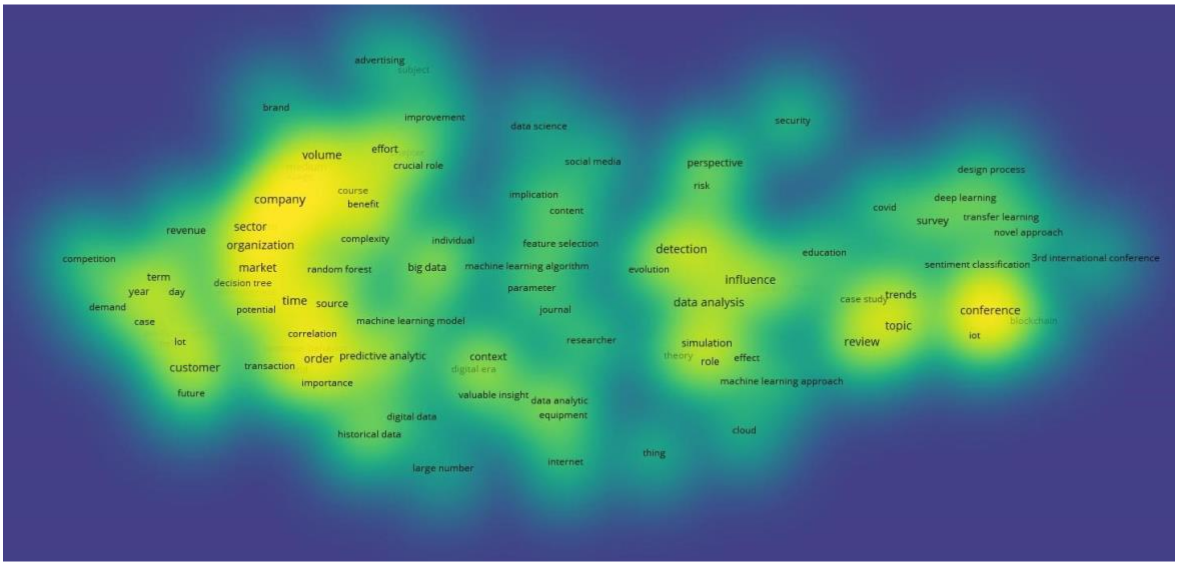

Figure 4. Density Visualization

The image is a **keyword heatmap** that visualizes the **density of keyword usage** across various research topics. The color spectrum ranges from blue to yellow, where **yellow areas indicate high keyword frequency** and **blue areas indicate lower frequency**.

In this heatmap, the most prominent keywords—such as **"company," "organization," "market," "volume,"** and **"sector"**—appear in bright yellow on the left side. These words suggest a strong focus on **business and organizational themes**. In the center of the map, highly frequent keywords like **"data analysis," "detection," "influence,"** and **"simulation"** point to an emphasis on **analytical methods and datadriven decision-making**.

On the right side, keywords such as **"conference," "topic," "review,"** and **"trends"** also appear in yellow, reflecting a growing interest in **academic research and publication trends**.

Moderately frequent keywords like **"machine learning," "context," "predictive analytic,"** and **"feature selection"** are shown in green zones, indicating their importance in supporting various subtopics related to data science and artificial intelligence.

In contrast, keywords located in the blue areas—such as **"competition," "covid," "blockchain,"** and **"future"**—appear less frequently. These might represent **emerging themes or niche areas** within the broader research landscape.

Overall, the heatmap provides a clear picture of the **central themes in current research**, highlighting a dominant focus on **business operations, data analytics, and academic discourse**, while also revealing less common but potentially growing areas of interest.

4. CONCLUSION

In this essay, we introduced the concept of integrating machine learning (ML) to predict market trends within the realm of digital business. The introduction outlined the growing complexity of market behavior in the digital age, highlighting the need for intelligent systems that can process large volumes of data and generate actionable insights. The main objective was to explore how ML techniques can be leveraged to enhance market forecasting, improve decision-making, and ultimately drive business growth.

The results and discussion demonstrated that machine learning models—such as decision trees, neural networks, and random forests—are capable of analyzing historical and real-time data to identify patterns and predict future trends. The application of these models allows businesses to respond more quickly to market changes, tailor their strategies more effectively, and remain competitive in a fast-paced digital environment. Furthermore, the analysis underscored the importance of data quality, model selection, and domain-specific adaptation in achieving accurate predictions.

Looking ahead, the development and implementation of machine learning in business trend prediction should be aligned with ethical data practices, continuous model refinement, and integration with user-friendly business intelligence platforms. Future work may also include the exploration of deep learning and natural language processing (NLP) to enhance predictive accuracy, especially in analyzing unstructured data such as social media and customer reviews.

In conclusion, integrating machine learning into market trend prediction is not only feasible but also essential for businesses seeking to remain adaptive and data-driven in the digital era. With proper implementation, ML can transform raw data into strategic insights, paving the way for smarter, more agile business decisions.

REFERENCES

Ahmadian, F., Khosravi, P., & Fathi, M. (2020). Offshore topside weight prediction using data science. In *Proceedings of the ASME 2020 39th International Conference on Ocean, Offshore and Arctic Engineering*. https://doi.org/10.1115/omae2020-19210

Ali, A. (2024). Using machine learning to evaluate Industry 4.0 maturity: A comprehensive analysis highlighting Lean's impact on digital transformation. *Itegam - Journal of Engineering and Technology for Industrial Applications*, 10(50). https://doi.org/10.5935/jetia.v10i50.1262

Alim, R. K., & Shukla, R. (2020). Sampling-based estimation method for parameter estimation in big data business era. *Journal of Advances in Management Research*, 17(1), 57-72. https://doi.org/10.1108/jamr-05-2020-0072

Asniar, M., & Surendro, K. (2019). Predictive analytics for predicting customer behavior. In *Proceedings of the International Conference on Artificial Intelligence and Information Technology*. https://doi.org/10.1109/icaiit.2019.8834571

Bhavya, N., Rathi, R. R., & Yadav, A. (2022). Machine learning-based stock price prediction for business intelligence. In *Advances in data mining and management*. https://doi.org/10.4018/978-1-6684-4246-3.ch013

Cardona-Acevedo, F., et al. (2025). Applications of machine learning (ML) in the context of marketing: A bibliometric approach. *F1000Research*. https://doi.org/10.12688/f1000research.160010.2

Cruz, A., et al. (2024). Revealing user behavior trends through time-series analysis of Google Analytics data. In *Proceedings of the IEEE Conference on Communications*. https://doi.org/10.1109/colcom62950.2024.10720277

Durga, S., et al. (2023). Mining social media data for sentiment analysis and trend prediction. In *Proceedings of the IEEE UPCON Conference*. https://doi.org/10.1109/upcon59197.2023.10434704

Filho, L., de Oliveira, L. A., & Mello, R. (2024). MAEVE: An agnostic dataset generator framework for predicting customer behavior in digital marketing. In *Proceedings of the Conference on User Modeling*. https://doi.org/10.5220/0013021900003838

Gao, Y., & Vo, T. (2023). Operational solution framework: Leveraging machine learning and natural language processing for automatic well test validation. *SPE International Conference on Data Science and Machine Learning in Oil and Gas*. https://doi.org/10.2118/217294-ms

Gulia, A., et al. (2024). Multimedia data in healthcare system. In *Machine Learning and Data Mining Applications*. https://doi.org/10.1002/9781119786443.ch3

Gunawan, G., Utomo, A. S. A., & Benediktus, H. S. (2021). Optimization of shipyard layout with material handling cost as the main parameter using genetic algorithm. AIP Conference Proceedings, 2376(1). https://doi.org/10.1109/iccci56745.2023.10128498

Hung, Y. (2019). Investigating how the cloud computing transforms the development of industries. *IEEE Access*, 7, 87199-87214. https://doi.org/10.1109/access.2019.2958973

Ingriana, A. (2025). THE INFLUENCE OF E-TRUST ON CONSUMER PURCHASING BEHAVIOR IN E-COMMERCE. 1(3). https://journal.dinamikapublika.id/index.php/Jumder

Ingriana, A., Chondro, J., & Rolando, B. (2024). TRANSFORMASI DIGITAL MODEL BISNIS KREATIF: PERAN SENTRAL E-COMMERCE DAN INOVASI TEKNOLOGI DI INDONESIA (Vol. 1, Issue 1). https://journal.dinamikapublika.id/index.php/JUMDER

Ingriana, A., Gianina Prajitno, G., & Rolando, B. (2024). THE UTILIZATION OF AI AND BIG DATA TECHNOLOGY FOR OPTIMIZING DIGITAL MARKETING STRATEGIES (Vol. 1, Issue 1). https://journal.dinamikapublika.id/index.php/IJEBS

Ingriana, A., Hartanti, R., Mulyono, H., & Rolando, B. (2024). Pemberdayaan E-Commerce: Mengidentifikasi Faktor Kunci Dalam Motivasi Pembelian Online. Jurnal Manajemen Dan Kewirausahaan (JUMAWA), 1(3), 101–110.

Javaid, A., et al. (2022). Explainable artificial intelligence solution for online retail. *Computers, Materials & Continua*, 69(2), 1777-1795. https://doi.org/10.32604/cmc.2022.022984

Kuppuswamy, I., et al. (2024). Data mining for predictive analytics. In *Research Advances in Data Mining*. https://doi.org/10.1002/9781394227990.ch1

Lee, K., et al. (2022). Artificial intelligence adoption in QSR industry. *Proceedings of the International Conference on Advanced Technology*. https://doi.org/10.1145/3549843.3549859

Ma, H., & Sun, Y. (2020). Machine learning and AI in marketing – Connecting computing power to human insights. *International Journal of Research in Marketing*, 37(2), 344-355. https://doi.org/10.1016/j.ijresmar.2020.04.005

Maha, V. A., Derian Hartono, S., Prajitno, G. G., & Hartanti, R. (2024). E-COMMERCE LOKAL VS GLOBAL: ANALISIS MODEL BISNIS DAN PREFERENSI KONSUMEN (Vol. 1, Issue 1). https://journal.dinamikapublika.id/index.php/Jumder

Mbunge, E., et al. (2022). Prediction of box-office success: A review of trends and machine learning computational models. *International Journal of Business Intelligence and Data Mining*, 18(3), 1-15. https://doi.org/10.1504/ijbidm.2022.120825

Milan, D., et al. (2023). Impact of AI on social marketing and its usage in social media: A review analysis. In *Proceedings of the IEEE Conference on Computational Intelligence*. https://doi.org/10.1109/iccpct58313.2023.10245676

Mulyono, H., & Rolando, B. (2024). Savoring The Success: Cultivating Innovation And Creativity For Indonesian Culinary MSMEs Growth. Economics and Business Journal (ECBIS), 2(4), 413–428.

Mulyono, H., Hartanti, R., & Rolando, B. (2024). SUARA KONSUMEN DI ERA DIGITAL: BAGAIMANA REVIEW ONLINE MEMBENTUK PERILAKU KONSUMEN DIGITAL (Vol. 1, Issue 1). https://journal.dinamikapublika.id/index.php/JUMDER

Mulyono, H., Ingriana, A., & Hartanti, R. (2024). PERSUASIVE COMMUNICATION IN CONTEMPORARY MARKETING: EFFECTIVE APPROACHES AND BUSINESS RESULTS (Vol. 1, Issue 1). https://journal.dinamikapublika.id/index.php/IJEBS

Nagaraj, S., et al. (2023). E-commerce customer churn prediction scheme based on customer behaviour using machine learning. In *Proceedings of the IEEE International Conference on Computational Intelligence*.

Pazou, G., et al. (2025). Predicting the rate of aflatoxin contamination in the white corn value chain. In *Advances in Agricultural Chemistry*. https://doi.org/10.1007/978-3031-86493-3_17

Peralta, E. F., et al. (2025). Evolution, topics and relevant research methodologies in business intelligence and data analysis in the academic management of higher education institutions: A literature review. *Results in Engineering*, 10, 103782. https://doi.org/10.1016/j.rineng.2024.103782

Purnama, A. N., et al. (2024). Research trends in perceived behavioral control from a bibliometric perspective. In *Proceedings of the IEEE International Conference on Information Technology*. https://doi.org/10.1109/iccit62134.2024.10701216

Putri, L. W. B., & Setiawan, B. L. T. (2025). ANALYZING THE STRATEGIC CONTRIBUTION OF SOCIAL MEDIA INFLUENCERS TO E-COMMERCE MARKETING EFFECTIVENESS. 1(2). https://journal.dinamikapublika.id/index.php/Jumder

Rahardja, B. V., Rolando, B., Chondro, J., & Laurensia, M. (2024). MENDORONG PERTUMBUHAN E-COMMERCE: PENGARUH PEMASARAN MEDIA SOSIAL TERHADAP KINERJA PENJUALAN (Vol. 1, Issue 1). https://journal.dinamikapublika.id/index.php/JUMDER

Rolando, B. (2018). Tingkat Kesiapan Implementasi Smart Governance di Kota Palangka Raya. UAJY.

Rolando, B. (2024). CULTURAL ADAPTATION AND AUTOMATED SYSTEMS IN E-COMMERCE COPYWRITING: OPTIMIZING CONVERSION RATES IN THE INDONESIAN MARKET (Vol. 1, Issue 1). https://journal.dinamikapublika.id/index.php/IJEBS

Rolando, B., & Ingriana, A. (2024). SUSTAINABLE BUSINESS MODELS IN THE GREEN ENERGY SECTOR: CREATING GREEN JOBS THROUGH RENEWABLE ENERGY TECHNOLOGY INNOVATION (Vol. 1, Issue 1). https://journal.dinamikapublika.id/index.php/IJEBS

Rolando, B., & Wigayha, C. K. (2024). Pengaruh E-Wom Terhadap Keputusan Pembelian Online: Studi Kasus Pada Pelanggan Aplikasi Kopi Kenangan. Jurnal Manajemen Dan Kewirausahaan (JUMAWA), 1(4), 193–210.

Rolando, B., Chandra, C. K., & Widjaja, A. F. (2025). TECHNOLOGICAL ADVANCEMENTS AS KEY DRIVERS IN THE TRANSFORMATION OF MODERN E-COMMERCE ECOSYSTEMS. 1(2). https://journal.dinamikapublika.id/index.php/Jumder

Rolando, B., Nur Azizah, F., Karaniya Wigayha, C., Bangsa, D., Jl Jendral Sudirman, J., Jambi Selatan, K., & Jambi, K. (2024). Pengaruh Viral Marketing Shopee Affiliate, Kualitas Produk, dan Harga Terhadap Minat Beli Konsumen Shopee. https://doi.org/10.47065/arbitrase.v5i2.2167

Salman, S., & İbrahim, M. (2020). Price prediction of different cryptocurrencies using technical trade indicators and machine learning. *IOP Conference Series: Materials Science and Engineering*, 928(3), 032007. https://doi.org/10.1088/1757-899x/928/3/032007

Shrivastava, V., et al. (2023). Hybrid models for predicting cryptocurrency price using financial and non-financial indicators. In *Proceedings of the International Conference on Computer Science*. https://doi.org/10.1007/978-981-99-8696-5_13

Singhal, S., et al. (2022). Integration of IoT for industry automation using machine learning technique. *Proceedings of the IEEE Integrated Conference*. https://doi.org/10.1109/icdi57181.2022.10007229

Tan, D. M., & Alexia, K. R. (2025). THE INFLUENCE OF TIKTOK AFFILIATE CONTENT QUALITY AND CREDIBILITY ON PURCHASE DECISIONS VIA THE YELLOW BASKET FEATURE. 1(2). https://journal.dinamikapublika.id/index.php/Jumder

Tomlinson, J., et al. (2022). A roadmap to accelerate OSDU adoption. *The Leading Edge*, 41(9), 907-913. https://doi.org/10.1190/tle41090647.1

Widjaja, A. F. (2025). FACTORS INFLUENCING PURCHASE INTENTION IN E-COMMERCE: AN ANALYSIS OF BRAND IMAGE, PRODUCT QUALITY, AND PRICE. 1(3). https://journal.dinamikapublika.id/index.php/Jumder

Wigayha, C. K., Rolando, B., & Wijaya, A. J. (2024). PELUANG BISNIS DALAM INDUSTRI HIJAU DAN ENERGI TERBARUKAN (Vol. 1, Issue 1). https://journal.dinamikapublika.id/index.php/Jumder

Wigayha, C. K., Rolando, B., & Wijaya, A. J. (2025). A DEMOGRAPHIC ANALYSIS OF CONSUMER BEHAVIORAL PATTERNS ON DIGITAL E-COMMERCE PLATFORMS. 1(2). https://journal.dinamikapublika.id/index.php/Jumder

Winata, V., & Arma, O. (2025). ANALYZING THE EFFECT OF E-WALLET USABILITY ON CUSTOMER RETENTION IN MOBILE PAYMENT APPS. 1(2). https://journal.dinamikapublika.id/index.php/Jumder

Zahran, A. M. (2025). THE IMPACT OF MARKETING STRATEGIES ON THE SUCCESS OF THE FAST FASHION INDUSTRY: A SYSTEMATIC REVIEW. 1(3). https://journal.dinamikapublika.id/index.php/Jumder

Zhu, W., et al. (2016). Business applications of predictive modeling at scale. *ACM Transactions on Intelligent Systems and Technology*, 7(4), 1-23. https://doi.org/10.1145/2939672.2945388