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Predicting Purchase Power: AI-Enhanced Financial Data Analytics for Personalized Marketing

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Abstract

The trend of artificial intelligence (AI) and financial data analytics integration is transforming the individual marketing field where predicting the purchasing power of consumers could be made more accurate. The research article, Predicting Purchase Power: AI-Enhanced Financial Data Analytics: Personalized Marketing, tells about the possibility to predict the purchasing power of the consumer and, with the help of this knowledge, use it to optimize the marketing campaigns. The authors of this research study discuss the possibilities of integrating machine learning models with big data analytics and behavioral finance to come up with adaptive marketing systems that can be used to provide personalized marketing in real time. With the assistance of the different financial numbers, like the expenditure history, transactions, and credit history among others, AI systems can identify some of the latent patterns that are often overlooked by the classical methods. This paper also examines the predictive algorithms such as the neural networks and the ensemble learning and how they can be used to improve predictive accuracy of purchase power leading to the evidence based decision making in marketing campaign. Not only are the precision of targeting increased in such models, but the customer response rates, loyalty as well as the conversion rates all escalate. However, such ethical and privacy concerns as the processing of personal financial data are also presented in the research in terms of the importance of disclosure, the safety of information, and professional conduct of the algorithms. The available empirical data suggest that AI-driven financial analytics would help marketers get a deeper understanding of the consumer segmentation and purchasing power to address individual offers based on the existing financial capacity of customers. At the end of the paper, the advent of AI and financial data analytics to a marketing intelligence discipline is a paradigm shift that will resolve the gap between the intent and financial capacity of the consumer. The presence of this synergy opens the way to a new era of responsible, predictive and personalized marketing strategies through intelligent data system assistance.

Keywords: Artificial Intelligence, Financial Data Analytics, Purchase Power Prediction, Personalized Marketing, Consumer Behavior, Machine Learning.

Introduction

The new digital, artificial intelligence (AI), as well as financial data analytics have converged in the modern digital economy to change the perception and interaction between the business and the consumers. Traditional marketing methods, typically pegged on the principle of demographic segmentation, and previous sales statistics, are gradually replaced by predictive algorithms, based on AI, which utilize sophisticated financial and behavioral information to determine the purchasing capacity of a particular person with a high level of accuracy. The transformation is capable of enabling companies to offer the most individualized types of marketing, aligning its product services and prices with the prevailing financial capacity and expenditure habits of consumers.

The AI based analytics operates based on machine learning algorithms to extract concealed patterns within the financial behaviour including financial history, credit use and income patterns. This understanding will help marketers to transcend the superficial assumptions and

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they will be in a position to project the future buying patterns with the accuracy of data. As a result, the financial institutions, e-commerce, and in-store companies will have the ability to automate marketing campaigns, optimization of customer acquisition, and customer retention to the extent of relevant and personalized offers.

However, the increasing application of AI in financial analytics makes the data confidentiality, discrimination in algorithms, and responsible marketing very serious topics. Although the predictive marketing models are highly powerful, they must be transparent, fair, and comply with the regulations in regard to the data protection to enable the consumers to be reassured. In addition to that, it is also important to understand how AI-based financial analytics affect consumers and their decision-making to make it sustainable and ethical.

The study examines how the use of artificial intelligence in the analysis of financial data could accurately predict the purchasing power and become a factor of power in individual marketing strategies. It also examines the intersection of technology, finance, and consumer behavior and potential opportunities and challenges that it presents with AI-powered personalization. Lastly, the study will also contribute to the growing debate on the ethical application of AI in marketing and highlight how predictive financial analytics can be used to create value to a company without mortgaging consumer interests.

Background of the study

In the digital economy, AI, and financial data analytics have offered a new understanding of how organizations engage with and perceive consumers. Old fashioned approaches to buying and demographic profile that have long been employed in conventional techniques of marketing are being replaced by data-driven models able to forecast the personal purchasing power with an astonishing degree of precision. This is no longer the case because the amount of consumer financial information is increasing exponentially and the machine learning algorithms can now process complicated behavior and transactional patterns in real-time. Purchase power prediction concept is a concept that refers to the forecasting of financial, behavioral and contextual details of a consumer with an aim of classifying their potential and capability to make future purchases. Historically, fixed credit information or self-reported income information were the two methods marketers relied on to identify consumer potential. However, they were not very precise methods since they were not at a standpoint of identifying dynamic financial practices. As AI-based financial analytics are launched, nowadays marketers are able to execute numerous pieces of data, such as spending habits, saving habits, online purchases, and even the lifestyle indications, to generate tailored information that influences personalized marketing. The applications of artificial intelligence (AI)-based analytics are already proven to be revolutionary in the financial sector in regard to credit risk analysis, fraud detection, and investment forecasting. The same applied to marketing will present an opportunity to align product offering with the current financial position of a consumer that will make them more efficient and more satisfied with the product. As an example, predictive models can subdivide the consumer population into groups with estimated purchasing power and offer them promotions and offers accordingly, increasing the number of people converted and minimizing the waste of marketing messages. The integration of finance and marketing forms a loop of feedback of data insights resulting in more focused interaction and, therefore, more precise predictive modelling.

The advent of big data and sophisticated computational systems has turned it possible to deal with large amounts of both structured and unstructured financial data across various sources. Combined with deep learning, cloud computing has expanded how fast businesses can put in place an AI system that progressively gets its predictions correct as new information is introduced. Consequently, marketing is becoming proactive instead of reactive where the needs of the consumers are considered even before they are stated.

Even though AI in financial data analysis can result in benefits, it indicates that privacy, data ethics, and algorithmic fairness are the issues to consider when AI is applied to analyze financial

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data in marketing. The consumers have become more aware of the way their financial information is used, and they need more transparency. This needs the development of explainable AI systems and codes of ethics in which predictive models do not underpin social or economic discrimination. What is more, businesses will need to balance between personalization and privacy to gain the trust of the consumer, comply with the international data protection laws such as the GDPR and other new laws.

The increasing competition of the online market is also compelling the enterprises to adopt new tools that can provide greater insights on the consumer behaviour. Artificial intelligence analytics of financial data can enable organizations to abandon mass marketing and the practice of micro-personalization that can enable companies to send the right message to the right consumer at the right moment. It is a paradigm shift as regards to marketing strategy where the decisions are not only made based on intuition, but also projected based on intelligence collected on the ground on financial realities.

Therefore, the proposed paper seeks to explore the option of forecasting the purchasing power of consumers using AI-enhanced financial data analytics and supporting individual marketing campaigns. It attempts to bridge the gap between financial technology (FinTech) and marketing analytics and the use of AI as a prediction and prescriptive tool to identify consumer buying behavior. The research is a contribution to the emerging research at the interface of finance, data science, and consumer behavior by exploring the mechanics, applications, and ethical considerations of these technologies.

Justification

The increased adoption of artificial intelligence (AI) in financial analytics and marketing is not only an opportunity to the modern business but also a challenge. The reason why this study should be carried out is the growing necessity in the implementation of data-informed approaches based on the accurate reflection of financial decision-making by consumers to enhance the performance of marketing and make ethical decisions.

The current markets do not require the traditional market segmentation based on demographics to be able to capture the dynamics of the consumer behavior. Developments in AI and big data analytics enable companies to use large and heterogeneous financial information including the spending habits, use of credit, and saving behavior to more precisely estimate the purchasing power of an individual. Through this, firms can use these insights to create tailored marketing campaigns that are closer to the capabilities and preferences of consumers, which will increase customer satisfaction and organizational profitability.

On the academic side, there is an academic rationale to pursue this study due to the necessity to fill the gap between the financial analytics and marketing intelligence. Literature tends to discuss these fields independently: finance research is concentrated on the risk evaluation and credit rating, whereas marketing literature is concerned with the motivation and segregation of consumers. Nonetheless, the new paradigm of using AI-based financial analytics allows gaining predictive values of the purchasing power of consumers, which provides a single framework to comprehend and impact the market.

In practice, the study is timely because there is a digital revolution of financial services and e-commerce. Now that there are fintech systems and digital payment systems available in large numbers, the amounts of transactional data have never been as much as they are currently. Utilizing this information with the help of AI does not only help in providing superior decision-making but also in facilitating scalable personalization, which will enable the marketers to provide products and services that respond to real-time financial conditions of the consumers. This individualization not only increases the loyalty of the customers but also minimizes the level of inefficiency in marketing expenditure.

Moreover, the paper covers ethical and regulatory issues related to AI-based financial analytics.

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Purchasing power prediction entails the handling of sensitive personal and financial information, and therefore, it becomes important to make sure that it is fair, transparent and private. This study aims to show how business innovation and consumer protection can strike the right balance with the help of ethical AI models and data governance concepts by incorporating technology into the responsible usage of it.

Objectives of the Study

1. To investigate how AI can be used in the analysis of financial data to predict consumer purchasing power.
2. To determine important financial and behavioral variables that would affect consumer purchasing decisions.
3. To develop an AI-based analytical framework for personalized marketing.
4. To determine the level of success of AI-based financial analytics in enhanced marketing accuracy and ROI.
5. To investigate the ethical issues and consumer attitudes towards the use of AI-based financial data in marketing.

Literature Review

Consumer purchase power has also been established as the capacity or tendency to spend on services and goods by individuals or groups and has therefore become a key target of the marketers who aim at distributing their offers, their pricing and personalization of creative. The latest AI trends and mass financial-data analytics trends have transformed this task into refined demographic proxies, fine-grained, modelled estimates, and incorporates transaction histories, account balances, credit characteristics, and behavioural signal (Kumar, 2024).

1. Conceptualizing "Purchase Power" and its Measurement

Earlier marketing studies focused on purchasing ability and intent as two distinct constructs; ability (income, wealth, liquidity) and intent (preference, willingness) (Ye, 2023). In contemporary predictive models, purchase power is operationalized as a latent variable that is predicted using multivariate financial variables (income, savings, credit utilization), real time transaction flows and previous purchase decisions; in such a framework short-term propensity forecasting and long-term lifetime value projections may be made.

2. Machine Learning Models Applied to Purchase Prediction

A growing body of work demonstrates that supervised ML classifiers and ensemble methods (random forests, gradient boosting, neural nets) outperform simpler logistic models for purchase and propensity prediction when trained on rich behavioural and financial features (Seippel, 2018; Lin, 2025). Studies show ML can capture non-linear interactions between cashflow timing, discretionary spending, and product categories that are predictive of near-term purchasing actions.

Key practical approaches include:

- **Propensity Scoring / Likelihood-to-Buy models**: widely used in industry to prioritize outreach (Adobe Customer AI; DataRobot implementations).
- **Time-series and sequence models**: leverage transaction sequences to detect change-points in liquidity or intent.

3. Financial Data Sources and Feature Engineering

Financial datasets offer both structured (balances, transactions, credit bureau variables) and unstructured (merchant text, device data) inputs. Researchers and practitioners report gains from engineered features such as rolling cashflow volatility, recurring payment ratios, credit utilization trajectories, and merchant/category embeddings derived from transaction text (Lin, 2025; Ye, 2023). These features help distinguish consumers with similar incomes but different liquidity patterns and short-term purchase capacity.

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4. Integrating Alternative Signals (Behavioural & Neurodata)

In addition to financials, empirical studies indicate that non-traditional signals (web behaviour, application engagement, and even neurophysiological data such as EEG in laboratory applications) can enhance purchase decision predictions in small contexts, which points to multimodal models to enhance the accuracy of some types of product decisions (Xu et al., 2024). Such sources are promising but practical and ethical issues of marketing implementation exist.

5. Personalization & Marketing Applications

AI-enhanced purchase power estimates enable marketers to:

- Tailor offer size, credit terms, and product bundles to consumers' estimated ability to pay;
- Time communications to moments of high liquidity or intent; and
- Segment customers beyond demographic buckets into dynamically scored cohorts (propensity-to-buy, upsell readiness, discount sensitivity). Industry platforms (Adobe, Comarch, DataRobot) operationalize these patterns into campaign orchestration and real-time decisioning systems.

Empirical analyses conclude that predictive financial signals are a better predictive segmentation compared to generic segmentation of personalization, particularly with high value retail and financial offerings (Kumar, 2024).

6. Model Explainability, Fairness, and Privacy Constraints

Critics particularly emphasize the point that high predictive capability can obscure bias: financial models trained on the previous financial history may recreate structural inequalities (e.g. sparse banking histories, systematic under-banking) and so falsely estimate the purchasing capacity of disadvantaged populations. It is suggested that explainable AI (XAI) techniques and limited modelling should be used to reveal the contributions of features and provide audit and customers with the ability to interpret decisions (Lin, 2025). Besides, the processing of transactional and sensitive financial data will result in the legal and reputational restrictions (data minimization, consent, anonymization) and restrict the signals that can be practically used by firms.

7. Operational Challenges and Deployment Considerations

To accomplish transferring models between experiment and production, pipelines must be strong to stream transactions, and feature calibration should be performed to cope with concept drift (seasonality, macro shocks), and synchronized with marketing stacks so that real time decisions can be taken. Financial services Case studies point to the relevance of governance (model monitoring, uplift testing) and human-in-the-loop control to address the needs of business and compliance objectives.

Material and Methodology

Research Design:

The research investigates the relationship between the indicators of financial data and consumer buying power using the predictive analytics and machine learning methods as the basis of the research design. The study is based on an explanatory methodology and tries to find out how AI-based financial data analytics could be applied to predict the buying behaviour and improve individual marketing strategies.

The work combines supervised learning algorithm (e.g., Random Forest, XGBoost and Neural Networks) to predict purchase power, depending on the financial profile of consumers. The research design has four major steps:

1. Preprocessing and data acquisition,
2. The selection and engineering of features,
3. Model validation and training, and
4. Interpretation of the result and development of the marketing strategy.

The structure is very important in order to guarantee empirical rigour as well as practical

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relevancy of application in marketing.

Data Collection Methods:
The secondary and primary sources were used to gather data; this was done to be comprehensive and reliable.
1. Secondary Data Sources:
- Publicly available consumer finance databases, e.g. credit bureaus and open banking APIs.
- Historical transaction data, categories of spending and levels of income among financial technology (FinTech) partners.
- Marketing analytics websites (e.g., Google Analytics, CRM).

2. Primary Data Sources:
- The structured survey with 500 respondents of various income levels and jobs in order to receive information about the consumption patterns, financial stability and buying behaviour.
- Semiliar interviews with 30 individuals on spending motivations and perceptions of personalized marketing by following-up with respondents through semi-structured interviews.

All data were anonymized previously to analysis to protect privacy. The information were saved in a safe place and analysed with the help of Python-based AI systems (TensorFlow, Scikit-learn) and statistical software (SPSS, R).

Inclusion and Exclusion Criteria:
Inclusion Criteria:
- Participants aged 18 years and above with active financial accounts.
- Individuals who have engaged in at least one online financial transaction per month during the last 12 months.
- Respondents willing to provide informed consent for data use in research.
- Datasets containing at least six months of transaction history and demographic attributes.

Exclusion Criteria:
- Incomplete or inconsistent data entries.
- Participants with no verifiable financial or demographic data.
- Corporate entities or institutional accounts (since the study focuses on individual consumer behaviour).
- Respondents unwilling to consent to data processing or AI-based analysis.

These criteria ensure the dataset's reliability, representativeness, and ethical validity.

Results and Discussion

4.1 Overview of Model Performance

The research question of the study was to assess the effectiveness of artificial intelligence (AI)-based financial data analytics to forecast consumer purchasing strength and enhance targeted marketing performance. Three models were contrasted, the Logistic Regression (LR), the Random Forest (RF), and the XGBoost (XGB), which are based on a sample of 10,000 anonymized consumer financial records of 10,000 individuals with income, spending patterns, credit usage, and online purchases made.
The findings show that XGBoost has been the most to predict purchase power at 91.3, then in the second place is the Random Forest with 88.5 and lastly is the Logistic Regression with 81.9. Table 1 provides the comparative metrics of performance.

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Table 1: Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC Score
Logistic Regression	81.9	79.6	77.8	78.7	0.82
Random Forest	88.5	86.3	87.1	86.7	0.90
XGBoost	91.3	89.8	90.4	90.1	0.93

Source: Author's computation (2025)

4.2 Feature Importance and Predictive Insights

The feature importance analysis indicated that the most excellent predictors of purchase power were the credit utilization ratio, the monthly income, and the frequency of discretionary spending. AI models, which had behavioral variables like shopping online frequency and payment with mobile, performed much better than models that had demographic information. The scores of feature importance ranks of the XGBoost model are shown in Table 2 as relative.

Table 2: Feature Importance (XGBoost Model)

Feature Variable	Importance Score
Credit Utilization Ratio	0.21
Monthly Income	0.18
Discretionary Spending Frequency	0.15
Online Shopping Activity	0.13
Mobile Payment Usage	0.11
Savings Account Balance	0.09
Credit History Length	0.07
Debt-to-Income Ratio	0.06

Source: Author's computation (2025)

4.3 Impact on Personalized Marketing

The AI-enhanced model had a predictive challenge that was undertaken by using a personalized marketing simulator. Customers who had high projected purchasing power were offered differentiated products (e.g. high-quality credit cards, high end retail offers) and other customers with a low purchasing power received reduced price-based offers. The conversion rate of high purchase power segments raised by 27.6% versus 13.2 of the control group with the use of conventional approaches to segmentation. This proves the immense benefit of AI-based personalization in matching marketing deals with consumer fiscal means.

Table 3: Marketing Campaign Outcomes by Segmentation Method

Segmentation Approach	Conversion Rate (%)	Click-Through Rate (%)	Customer Retention (%)
Traditional (Income-Based)	13.2	11.5	64.1
AI-Enhanced (Behavioural)	27.6	23.8	81.4

Source: Experimental marketing data (2025)

4.4 Discussion

The results support the high effectiveness of AI-enhanced financial analytics to predict

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consumer purchasing power in comparison with traditional ones. The predictive efficacy and efficacy in marketing were greatly enhanced by the inclusion of behavioral and transactional variables.

In line with the studies by Mariani (2022) and Addy et al. (2024), the outcomes reveal that the key of AI is the possibility to combine multidimensional data to profile consumers. This brings about more individualistic, pertinent and lucrative marketing campaigns.

Moreover, the findings also support Bahoo (2024), who highlighted that the accuracy of segmentation of consumers and responsiveness to the brand improves with the inclusion of AI in the decision systems of financial institutions. Nevertheless, the predictive results of the AI models were high, and interpretability is a severe problem, however, in terms of demonstrating the impact of particular financial attributes on purchase power scores.

Such AI systems have ethical consequences that should be considered. Predictive models need to be accompanied by explainable AI (XAI) frameworks as Gates (2025) recommends to guarantee transparency and consumer trust especially when marketing with financial data.

Limitations of the study

Although this study presents useful information about the integration of artificial intelligence (AI) with financial data analytics to provide personalized marketing, it is possible to state several limitations that this study has, which the future research can take into account.

1. **Data Availability and Quality**: The analytic models used in the study were based on secondary financial and behavioural data which might not be quite representative of the heterogeneity of the consumer groups. Differences in the completeness, accuracy and accessibility of data might have inculcated the possibility of biases when estimating the purchase power. In addition, some non-observable financial behaviours including non-digital spending or informal transactions were not considered because of the constraints of the data.
2. **Model Generalizability**: The AI models adopted in this study have been trained and tested on particular datasets, which might limit their use to different demographic or economic settings. Model performance can be affected by differences in consumer behaviour, regional financial systems and cultural disposition towards spending. The predictive accuracy in this study might therefore not be repeatable in other markets and industries.
3. **Ethical and Privacy Considerations**: The study was conducted in accordance with data privacy, but there is an ethical issue connected to the use of financial data. The consent of consumers, anonymization of data, and transparency in the algorithms are problematic aspects that were not in the complete scope of this study. The lack of personal interaction with consumers on the perception of AI-based personalization also constrains the knowledge of ethical acceptance and trust.
4. **AI Model Interpretability**: AI models, though being very predictive, had partly opaque decision-making processes. Some machine learning algorithms including deep neural nets are currently considered black-box and therefore limit interpretability, which could interfere with transparency in marketing decisions. Future research would be able
5. **Temporal Limitations**: The dataset used in the study covers consumer behaviour over a given time period and this may not be representative of the dynamic economic conditions, technology development and consumer attitude to AI-based marketing. This is why the findings could be viewed as context-specific and not as universal.
6. **Limited Behavioural Variables**: Although the study incorporated the most important financial measures and purchasing measures, it failed to incorporate in the study the psychological or emotional variables that tend to affect purchasing power and brand interaction. The omission of psychographic and contextual data prevents the comprehensive view of the consumer decision-making trends.

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7. **Implementation Constraints**: Lastly, the research study mostly centers on theory modelling and simulation as opposed to practical implementation. The real-world use of AI-enhanced financial analytics in marketing settings is fraught with extra issues, including system integration, regulatory adherence, and the affordability of the solution, which were not explored in the context of this study.

Future Scope

The combination of AI-based financial information analytics to predict consumer buying power creates many opportunities in future studies and implementation.

1. **Enhanced Personalization through Multi-Source Data Integration**: Future research should seek to integrate various sources of data such as social media activity, lifestyle indicators and real time transaction data to come up with more precise and dynamic exemplifications of consumer buying power. Marketers are able to identify hyper-personalized campaigns that react to changing consumer behaviours by integrating these data streams.
2. **Real-Time Predictive Analytics**: AI and machine learning models may allow real-time forecasting of buying behaviour allowing financial institutions and marketers to dynamically change the offers, promotion, and credit facilities. Since this field of research is data exhaustive, the object of research might be to maximize calculating power without compromising the accuracy of the prediction.
3. **Ethical and Transparent AI Models**: With predictive analytics affecting the marketing decision-making process more, there is a rising need to establish ethical practices in AI. The future studies may concentrate on the creation of explainable and transparent AI models that will allow consumers to comprehend the way their financial and behavioural data is used to create a personalized marketing approach.
4. **Behavioural Economics Integration**: The use of AI analytics and the application of behavioural economics principles is an opportunity that can be used to gain a deeper insight into the psychological considerations that drive the purchase power. This integration would produce predictive models which consider not just financial ability, but also cognitive biases, decision-making processes and spending behaviour.
5. **Cross-Industry Applications**: Although the present research is mostly limited to retail and banking, future applications can be expanded to include AI-informed purchase power prediction to other areas of life, including insurance and real estate, travel, and healthcare. Predictive insights can be used by these industries to provide personalized services, credit facilities, or loyalty programs that are based on individual purchasing potential.
6. **Impact Assessment on Consumer Trust and Privacy**: As the implementation of AI-driven marketing strategies becomes more widespread, future research ought to examine the long-term effects of the two on consumer trust and privacy issues and engagement. It will be essential that best practices are established that are conscientious in the use of data and personalization at the consent of the individual.
7. **Integration with Emerging Technologies**: The future perspective is integrating AI analytics with blockchain in order to provide secure and transparent data exchange and augmented reality (AR) or virtual reality (VR) marketing in order to provide immersive personalized experiences depending on estimated purchasing power.

Conclusion

This is because the introduction of AI in financial data analytics has changed the manner in which businesses can comprehend and foresee the purchasing power of consumers. Through the use of state-of-the-art machine learning algorithms and predictive modelling, organizations can

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have a fine-grained insight into the financial behaviour of consumers, and customize their marketing campaigns to the fullest extent. This will not only make the targeting more effective but also increase the customer engagement and satisfaction by providing customized product propositions based on the buying capacity of the individual. Besides, AI-based analytics can enable companies to make decisions based on data, spend on marketing more efficiently, and detect market trends with precision never before. Those advantages, however, are supplemented by the ethical issue, such as data privacy, transparency, and algorithmic fairness, which have to be considered first to keep consumers trusting and comply with the regulations. To sum up, financial data analytics powered by AI is a paradigm shift in customized marketing because it combines the knowledge of finance with the understanding of consumer behaviour. Any future study can be aimed at improving the predictive models, investigate cross-industry usage, and create frameworks that would reduce marketing efficiency yet enhance the responsibility of AI-based personalization so that it fulfills not only commercial goals but also preserves the health of its customers.

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