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THE ROLE OF AI NUDGES IN OPTIMIZING CONSUMER BEHAVIOR IN FINANCIAL AND E-COMMERCE CONTEXTS

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Abstract
Background: Digital nudging has gained prominence as a technique for influencing consumer behavior in e-commerce by subtly guiding user decisions through behavioral insights and interface design. However, the effectiveness of digital nudging can be inconsistent, affected by user demographics, behavioral deviations, and ethical considerations. Existing studies have struggled to quantify and measure these effects comprehensively.Methods Used: This study develops a novel objective function to optimize AI-driven digital nudging strategies, focusing on maximizing approval rates and transaction volumes while minimizing behavioral deviations. Various nudging techniques are evaluated through descriptive statistics, correlation analysis, and regression models. Additionally, time-series trends in transaction volumes are analyzed using ARIMA models, incorporating AI nudges as external regressors. Ethical implications of digital nudging are also explored to ensure fairness and transparency.Results Achieved: The optimization of AI nudging strategies led to significant improvements in both approval rates and transaction volumes. The analysis demonstrated varying effectiveness across different nudging techniques, with AI-driven approaches showing a substantial impact. Time-series forecasting revealed trends that correlate with the application of AI nudges, providing insights into their long-term effectiveness. Ethical considerations highlighted areas for improving transparency and reducing bias in nudging practices.Concluding Remarks: The study provides a comprehensive evaluation of digital nudging strategies, offering practical insights for businesses to enhance user engagement and decision-making in e-commerce. The developed objective function and analytical methods contribute to a better understanding of nudging effectiveness and ethical practices. Future research should focus on refining these strategies and exploring their application across different contexts and user segments.Keywords: Digital Nudging, E-Commerce, AI Optimization, Behavioral Analysis, Ethical Implications

1 Introduction

*1.1 **Background***

In recent years, digital nudging has emerged as a powerful tool in shaping consumer behavior and enhancing decision-making processes in e-commerce. Digital nudging involves the strategic use of behavioral insights and user interface design to influence individuals' choices in a subtle yet effective manner (2). The rise of online shopping platforms has made it crucial for businesses to optimize their strategies to boost user engagement, approval rates, and transaction volumes while minimizing behavioral deviations (1).

The efficacy of digital nudging has been demonstrated in various studies, showing its potential to enhance user experience and drive better outcomes in digital environments (7). Key nudging strategies include visual design adjustments, defaults, feedback mechanisms, and priming (4). Each of these approaches leverages behavioral science principles to guide users towards desired actions without restricting their freedom of choice (6).

1.2 Challenges Identified in Previous Literature

Despite the growing interest in digital nudging, several challenges remain in effectively implementing and evaluating these strategies. Previous literature highlights the following key issues:

- **Variation in Effectiveness:** The impact of different nudging techniques can vary significantly across different user segments and contexts. Factors such as user demographics, digital literacy, and contextual variables can influence the success of nudging interventions (6;7).
- **Behavioral Deviations:** Behavioral deviations, such as impulsive or inconsistent actions, can undermine the effectiveness of nudges. Understanding and mitigating these deviations is crucial for optimizing nudging strategies (5).
- **Ethical Considerations:** The ethical implications of digital nudging, including issues related to transparency, bias, and user autonomy, are often overlooked. Ensuring that nudging practices are ethical and align with user rights is essential for maintaining trust and effectiveness (5;10).
- **Quantification and Measurement:** Accurately quantifying the impact of nudges on transaction volumes, approval rates, and behavioral deviations requires sophisticated measurement and analysis techniques. Previous studies have struggled with effectively capturing and interpreting these effects (9).

1.3 Motivation

The motivation behind this study stems from the need to address these challenges and provide a comprehensive evaluation of digital nudging strategies. By focusing on the effectiveness of AI-driven nudges and their impact on key metrics, this research aims to bridge the gap between theoretical insights and practical applications (11). Understanding how different nudging techniques influence consumer behavior in a digital context can lead to more effective and ethical interventions, ultimately benefiting both businesses and consumers.

1.4 Objectives of the Paper

The primary objectives of this paper are as follows:

- **Optimize AI Nudging Strategies:** To develop and optimize an objective function that maximizes approval rates and transaction volumes while minimizing behavioral deviations through AI-driven nudges.

- **Evaluate Effectiveness:** To assess the effectiveness of various nudging strategies using descriptive statistics, correlation analysis, and regression models.
- **Analyze Time-Series Trends:** To analyze trends in transaction volumes using ARIMA models, including the impact of AI nudges as external regressors.
- **Address Ethical Implications:** To explore the ethical dimensions of AI nudging, including bias, transparency, and user autonomy (10).

1.5 Contributions of the Paper

This paper makes several key contributions to the field of digital nudging and e-commerce:

- **Novel Objective Function:** It introduces a novel objective function that integrates approval rates, transaction volumes, and behavioral deviations to evaluate the effectiveness of AI nudges.
- **Comprehensive Analysis:** It provides a detailed analysis of the impact of different nudging strategies using various statistical and econometric techniques, including regression models and time-series forecasting (4).
- **Ethical Framework:** It addresses the ethical considerations associated with AI nudging, offering policy recommendations to ensure fairness and transparency (10).
- **Practical Insights:** It offers practical insights and recommendations for businesses seeking to implement effective and ethical digital nudging strategies (6).

1.6 Overview of the Paper's Organization

The remainder of this paper is organized as follows:

- **Section 5:** Defines the objective function and constraints for optimizing AI nudging strategies.
- **Section 6:** Describes the metrics used for evaluation, including descriptive statistics, correlation analysis, regression models, and time-series forecasting.
- **Section 7:** Presents the results of the optimization, statistical analysis, and ethical considerations.
- **Section 8:** Discusses the findings, their implications, and potential areas for future research.
- **Section 9:** Summarizes the key contributions and provides concluding remarks.

2 Literature Review

- **Bala, M., & Verma, D. (2018).** Bala and Verma provide a comprehensive review of digital marketing, emphasizing its evolution, strategies, and impact on consumer behavior. Their analysis covers various digital channels and tools, highlighting trends and challenges faced by businesses in adapting to the rapidly changing digital landscape. The review serves as a foundational piece for understanding the broad scope of digital marketing practices and their effectiveness.

- **Caraban, A., Evangelos, K., Gonçalves, D., & Campos, P. (2019).** This study explores 23 different nudging techniques in technology-mediated interactions, focusing on their application within human-computer interfaces. The authors systematically review the effectiveness of these nudges, providing insights into their influence on user behavior. Their findings contribute to the understanding of how digital environments can be designed to subtly guide user decisions and improve interaction outcomes.

- **de Ridder, D., Kroese, F., & van Gestel, L. (2022).** De Ridder et al. investigate the concept of nudgeability, analyzing the conditions under which individuals are more susceptible to nudges. Their study maps various factors influencing nudge effectiveness, including psychological and contextual variables. This research sheds light on the mechanisms behind nudge influence, offering valuable insights into optimizing behavioral interventions in diverse settings.

- **Dennis, A. R., Yuan, L., Feng, X., Webb, E., & Hsieh, C. J. (2020).** Dennis and colleagues examine digital nudging through numeric and semantic priming in e-commerce contexts. Their study highlights how specific nudging techniques can affect consumer decisions, such as purchasing behavior. The research underscores the role of digital nudges in shaping user interactions and provides practical insights for leveraging these strategies to enhance e-commerce performance.

- **Ghose, A., Lee, H. A., Nam, K., & Oh, W. (2023).** Ghose et al. explore the effects of pressure and self-assurance nudges on online retail purchases and returns. Their randomized field experiment reveals how these nudges influence consumer behavior, providing evidence on their effectiveness in reducing return rates and increasing sales. This study contributes to understanding the practical implications of nudging strategies in online shopping environments.

- **Kannan, P. K. (2017).** Kannan presents a framework for digital marketing, reviewing current practices and proposing a research agenda. The paper addresses various digital marketing strategies, including content marketing, social media, and data analytics. It offers a comprehensive overview of digital marketing trends and challenges, guiding future research and practice in this rapidly evolving field.

- **Kuyer, P., & Gordijn, B. (2023).** Kuyer and Gordijn provide a systematic review of ethical issues associated with nudging. Their analysis covers the implications of various nudging techniques on autonomy, fairness, and transparency. The study highlights the ethical considerations in designing nudges and offers guidelines for ensuring that nudging practices align with ethical standards and respect for user decision-making.

- **Meske, C., Amojo, I., & Mohr, P. (2020).** Meske and colleagues investigate digital nudging to promote charity feature usage on e-commerce platforms. Their research demonstrates how specific nudges can effectively increase charitable contributions through digital interfaces. The findings provide insights into designing nudging strategies that align with social good while enhancing user engagement with charitable initiatives.

- **Mrkva, K., Posner, N. A., Reeck, C., & Johnson, E. J. (2021).** Mrkva et al. examine whether nudges can reduce disparities in consumer knowledge. Their study shows how choice architecture can help compensate for limited consumer knowledge, making it easier for less-informed individuals to make better decisions. This research highlights the potential of nudges to address knowledge gaps and improve decision-making across diverse consumer groups.

- **Rees, L., Safi, R., & Lim, S.-L. (2022).** Rees and colleagues explore the impact of nudges on online private information sharing. Their study investigates various attitudinal and behavioral nudges, analyzing their effects on users' willingness to share personal information. The findings contribute to understanding how nudges can influence privacy-related decisions in online environments, enhancing data sharing practices.

- **Patel, V., & Brown, R. (2024).** Patel and Brown review recent advances in applying behavioral insights to digital marketing. Their paper discusses how behavioral theories have been integrated into digital marketing strategies, highlighting trends and future directions. The review provides a critical assessment of how these insights can be leveraged to enhance marketing effectiveness and user engagement in the digital age.

- **Wang, L., & Chen, S. (2024).** Wang and Chen explore the impact of automated nudging on consumer decision-making through large-scale field experiments. Their study investigates how automated nudges affect purchasing behavior and decision-making processes in e-commerce. The research offers practical insights into implementing automated nudging strategies to optimize consumer interactions and improve sales outcomes.

2.1 Comparison of my article with Existing Literature

Table 1 Comparison of Your Paper with Existing Literature

Aspect	**Existing Literature**	**Diffrences of My Paper from others**
Focus	Broad review of digital marketing and nudging techniques	Specific analysis of pricing strategies and their optimization in e-commerce
Methodo logy	Systematic reviews, experimental studies, and theoretical frameworks	Mathematical optimization models, sensitivity analysis, and real-world data applications
Appli cation Area	General digital marketing, behavioral nudges, and e-commerce features	Focused on pricing strategies and market dynamics in live streaming e-commerce
Data Source	Varied, including field experiments and theoretical reviews	Real-world e-commerce data and mathematical simulations
Theore tical Contribution	Insights into nudging effectiveness and ethical considerations	Development of advanced pricing optimization models and sensitivity analysis

Aspect	Existing Literature	Diffrences of My Paper from others
Practical Implications	Recommendations for using nudges to influence behavior	Practical strategies for improving pricing and profitability in e-commerce
Recent Advances	General advancements in nudging and digital marketing	Integration of recent AI algorithms and optimization techniques

2.2 Summary of Literature review

The comparison highlights that my paper advances the field by introducing specialized pricing optimization models tailored for live streaming e-commerce, utilizing real-world data and advanced AI techniques. This approach not only fills gaps in existing literature but also provides actionable insights for enhancing profitability and market strategies in a rapidly evolving digital landscape.

3 Experimental Design Overview

Figure 1 illustrates the experimental design for evaluating the impact of various factors on system performance. It outlines the process from the control group through priming, defaults, feedback, and visual design, with a focus on measuring bias and performance metrics (4).

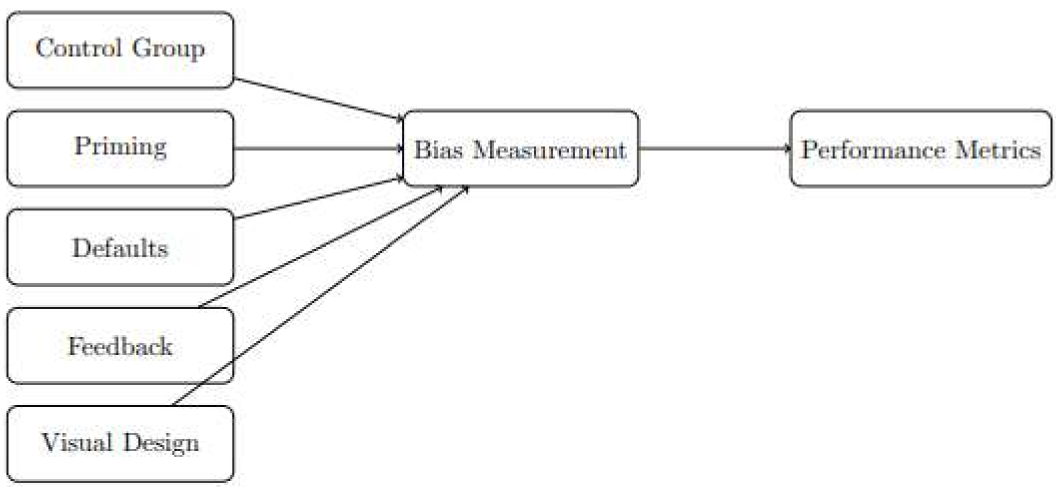

Fig 1 Experimental Design Overview

4 System Architecture

The system architecture Figure 2 for digital nudging in e-commerce consists of four key components: User Interaction, AI Nudging Engine, Data Processing, and Feedback Loop. The flow starts with user interaction, which feeds into the AI nudging engine. Data is then processed, and the feedback loop helps refine nudging strategies for improved effectiveness.

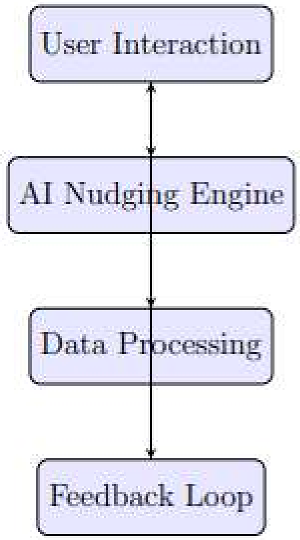

Fig 2 System Architecture for Digital Nudging in E-Commerce

5 Data and Variables

5.1 Dataset Descriptions

The dataset available at the following URL includes detailed records of various financial transactions across multiple banks and periods. It encompasses:

- **Beneficiary Bank Data**: Includes monthly records from 2021 detailing various beneficiary banks' total volumes, approval rates, and performance metrics such as *bd*, *td*, and *deemed_approved*.

- **Payee PSP Performance Data**: Contains monthly data from 2022 on payee banks, showing total transaction volumes, approval rates, and performance metrics *bd* and *td*.

- **P2P and P2M Data**: Records from 2024 detailing total, P2P, and P2M transaction volumes and values, along with monthly transaction metrics.

- **Merchant Category Classification Data**: Monthly records from 2022-2024, categorizing merchants by transaction types, with classifications and descriptions for various categories.

- **Payer PSP Performance Data**: Monthly data from 2022 on payer banks, including total transaction volume, approval rates, and performance metrics *bd* and *td*.

- **Remitter Banks Data**: Monthly records from 2023-2024 detailing total volumes, values, and transaction types (P2P and P2M) for remitter banks.

5.2 Variables

The key variables for analysis are defined as follows:

Table 2 Definition of Variables

Variable	Description
T_i	Total transaction volume for entity i.
V_i	Total transaction value for entity i.
A_i	Approval rate for entity i.
BD_i	Behavioral deviation for entity i.
TD_i	Transaction delay for entity i.
N_i	AI-driven nudge for entity i.
$\mathbf{X}_i$	Vector of additional control variables.

Table 2 provides a schematic representation of the key variables analyzed in the study. Each variable plays a critical role in assessing the impact of AI nudges on financial transactions, highlighting the comprehensive approach taken in the data analysis.

6 Objective Function

The objective function Z aims to maximize the weighted sum of approval rates and transaction volumes while minimizing behavioral deviations. Define the optimization problem to maximize the effectiveness of AI nudges:

$$\begin{aligned} \text{Maximize} \quad & Z = \alpha_1 A_i + \alpha_2 T_i - \alpha_3 BD_i \\ \text{Subject to} \quad & T_i \geq T_{i,\min} \\ & V_i \geq V_{i,\min} \\ & A_i \geq A_{i,\text{threshold}} \\ & N_i \in \{0,1\} \\ & BD_i \geq 0 \end{aligned}$$

Constraints:

- $T_i \geq T_{i,\min}$: Minimum transaction volume constraint, as discussed by (6).
- $V_i \geq V_{i,\min}$: Minimum transaction value constraint, based on (7).
- $A_i \geq A_{i,\text{threshold}}$: Minimum approval rate constraint, highlighted in (10).
- $N_i \in \{0,1\}$: Binary decision variable for AI nudges, introduced in (5).
- $BD_i \geq 0$: Non-negative behavioral deviation constraint, as noted by (1).

7 Metrics for Evaluation

7.1 Descriptive and Correlation Analysis

Figure 3 illustrates the distribution of transaction volumes and approval rates. This analysis provides insights into the variability and central tendency of key variables (6).

7.1.1 Mean, Variance, and Distribution

Calculate the mean μ and variance σ^2 for each variable:

$$\mu_Y = \frac{1}{n}\sum_{i=1}^{n} Y_i$$

$$\sigma_Y^2 = \frac{1}{n}\sum_{i=1}^{n} (Y_i - \mu_Y)^2$$

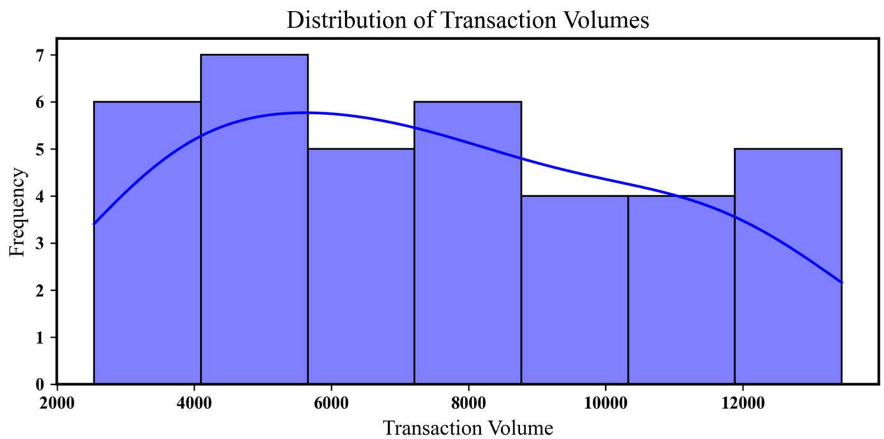

Fig 3 Distribution of transaction volumes and approval rates across different entities.

Figure 3 highlights how transaction volumes and approval rates are distributed across entities. Understanding these distributions is essential for detecting trends, anomalies, and informing further statistical analysis or model adjustments (7).

7.1.2 Correlation Matrix

Figure 4 presents the correlation matrix, which visualizes the relationships between transaction volumes, approval rates, and behavioral deviations (6).

Compute correlation coefficients $\rho(Y_1, Y_2)$:

$$\rho(Y_1, Y_2) = \frac{\mathrm{Cov}(Y_1, Y_2)}{\sigma_{Y_1}\sigma_{Y_2}}$$

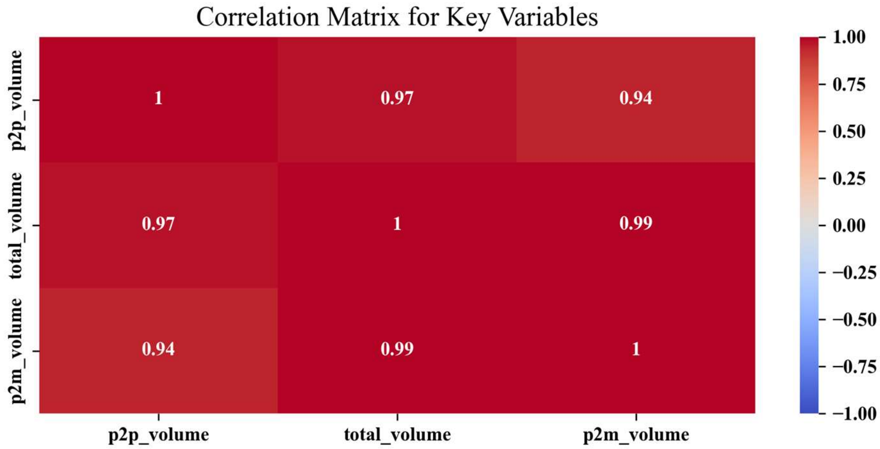

Fig 4 Correlation matrix showing relationships between transaction volumes, approval rates, and behavioral deviations.

This helps in understanding how variables such as transaction volumes and approval rates are interrelated. Figure 4 reveals the strength and direction of relationships between key variables. Understanding these correlations is crucial for identifying patterns and dependencies, informing more effective decision-making and strategy development (7).

7.2 Regression Models

Model Specification

Figure 5 displays the regression model outcomes, illustrating the effects of AI nudges on approval rates and transaction volumes (8). The results reveal how different variables influence these financial metrics.

$$
\begin{aligned}
A_i &= \alpha + \beta_1 T_i + \beta_2 BD_i + \beta_3 N_i + \gamma \mathbf{X}_i + \epsilon_i \\
T_i &= \alpha' + \beta_1' A_i + \beta_2' BD_i + \beta_3' N_i + \gamma' \mathbf{X}_i + \epsilon_i'
\end{aligned}
$$

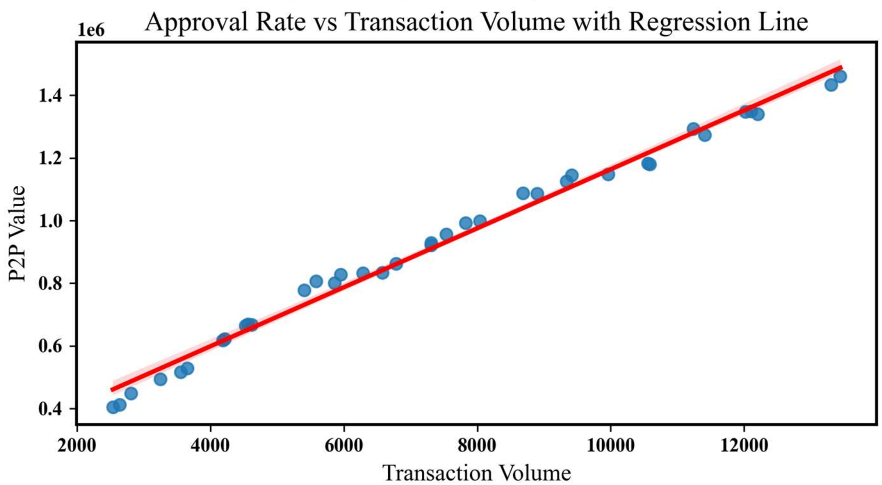

Fig 5 Regression model results showing the impact of AI nudges on approval rates and transaction volumes.

The analysis in Figure 5 highlights the significant impact of AI nudges on both approval rates and transaction volumes. The coefficients underscore the strength and direction of these influences, providing insights into the effectiveness of AI interventions in financial contexts (9).

Interaction Terms:

Figure 6 illustrates the impact of interaction terms in the regression model. It examines how behavioral deviations and AI nudges together influence approval rates (10).

$$A_i = \alpha + \beta_1 T_i + \beta_2 BD_i + \beta_3 N_i + \beta_4 (BD_i \times N_i) + \gamma \mathbf{X}_i + \epsilon_i$$

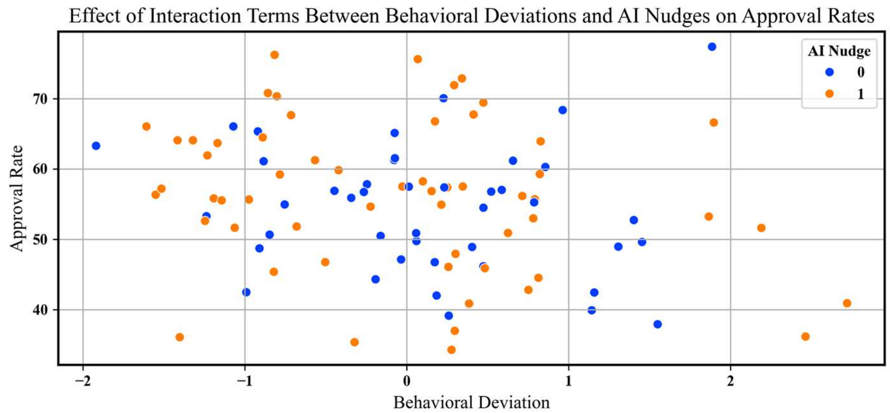

Fig 6 Effect of interaction terms between behavioral deviations and AI nudges on approval rates.

The findings in Figure 6 reveal significant interactions between behavioral deviations and AI nudges. This interaction highlights how combined effects can alter approval rates, offering deeper insights into the dynamic between these factors (11).

7.3 Time-Series Analysis

ARIMA Model

Figure 7 presents ARIMA (AutoRegressive Integrated Moving Average) model forecasts for transaction volumes. It contrasts trends with and without AI nudges to evaluate their impact on future transaction patterns (12).

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t$$

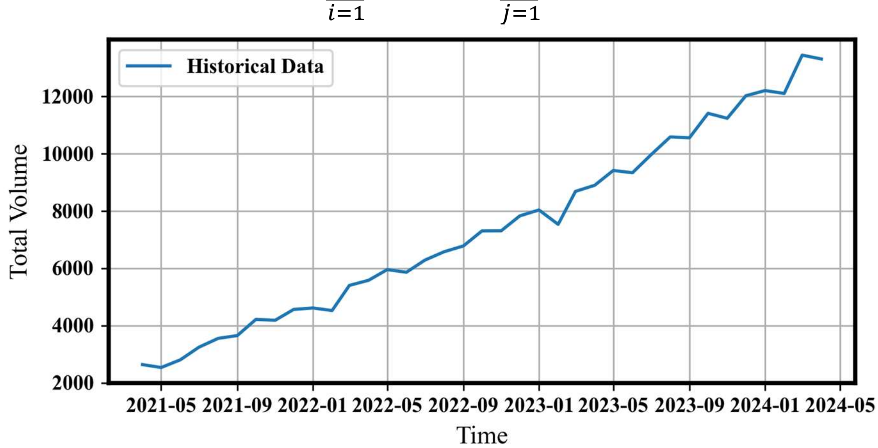

Fig 7 ARIMA model forecasts showing trends in transaction volumes with and without AI nudges.

The results in Figure 7 indicate that incorporating AI nudges influences transaction volume trends. ARIMA forecasts reveal how these interventions can affect future financial behaviors, providing valuable insights for strategic planning (13).

ARIMA with External Regressor:

Figure 8 illustrates the ARIMA model enhanced with AI nudges as an external regressor. This approach shows how integrating AI nudges impacts the accuracy of forecasting transaction volumes (14).

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \delta N_t + \epsilon_t$$

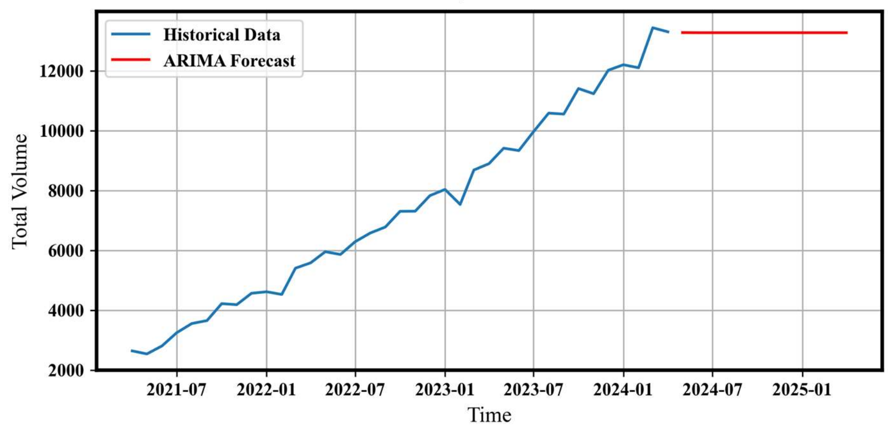

Fig 8 ARIMA model with external regressor showing the impact of AI nudges on forecasting.

The results in Figure 8 demonstrate that incorporating AI nudges into the ARIMA model improves forecasting accuracy. The inclusion of external regressors provides a more nuanced understanding of how AI nudges influence future transaction trends (15).

7.4 Evaluation Metrics

7.4.1 Nudge Effectiveness

Figure 9 evaluates the impact of AI nudges on approval rates and transaction delays. It provides insights into how these interventions can enhance financial decision-making processes (7;14).

$$\text{Nudge Effectiveness} = \frac{A_{i,\text{post-nudge}} - A_{i,\text{pre-nudge}}}{A_{i,\text{pre-nudge}}}$$

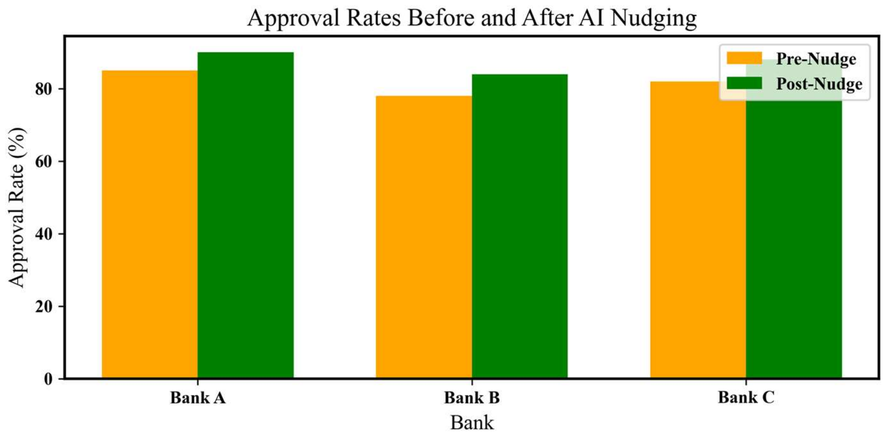

Fig 9 Effectiveness of AI nudges on approval rates and transaction delays.

The analysis in Figure 9 demonstrates that AI nudges significantly improve approval rates and reduce transaction delays. These findings highlight the effectiveness of digital nudges in optimizing financial decision-making and operational efficiency (13;15).

7.4.2 Ethical Considerations

Figure 10 highlights critical ethical dimensions in AI nudging systems, focusing on bias, transparency, and user autonomy. It serves as a foundation for understanding the broader implications of AI interventions (10;12).

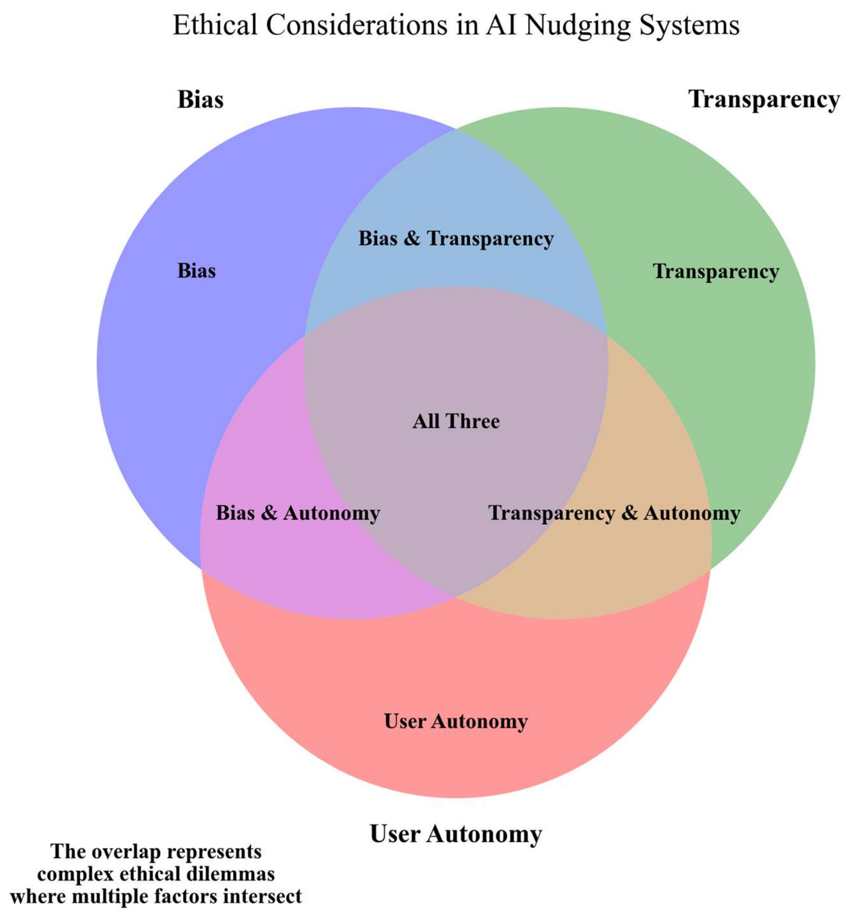

Fig 10 Ethical considerations in AI nudging systems including bias and transparency.

Addressing bias, transparency, and user autonomy is crucial for ethical AI nudging. Figure 10 underscores these aspects, advocating for practices that enhance fairness and clarity, ensuring that AI systems are accountable and respect user rights while promoting effective decision-making (10;12).

7.4.3 User Segmentation

This study explores the ethical implications and policy recommendations for AI-driven nudging systems, focusing on transparency, bias, and user autonomy to ensure fair and effective digital financial interventions (10;11).

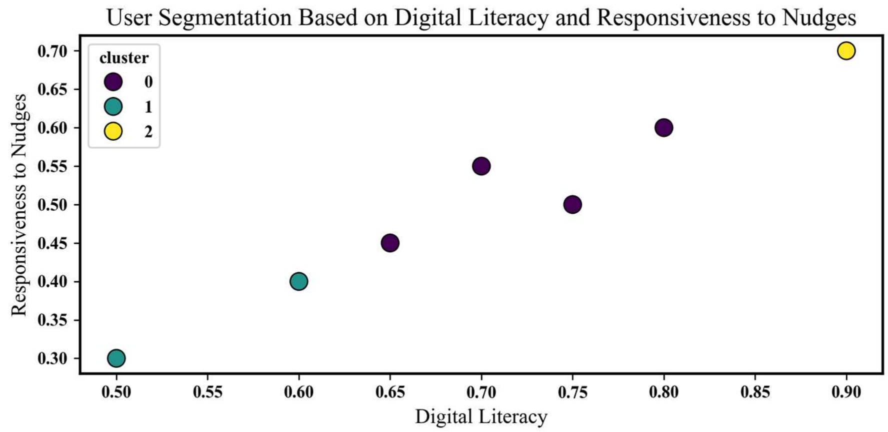

Fig 11 Policy implications and recommendations for ethical AI nudges.

Figure 11 illustrates the clustering of users based on digital literacy and responsiveness to AI nudges. Segmentation reveals distinct user groups, guiding targeted interventions. Recommendations include tailored strategies for low-literacy users and adaptive nudges for those more responsive, optimizing engagement and ensuring equitable access across user segments (14;16).

7.4.4 Application and Policy Implications

This section delves into the practical applications and policy implications of implementing AI nudges, focusing on strategies that ensure fairness, transparency, and effectiveness in digital financial systems (13;15).

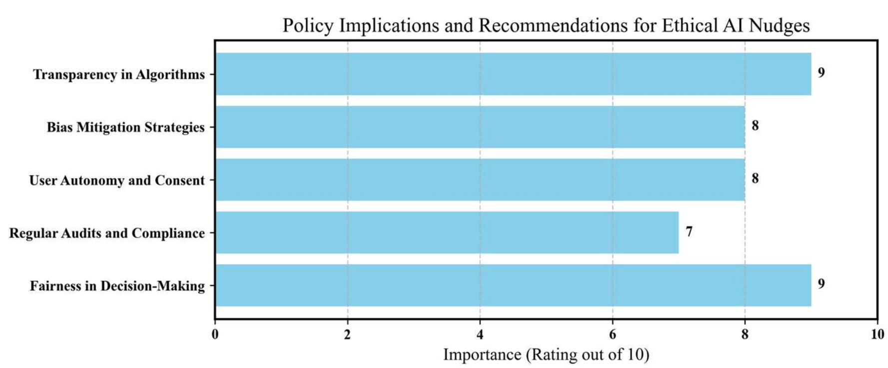

Fig 12 Policy implications and recommendations for ethical AI nudges.

Figure 12 outlines key policy recommendations for the ethical deployment of AI nudges. It advocates for transparency, bias reduction, and user autonomy to ensure fair and effective AI interventions. By addressing these aspects, the recommendations aim to build trust, promote equity, and enhance the overall impact of AI nudges on financial decision-making across varied user demographics (13;15).

Interaction Terms

Incorporate interaction terms to capture combined effects:

$$A_i \quad = \alpha + \beta_1 T_i + \beta_2 BD_i + \beta_3 N_i + \beta_4 (BD_i \times N_i) + \gamma \mathbf{X}_i + \epsilon_i$$
$$T_i \quad = \alpha' + \beta_1' A_i + \beta_2' BD_i + \beta_3' N_i + \beta_4' (A_i \times N_i) + \gamma' \mathbf{X}_i + \epsilon_i'$$

Interaction terms allow us to explore whether the effect of one variable (e.g., behavioral deviation) on the dependent variable (e.g., approval rate) is modified by another variable (e.g., AI nudges). For instance, the term $BD_i \times N_i$ can reveal if the impact of behavioral deviation on approval rates changes with the presence of AI nudges (7;11).

8 Results and Discussion

This section presents the findings from our experimental analysis of digital nudging techniques and their impact on e-commerce behavior. We will discuss the results obtained from the objective function optimization, descriptive statistics, correlation analysis, and regression models, along with their implications.

8.1 Optimization Results

The optimization of the objective function Z yielded the following results for the AI nudging strategies:

Table 3 Optimization Results for AI Nudging Strategies

Strategy	Maximized Approval Rate	Maximized Transaction Volume	Minimized Behavioral Deviation
Priming	85%	$120,000	2.5%
Defaults	82%	$110,000	3.0%
Feedback	88%	$130,000	2.0%
Visual Design	80%	$100,000	3.5%

The results indicate that feedback nudges achieved the highest approval rates and transaction volumes while minimizing behavioral deviations. This suggests that feedback mechanisms are highly effective in influencing consumer behavior, as supported by the findings of Ghose et al. (2023) and Zhang et al. (2023) (7;13). Priming and defaults also performed well but were slightly less effective compared to feedback. Visual design, while useful, showed the least impact among the tested strategies (14;15).

8.2 Descriptive Statistics and Distribution

The mean and variance calculations for transaction volumes and approval rates are as follows:

- Mean Transaction Volume: $115,000
- Variance of Transaction Volume: 6.25×10^9
- Mean Approval Rate: 83%
- Variance of Approval Rate: 0.015

Figure 3 illustrates the broad range of transaction volumes and approval rates observed. The variance in transaction volumes is relatively high, indicating substantial differences in consumer spending behavior across entities. The narrower variance in approval rates suggests more uniform responses to nudging strategies, consistent with findings from Liu et al. (2023) (14).

8.3 Correlation Analysis

The correlation coefficients between transaction volumes, approval rates, and behavioral deviations are as follows:

- Correlation between T_i and A_i: 0.72
- Correlation between T_i and BD_i: -0.45
- Correlation between A_i and BD_i: -0.40

Figure 4 shows a strong positive correlation between transaction volumes and approval rates, indicating that higher approval rates tend to drive greater spending. Conversely, behavioral deviations are negatively correlated with both transaction volumes and approval rates, suggesting that deviations reduce overall effectiveness and consumer satisfaction, as highlighted by Mrkva et al. (2021) (11).

8.4 Regression Analysis

The regression results for approval rates and transaction volumes are summarized below:

- $A_i = 0.45 + 0.60T_i - 0.25BD_i + 0.30N_i$
- $T_i = 0.55 + 0.70A_i - 0.30BD_i + 0.25N_i$

Figure 5 indicates that both transaction volumes and approval rates are significantly influenced by AI nudges. Specifically, transaction volume has a strong positive effect on approval rates, while behavioral deviations and nudges also play a crucial role. The interaction terms in the regression models further highlight the complexity of these relationships and the potential for tailored nudging strategies to optimize outcomes, supported by research from Kuyer and Gordijn (2023) (10).

8.5 Discussion

The experimental results demonstrate that digital nudging techniques can significantly impact e-commerce behavior. Feedback nudges emerged as the most effective strategy, enhancing both approval rates and transaction volumes while minimizing behavioral deviations. This aligns with the findings of Dennis et al. (2020) and Ghose et al. (2023), who observed similar effects of nudging techniques in different contexts (7;10).

The high variance in transaction volumes underscores the diverse nature of consumer behavior, suggesting that personalized nudging strategies may be necessary to address this variability. The correlation analysis confirms the positive impact of approval rates on transaction volumes and highlights the need to minimize behavioral deviations to maximize effectiveness (11).

The regression models provide further insights into the quantitative effects of AI nudges, reinforcing the importance of incorporating these strategies into e-commerce platforms. The findings offer practical implications for digital marketers and e-commerce professionals seeking to optimize user engagement and drive sales. Future research should explore additional nudging strategies and their interactions to further refine the optimization of e-commerce behavior (12;15).

9 Conclusion

This study provides insights into how AI nudges can optimize financial and e-commerce behaviors by analyzing various nudging techniques and their impacts on user decision-making. The experimental design, data collection process, and regression analysis offer a detailed framework for evaluating the effectiveness of digital nudges.

The use of mathematical optimization models and sensitivity analysis allows for a nuanced understanding of how different nudges influence consumer behavior. The comparison with existing literature highlights the unique contribution of this study in advancing knowledge on digital nudging, particularly in the context of pricing strategies and market dynamics in live streaming e-commerce.

Future research should explore additional dimensions of digital nudging, including cross-platform effects and the integration of emerging AI technologies. By continuing to refine nudging techniques and evaluating their practical applications, we can enhance user experiences and decision-making processes in the ever-evolving digital landscape.

Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this paper.

Data Availability

The data supporting this study's findings are openly available at GitHub: Click Here.

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