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AI-powered personalization in e-commerce: Governance, consumer behavior, and exploratory insights from big data analytics

Hager Turki

Management Department, Institute of Higher Commercial Studies, University of Carthage, Tunis, Tunisia

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ABSTRACT

AI-powered personalization is revolutionizing digital commercial platforms, presenting a plethora of opportunities and challenges related to governance, ethical considerations, and consumer behavior. This research explores the effects of algorithmic personalization on consumer behavior by employing a log-log regression analysis on transaction-level datasets obtained from Amazon during the period spanning 2018 to 2022. By examining the elasticity of consumer spending in response to price and quantity changes, it is shown that both variables exhibit nearly unitary responses, indicating that spending patterns in AI-personalized environments follow strong and consistent elasticity trends. While direct exposure to personalization signals is not measured, the behavioral patterns observed are consistent with personalization effects typical of platforms like Amazon. The present investigation, which applies a reduced-form elasticity model, situates the interconnection between personalization systems and the broader societal context. The findings provide compelling evidence that adaptive personalization technologies are associated with shifts in consumer expenditure behaviors but also user autonomy and the dynamics of digital trust. The model identifies behavioral regularities that support interpretive insights into AI-mediated commerce. Analyzing from a governance perspective, the findings reveal notable deficiencies in both transparency and regulatory frameworks, particularly regarding the fairness and ethical management of personal data. With algorithmic personalization growing more inscrutable, this paper advocates for an interdisciplinary methodology that synthesizes behavioral insights with accountable technology governance. Ultimately, this study contributes to the ongoing discussions concerning the influence of AI on market dynamics and the promotion of socially responsible innovation within the digital economy.

1. Introduction

Today, the global landscape of e-commerce is going through a sea-change occasioned by artificial intelligence (AI) and its fusion with big data analytics. This process is all the more manifest when you consider the fact that platforms are now using highly complex machine learning algorithms to anticipate what consumers want, segment their behavior and present them with hyper-personal experiences in real time. Consequently this redefines customer relation management as well marketing optimization and knowledge on the platform itself. But it also brings challenges entailing complications associated with data governance algorithmic transparency and ethically appropriate personalization, particularly as AI systems affect behavior choices made by humans of which they are unaware.

While personalization has emerged as the foundation of digital marketing, enabling e-commerce companies to pull together content, recommendations, and pricing strategies on a custom basis depending on historical data plus user interaction analysis and inferred intentions, the implications for consumer trust, autonomy and platform responsibility remain in their early developmental stages. At present, governance frameworks have not yet grown to regulate AI-powered personalization particularly well–especially when it comes to cases where algorithmic decision-making is opaque or biased.

The far-reaching impact of AI driven personalization on consumer behavior has recently been well-documented. For example, an improvement in customer engagement and satisfaction has evolved to a stage where it is essential for a company or a brand. This is all due in large part to processes that the e-commerce platform itself uses rather than people using it. Moreover, techniques grounded in artificial intelligence that are tailored to individual consumers exert considerable influence on purchasing behaviors. Customized suggestions and adaptive pricing strategies play a pivotal role in shaping consumer choices and establishing brand allegiance (Sherly Steffi et al., 2025).

The integration of artificial intelligence in the e-commerce sector

E-mail address: hager.turki@ihec.ucar.tn.

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introduces significant ethical dilemmas, notably in relation to data privacy and the presence of algorithmic bias. There is a growing unease among consumers about the methods used to gather and utilize their personal information, prompting demands for enhanced transparency and accountability within AI-driven personalization mechanisms (Hardcastle et al., 2025). Furthermore, the risk that AI algorithms may reinforce pre-existing biases or result in inequitable consequences highlights the urgent need for the establishment of governance frameworks aimed at promoting ethical AI conduct in the realm of e-commerce (Ferrara, 2023).

However, much of the existing research either examines the technical efficiency of recommender systems or discusses ethical risks in conceptual terms—without empirically linking user behavior to governance implications. In response, this study adopts an exploratory behavioral perspective using real-world e-commerce data to evaluate how consumer-spending patterns reflect platform-level personalization mechanisms. Rather than attempting to establish causal inference, this analysis uses elasticity modeling as a descriptive proxy to understand consumer responsiveness in a personalization-intensive environment.

This study aims to link technological capabilities with governance frameworks by investigating the behavioral and economic effects of AI-enabled personalization in the e-commerce industry. It employs a comprehensive dataset of U.S. Amazon transactions spanning from 2018 to 2022 to assess how variations in pricing and product engagement influence monthly consumer spending. Through the use of a log-log regression model, the study measures these influences and provides insights into the outcomes of personalization as manifested in observed purchasing behavior. The findings of this research contribute in two significant ways: first, it empirically demonstrates how AI-enhanced recommendation systems correlate with patterns in consumer spending; second, it theoretically merges innovation governance with consumer behavior modeling based on data. Crucially, the paper does not claim to measure the direct effect of AI exposure but instead offers a behavioral lens through which such influence may be interpreted. Ultimately, this study addresses the increasing demand for interdisciplinary strategies to comprehend digital transformation in consumer market behaviors.

This study is guided by the following research questions.

- How do AI-powered personalization mechanisms influence consumer-spending behavior in e-commerce environments?
- What are the governance and ethical implications of such algorithmic influence on market dynamics and user autonomy?

2. Literature review

2.1. The evolution of AI in E-commerce

Recent developments in artificial intelligence are profoundly reshaping the frameworks and approaches utilized in e-commerce. AI technologies, especially those that leverage deep learning, natural language processing, and real-time behavioral analytics, are becoming increasingly essential for delivering customized services. In the comprehensive research conducted by Singh and Singh (2024) the authors explore the amalgamation of artificial intelligence with extensive data across multiple platforms, inclusive of Amazon and Shopify. They underscore a considerable evolution from conventional rule-based frameworks to more adaptable learning models that progressively develop to optimize user experiences.

In the research, we tend to refer to AI-powered personalization as process of intelligent adaptation through machine-driven algorithms trained on user behavior data of content, product recommendations and pricing policies. Unlike traditional rule-based systems that follow pre-coded segmentation logic (e.g., “if user clicked X, show Y″), AI personalization continuously updates predictions using collaborative filtering, user embeddings, or deep learning architectures. These systems operate autonomously, often in real time, and undergo dynamic change as user behaviors and conditions on the platform evolve. This operational distinction is critical to our interpretation: we view the observed behavioral data as emerging from a dynamic personalization ecosystem, even though individual-level exposure to recommendations is not measured. Framing the analysis this way positions our study within the broader context of algorithmic decision-making systems that continuously adapt to user behavior and raise important governance concerns—particularly around transparency, fairness, and autonomy.

Recommender systems assume an indispensable position in the realm of e-commerce, owing to their capacity to anticipate users' preferences and assist in the discovery of novel products and services. A notably esteemed category of recommender systems is collaborative filtering employing matrix factorization techniques, which have garnered widespread acclaim in e-commerce and various internet platforms. The emergence of big data, characterized by the incessant accumulation of user behavior information, further catalyzes the advancement of recommendation systems. The advent of deep learning has given rise to a multitude of models that enhance recommendation accuracy; however, these models frequently function as "black boxes," prompting apprehensions regarding transparency and interpretability. Specifically, the application of deep neural networks within recommendation systems has enabled real-time personalization on a large scale, allowing e-commerce platforms to forecast and shape consumer decision-making with heightened precision. This progression corresponds with the observations made by Wang et al. (2024) and Parthasarathy and Sathiya Devi (2023), who emphasize the efficacy of hybrid recommender systems that amalgamate collaborative filtering with content-based methodologies. Such models not only augment customer engagement but also yield quantifiable improvements in revenue and retention rates.

Recent advances have highlighted the growing importance of hybrid recommender systems that integrate collaborative filtering, deep learning, and sentiment-aware modeling. For example, Darraz et al. (2025) propose an enhanced hybrid architecture that incorporates BERT-based sentiment analysis into traditional recommendation pipelines, significantly improving personalization accuracy and contextual relevance. In parallel, Kallel et al. (2025) present a deep reinforcement learning framework for dynamic optimization in hybrid environments—work that, while centered on microservice orchestration, offers conceptual insights transferable to adaptive recommendation mechanisms. These advances underscore the centrality of AI in driving personalization strategies; however, they also reinforce the need for empirical studies—such as ours—that attempt to observe user responses at scale, even in the absence of direct recommendation exposure data. These developments mark a shift toward more intelligent and context-sensitive personalization strategies, while also raising new challenges related to algorithmic interpretability and fairness, which we explore further in Section 4.

However, the behavioral effects of personalization are often studied in isolation from the larger data environment. Our approach instead analyzes consumer-spending behavior in a platform environment where personalization is assumed to be pervasive, thus offering a systems-level view of responsiveness—even though personalization intensity is not directly observed.

2.2. Personalization and consumer behavior

The personalization of digital experiences has a measurable influence on consumer preferences, engagement, and loyalty. Yin et al. (2025) show that AI-personalized recommendation engines significantly improve user interaction metrics such as click-through and conversion rates. Their research reveals that tailored content delivery enhances consumer perceptions of value, particularly in highly competitive online environments.

E-commerce has the features of instantaneity, versatility, interactivity, and personalization. It can store, maintain, and analyze more consumer data through computer technology. Under the framework of big data analytics, machine learning, data mining, modeling, and visualization are employed to understand consumer preferences. As companies obtain the big data of consumers, critical questions arise: how should the data be managed, and how does it influence consumer behavior? Understanding the aspects influencing online shopping behavior can help designers create e-commerce websites that appeal and respond effectively to customer needs.

Moreover, the act of personalization is profoundly linked to customer allegiance when it is crafted to align with user requirements as opposed to being driven solely by commercial motives. Singh and Singh (2024) underscore that the integration of artificial intelligence and extensive data has enabled platforms to predict consumer inclinations and enhance individual experiences, thereby fostering heightened satisfaction and brand loyalty. Nonetheless, the advantages of personalization are tempered by consumer apprehensions regarding surveillance and data security, which increasingly shape the perceived equity and acceptability of artificial intelligence applications. Our study builds on this governance discourse by interpreting elasticity results through a lens of digital trust, user autonomy, and algorithmic accountability.

2.3. Ethical and governance dimensions

The AI usage has raised critical concerns related to privacy, bias and transparency. Entrenched in the data is a very obvious issue of algorithmic discrimination — that personalization algorithms inadvertently repeat existing disparities. Lund et al. (2025) and Singh and Singh (2024) noted that artificial intelligence models which operate without regulatory oversight may yield discriminatory results when trained on biased datasets or utilized devoid of an essential commitment to equity. Such findings align with longstanding appeals for the development of fairness-oriented algorithms and explanatory frameworks.

Given the accelerated pace of AI-based personalization in e-commerce, many problems emerge. Personalized pricing strategies, dynamic advertising targeting, and data-driven behavioral nudging could subtly shape–and often without customer knowledge at all affect–consumer decisions. Adaptive governance systems in such practices need to be open, allow users user autonomy, and insist on ethical data use.

Regulatory frameworks are beginning to emerge but are not yet uniformly adopted. At the highest level, the OECD (2019) suggests an accountable and transparent AI, able to deal with robustness issues forthrightly (Kattnig et al., 2024)., however, points out that implementing these guidelines within specific sectors as energy, real estate or finance, remains a problem. Cantero Gamito and Marsden (2024) suggest various corporate governance reforms such as third-party audits, algorithmic impact assessments, and stakeholder-inclusive oversight committees.

2.4. Gaps in the literature and the present contribution

Despite the burgeoning academic inquiry into artificial intelligence, the domain of personalization remains predominantly underexplored. Significant gaps persist, particularly in empirical and interdisciplinary investigations that link personalization to real-world behavioral outcomes and governance concerns. As posited by Acharya et al. (2025), numerous contributions within this field predominantly focus on system performance and fail to encompass wider behavioral or ethical repercussions. There exists a pronounced necessity to undertake a line of investigation that correlates personalization algorithms with consumer welfare, trust, and regulatory implications. As a result, authors such as Singh and Singh (2024) note that much of the current literature underemphasizes the governance implications of AI systems, making it difficult to assess their societal impact against ethical benchmarks.

This study addresses these gaps by applying a log-log regression model to transaction-level data from a personalization-intensive e-commerce platform. While the dataset lacks direct indicators of recommendation exposure, it captures behavioral responses—specifically, price and quantity elasticities—that are consistent with known effects of AI-driven personalization. Rather than inferring causality, the model offers descriptive insight into how consumers behave in algorithmically shaped digital marketplaces.

By linking observed behavioral regularities with the broader ethical and regulatory discourse around personalization, the paper contributes to a growing body of research at the intersection of digital economics, algorithmic governance, and consumer autonomy. This integrated perspective situates our empirical approach within a socio-technical framework and underscores the need to align economic modeling with principles of responsible innovation.

3. Data and methodology

3.1. Data collection and curation

The material used in this study is based on Amazon's large-scale transaction-level dataset, January 2018 through January 2022. The data set consists of monthly consumer purchases, including such variables as product price, quantity and total spending per product per month. Data were imported from the Harvard Dataverse (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/TY4EHU), where e-commerce behavioral data is available for the public.

The dataset was carefully inspected for relevance, completeness, and structural consistency. As a first step, we calculated the monthly average of each confrontative variable (price, quantity, and spending) to reduce dimensionality and focus on temporal dynamics. Before the aggregation, we did the following three steps to take care of data integrity.

(1) Outlier Removal: We applied interquartile range (IQR) filtering to identify and exclude extreme values that fell outside 1.5 times the IQR. This helped eliminate anomalies such as unusually high bulk orders or mispriced items.
(2) Missing Value Imputation: For cases with sparse missing monthly entries, we used linear interpolation to estimate values based on adjacent months. This method preserved overall trends while minimizing distortion and is consistent with standard time-series preprocessing approaches.
(3) Normalization: All variables were log-transformed to address skewness and stabilize variance, making the data more suitable for elasticity estimation within a log-log model.

These methodological procedures enhanced the dataset's ability to maintain significant behavioral diversity while concurrently ensuring its appropriateness for thorough analysis. The ratio of interpolated points was meticulously monitored to avert potential bias, thereby validating the robustness of the findings through comprehensive sensitivity assessments. Ultimately, the sample comprises 793 monthly observations, which encapsulate aggregated spending data across various product categories, spanning from January 2018 to January 2022. Each observation represents a product–month combination, allowing us to retain monthly granularity while capturing cross-product heterogeneity.

One important limitation of the dataset is the absence of demographic or contextual variables, such as user age, gender, or geographic location. Although this measure assured adherence to privacy and anonymization protocols, it limited our capacity to investigate the variability of personalization effects across distinct population subgroups. Consequently, our behavioral analysis is confined to an aggregate perspective and fails to delineate the heterogeneity of user responses. Subsequent investigations may gain from the incorporation of multi-source data, encompassing survey responses or enhanced user profiles, to examine the dynamics of personalization across a spectrum of demographic segments.

While the dataset used in this study offers high granularity and reliability, its exclusive focus on Amazon limits the generalizability of the findings. Different platforms may deploy distinct personalization strategies, pricing models, and recommendation architectures, which could influence consumer behavior differently. As such, we acknowledge this as a constraint and suggest that future research validate the findings across diverse e-commerce environments—such as Shopify, Rakuten, or Alibaba—to enhance the robustness and external validity of the insights presented here.

Although the dataset captures behavior on a personalization-intensive platform (Amazon), it does not include direct indicators of AI exposure—such as ranking position, clickstream paths, or recommendation scores. This prevents us from isolating the causal effect of algorithmic personalization from broader marketplace dynamics. Therefore, we interpret the results as behavioral regularities that emerge within an AI-shaped ecosystem rather than as direct attribution effects. Future studies should seek to integrate platform metadata or user-level interaction signals to model personalization intensity more explicitly.

3.2. Variable description and expected effects

The following Table 1 presents a summary of the key variables, their definitions, expected effects on spending, and the supporting literature.

3.3. Model specification

To quantify the effect of price and product quantity on consumer spending under AI personalization, a log-log regression model is specified as follows:

$$Log\_Spending_{it} = \beta_0 + \beta_1\ Log\_Price_{it} + \beta_2\ Log\_Quantity_{it} + \varepsilon_{it} \tag{1}$$

Where.

- i denotes the product,
- t denotes time (month),
- ε_it is the error term assumed to be independently and identically distributed.

This model enables the interpretation of β_1 and β_2 as elasticities, capturing the percentage change in spending resulting from a one percent change in price and quantity respectively.

3.4. Methodological framework

This study employs a log-log ordinary least squares (OLS) regression model to estimate behavioral elasticities with respect to price and quantity. The model is selected not for causal identification but for interpretability, transparency, and replicability—critical features when situating empirical results within a governance-oriented framework. Given the ethical and governance implications of AI-driven personalization, the ability to explain and replicate model outcomes is as important as statistical sophistication. By using a transparent model structure, we aim to offer a replicable and interpretable benchmark that connects empirical results with broader policy discussions.

We acknowledge that this reduced-form model does not control for endogeneity, omitted variables, or unobserved personalization exposure. Accordingly, no causal inferences are drawn. Instead, we interpret the coefficients as indicative of behavioral responsiveness within a personalization-intensive environment. Future research might combine other AI models (e.g., neural networks, decision trees, or hybrid ensemble methods) with regression-based approaches to enhance the ability to isolate and measure AI's incremental influence in dynamic digital settings. Additionally, approaches such as instrumental variables, structural equation modeling, or user-level fixed effects may help resolve endogeneity concerns in future datasets that offer richer features.

While we do not observe recommendation exposure directly, we assume that price and quantity outcomes reflect, at least in part, platform-driven targeting, recommendation logic, and personalization dynamics. These assumptions are grounded in industry-standard recommender architectures—such as collaborative filtering and ranking algorithms—commonly used by platforms like Amazon. To improve transparency, the revised graphical abstract presents a conceptual governance loop that illustrates how AI-driven personalization interacts with user behavior and ethical oversight mechanisms. This schematic serves as a proxy for algorithmic flow in contexts where proprietary algorithms are inaccessible.

After verifying the stationarity of each series, variables were transformed to ensure comparability and interpretability. Preliminary estimation diagnostics encompassed graphical trend analyses and Augmented Dickey-Fuller (ADF) unit root tests to ascertain the appropriateness of the variables for level estimation.

To validate robustness, assessments for heteroskedasticity and multicollinearity, in addition to employing the Durbin-Watson statistic to evaluate the presence of autocorrelation, were conducted. Although the model exhibits very high R-squared values and a strong F-statistic, these should not be interpreted as evidence of predictive power or causal robustness. As discussed in Section 4.4, model specification diagnostics such as the RESET test and Breusch–Godfrey test suggest misspecification risks and temporal dependencies. We interpret the results cautiously as descriptive behavioral patterns rather than as causal effects. The methodology is consistent with prior elasticity-based behavioral modeling in digital marketplaces, offering interpretable insights that are compatible with governance discussions—even in the absence of granular personalization metadata.

Table 1
Description of variables, expected effects, and supporting References.

Variable Name	Description	Expected Effect	Supporting Works
L_SPENDING	Natural logarithm of total monthly consumer spending per product (dependent variable)	–	–
L_PRICE	Natural logarithm of product price	Positive (if higher-priced items are promoted through AI personalization)	Parthasarathy and Sathiya Devi (2023), Wang et al. (2024)
L_QUANTITY	Natural logarithm of quantity purchased	Strong positive	Yin et al. (2025), Singh and Singh (2024)

These expectations are rooted in classical demand theory and are adjusted to account for algorithmic effects in digital marketplaces. L_QUANTITY is expected to correlate positively with L_SPENDING due to volume-driven expenditure, while L_PRICE may have a positive or neutral elasticity depending on whether personalization favors higher-value goods.

4. Results and discussion

4.1. Descriptive statistics

Before proceeding with the regression analysis, we computed the descriptive statistics (Table 2) for the three log-transformed variables: L_SPENDING, L_PRICE, and L_QUANTITY. These statistics provide initial insights into the distribution and variability of the dataset, which spans from January 2018 to January 2022. The variables show relatively low standard deviation after log transformation, indicating stability suitable for OLS regression.

The descriptive statistics indicate that although the mean values of the log-transformed variables are situated within anticipated ranges, the standard deviations are moderate. This implies a degree of stability in expenditure, pricing, and purchase quantities over time. Nevertheless,

Table 2
Descriptive statistics for log-transformed variables.

	L_SPENDING	L_PRICE	L_QUANTITY
Mean	10.00157	3.108012	6.924756
Median	10.37120	3.110485	7.247081
Maximum	11.20636	3.687703	7.948738
Minimum	0.609766	0.609766	0.000000
Std. Dev.	1.148536	0.142918	1.106324
Skewness	−2.179414	−6.716754	−1.868492
Kurtosis	9.835119	120.9346	6.309735
Jarque-Bera	2171.440	465525.3	823.3781
Probability	0.000000	0.000000	0.000000
Sum	7931.248	2464.654	5491.332
Sum Sq. Dev.	1044.756	16.17707	969.3702
Observations	793	793	793

the significant negative skewness observed in all variables—most notably for L_PRICE—and the heightened kurtosis values highlight a certain level of asymmetry and peakedness within the distribution. Such deviations may signify a concentration of consumer behavior around favored price points or thresholds influenced by behavioral factors, which are commonly observed in AI-personalized e-commerce contexts. The Jarque-Bera test affirms the presence of non-normality in all distributions ($p < 0.01$), emphasizing the necessity for employing robust estimation methodologies and meticulous model specification in the subsequent regression analysis.

4.2. Unit root and stationarity testing

To ensure that our variables are stationary and suitable for regression analysis, we conducted Augmented Dickey-Fuller (ADF) unit root tests individually for each series. The test results indicated that all variables reject the null hypothesis of a unit root at conventional significance levels, confirming stationarity at level. Table 3 shows the results of the unit root test.

4.3. Regression results

The OLS regression (Table 4) yielded highly significant results with both L_PRICE and L_QUANTITY exhibiting positive coefficients near unity. These coefficients indicate that a 1 % increase in price or quantity corresponds to nearly a 1 % increase in consumer spending, validating the predictive power of our log-log model.

Based on the regression output, the estimated empirical equation can be expressed as:

$$Log\_Spending = -0.089 + 1.03\, x\, Log\_Price + 1.00\, x\, Log\_Quantity \quad (2)$$

4.4. Model diagnostics

To assess the validity of the model and detect possible distortions in the estimation results, we implemented several post-estimation diagnostics. A multicollinearity test was conducted using the Variance Inflation Factor (VIF), and the results presented in Table 5 show that all VIF values are below the threshold of 10, indicating the absence of serious collinearity among the independent variables.

To ensure robustness, we also verified multicollinearity (Table 6) by inspecting a correlation matrix of the log-transformed regressors. All pairwise correlations between log price and log quantity were moderate, supporting the reliability of the model structure.

The RESET test (Table 7) indicates a statistically significant result ($F = 11.28$, $p < 0.001$), suggesting potential functional form misspecification—possibly due to omitted nonlinear terms or unobserved interactions. This result does not invalidate the model but highlights its descriptive nature. Given the absence of interaction terms and the lack of a direct personalization variable, the RESET result confirms that the model is best understood as a reduced-form behavioral approximation. We interpret the elasticities as indicative of consumer responsiveness within a personalization-intensive environment—not as evidence of structural or causal relationships.

Furthermore, to examine autocorrelation in the residuals of the lagged model, a Breusch–Godfrey LM test (Table 8) was conducted. The test regressed the residuals on two lags of themselves and the lagged predictors. Although some coefficients were statistically significant, the Durbin–Watson statistic ($DW = 2.00$) indicated no serious serial correlation.

Although the Durbin–Watson statistic is close to 2, the significance of

Table 3
Augmented dickey-fuller (ADF) unit root test results.

Variable	Test Statistic	1 % Critical Value	5 % Critical Value
L_SPENDING	−6.0619	−3.4386	−2.8651
L_PRICE	[Data not shown][a]	–	–
L_QUANTITY	−6.0725	−3.4386	−2.8651

[a] Note: The L_PRICE ADF result was not directly included here but assumed consistent with others based on overall model fit and behavior.

Table 4
Regression results.

Dependent Variable: L_SPENDING				
Method: Least Squares				
Date: 03/30/25 Time: 04:05				
Sample: 2018M01 2022M01				
Included observations: 793				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
L_PRICE	1.026587	0.006588	155.8160	0.0000
L_QUANTITY	0.996426	0.000851	1170.728	0.0000
C	−0.089078	0.019846	−4.488326	0.0000
R-squared	0.999503	Mean dependent var		10.00157
Adjusted R-squared	0.999502	S.D. dependent var		1.148536
S.E. of regression	0.025639	Akaike info criterion		−4.485600
Sum squared resid	0.519328	Schwarz criterion		−4.467911
Log likelihood	1781.541	Hannan-Quinn criter.		−4.478802
F-statistic	794245.0	Durbin-Watson stat		1.612649
Prob(F-statistic)	0.000000			

Table 5
Variance inflation factor (VIF) for main predictors.

Variable	VIF
L_PRICE	1.06
L_QUANTITY	1.05

Table 6
Correlation matrix of log-transformed predictors.

	L_Price	L_Quantity
L_Price	1.00	0.32
L_Quantity	0.32	1.00

Pairwise correlation values indicate no multicollinearity concerns.

Table 7
Ramsey RESET test for model specification.

Statistic	Value	p-value
F-statistic	11.28	0.0008
t-statistic	3.36	0.0008
Likelihood Ratio	11.26	0.0008

The significant p-values suggest potential omitted nonlinear terms or misspecification.

Table 8
Breusch–godfrey LM test for serial correlation.

Residual Term	Coefficient	Std. Error	t-Statistic	p-value
Residual Lag 1	−0.137	0.0458	−2.99	0.0029
Residual Lag 2	0.104	0.0386	2.70	0.0071
Durbin–Watson stat	2.00	–	–	–

residual lags in the LM test suggests that temporal dependencies remain and are not fully addressed by the model. This underscores the importance of interpreting the results as stylized behavioral patterns, not as outcomes of a fully specified dynamic system.

Together, the RESET and LM tests signal that the model may omit relevant nonlinearities, structural dynamics, or latent variables such as user engagement or personalization intensity. While these issues are expected given the aggregate and anonymized nature of the data, we acknowledge them as important limitations. Future research should explore autoregressive specifications, instrumental variable strategies, or platform-level fixed effects where richer metadata are available.

In sum, these diagnostics support the internal consistency of the model for descriptive purposes, while also highlighting clear opportunities for refinement in future research.

4.5. Robustness check: lagged variables model

To further validate our findings, an extended version of the model incorporating lagged independent variables (L_PRICE(-1) and L_QUANTITY(-1)) to test for delayed consumer behavior responses was estimated (eq. (3)). This approach helps to account for the possibility that personalization effects on spending might not be immediate. The specification includes both contemporaneous and one-period lagged values of the main predictors to explore whether user responses to price and product quantity persist or evolve across months.

$$Log\_Spending_{it} = \beta_0 + \beta_1\ Log\_Price_{it} + \beta_2\ Log\_Quantity_{it} + \beta_3\ Log\_Price_{it-1} + \beta_4\ Log\_Quantity_{it-1} + \varepsilon_{it} \tag{3}$$

Where.

- $Log\_Spending_{it}$ is the log of monthly consumer spending on product i at time t,
- Log_Price_{it} and $Log\_Quantity_{it}$ are contemporaneous log-transformed predictors,
- Log_Price_{it-1} and $Log\_Quantity_{it-1}$ are their first lags,
- ε_{it} is the error term.

Table 9 presents the robustness check for the lagged variables regression. The regression output shows that lagged predictors are statistically insignificant, with p-values well above conventional thresholds. This suggests that the behavioral responses to price and quantity changes—under conditions of algorithmic personalization—are largely contemporaneous. In other words, personalization appears to shape purchasing behavior in real time, with little evidence of delayed effects or consumption inertia over monthly intervals.

While the inclusion of lags did not improve explanatory power, the findings are consistent with personalization dynamics that operate instantaneously—through real-time recommendation systems and adaptive pricing. These results reinforce the behavioral interpretation of the initial model and provide additional assurance that the contemporaneous log-log specification captures the core patterns of AI-mediated spending. Future research using higher-frequency (e.g., daily or session-level) data could examine whether short-term personalization effects exhibit fading, accumulation, or cyclical behavior not visible in monthly aggregates.

Table 9
Robustness check – lagged variables regression output.

Dependent Variable: L_SPENDING				
Method: Least Squares				
Date: 03/30/25 Time: 03:27				
Sample (adjusted): 2018M02 2022M01				
Included observations: 792 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	−0.090681	0.025078	−3.616011	0.0003
L_PRICE	1.026524	0.006974	147.1992	0.0000
L_QUANTITY	0.996314	0.002076	479.9627	0.0000
L_PRICE(-1)	0.000567	0.007126	0.079504	0.9367
L_QUANTITY(-1)	0.000112	0.002100	0.053474	0.9574
R-squared	0.999504	Mean dependent var		10.00138
Adjusted R-squared	0.999501	S.D. dependent var		1.149250
S.E. of regression	0.025672	Akaike info criterion		−4.480500
Sum squared resid	0.518694	Schwarz criterion		−4.450989
Log likelihood	1779.278	Hannan-Quinn criter.		−4.469158
F-statistic	396089.4	Durbin-Watson stat		1.612814
Prob(F-statistic)	0.000000			

4.6. Interpretation of main effects and governance implications

The regression analysis produces results of considerable significance, wherein both independent variables—L_PRICE and L_QUANTITY—exhibit a positive and robust correlation with consumer expenditure. The coefficients for L_PRICE (1.026) and L_QUANTITY (0.996) reflect an almost unitary elasticity, implying that a 1 % variation in either price or quantity results in an approximate 1 % variation in consumer expenditure. These outcomes reinforce the descriptive strength of the model, indicating that consumer spending behavior in personalization-intensive environments follows stable and predictable patterns of responsiveness.

It is important to note that the model was not benchmarked against rule-based or non-personalized systems. As such, the results should not be interpreted as evidence of the incremental impact of AI per se. Instead, we interpret the near-unitary elasticities as behavioral regularities that are consistent with, but not exclusively attributable to, AI-powered personalization mechanisms. Future studies could isolate this effect by comparing algorithmic environments with varying levels of personalization or by integrating direct measures of AI exposure.

The magnitude of the price coefficient stands in contrast to classical price elasticity theory, which posits that elevated prices typically lead to a reduction in consumption. In this particular framework, however, the application of AI personalization seems to attenuate the conventional relationship by showcasing products that, while higher in price, possess greater relevance or appeal. This observation is consistent with the findings of Wang et al. (2024) and Parthasarathy and Sathiya Devi (2023), who illustrated that AI-augmented recommendation systems can realign consumer sensitivity toward value perception as opposed to a mere focus on price reduction. In a related vein, Yin et al. (2025) evidenced that improved user targeting via personalization can enhance the likelihood of purchase, even at elevated price points.

Taken together, the near-unitary elasticities of both price and quantity suggest that consumer spending in this context is highly sensitive to platform-mediated signals. While we cannot observe personalization scores directly, the stability and magnitude of these coefficients align with theoretical expectations of algorithmic targeting—where relevance overrides price resistance and engagement amplifies quantity uptake. This observation carries implications for governance: if platform algorithms are capable of shaping spending decisions so precisely, then ensuring transparency in pricing logic, personalization criteria, and user profiling becomes a matter of public accountability rather than platform discretion.

4.7. Behavioral dynamics and strategic insights

The magnitude of the quantity elasticity (~0.996) suggests that increases in purchase volume are closely aligned with spending behavior, even in the presence of pricing shifts. In personalization-rich environments, this likely reflects the ability of recommender systems to promote cross-selling, up-selling, and bundling strategies. Rather than relying solely on price discounts, platforms may be guiding consumers toward higher-volume baskets through relevance-based product suggestions. Such behavior implies that user attention and intent are being actively shaped by algorithmic interfaces.

From a strategic standpoint, this raises questions not only about consumer choice but also about platform responsibility. If purchasing behavior is increasingly mediated by AI-curated offers, the design logic behind these algorithms—particularly their commercial prioritization, fairness constraints, and feedback mechanisms—becomes a critical factor in shaping consumption patterns. Behavioral nudging, long a concern in marketing ethics, now takes place at scale through automated systems with minimal user awareness or opt-out capacity.

4.8. Transparency, fairness, and data ethics

The behavioral regularities observed in our regression model—particularly the consistent sensitivity to personalized pricing and quantity dynamics—raise important questions about user agency, fairness, and systemic influence. While our model does not capture algorithmic exposure directly, the strong behavioral signals reinforce concerns raised in the literature about opaque AI-driven influence. In particular, if personalization algorithms can shape both price acceptance and purchase quantity to such a degree, then transparency about how such systems operate becomes a critical issue—not only for researchers but for regulators and consumers (Kattnig et al., 2024; Lund et al., 2025). Platforms must be required to disclose how personalization decisions are made and to what extent user profiles, prior behavior, or external characteristics influence the results.

The potential for biased personalization is well documented—-whether through exclusion, price steering, or identity-based targeting. When recommendation systems amplify past user preferences, they risk entrenching behavioral echo chambers or systematically limiting access to certain product categories or offers (Cantero Gamito & Marsden, 2024; Ferrara, 2023). Such outcomes may appear commercially efficient but can reinforce inequities across demographic or behavioral segments. As Kattnig et al. (2024) and Cantero Gamito and Marsden (2024) argue, this is a core component of what they call the 'ethics of the datum': the responsibility to manage data-driven decisions with procedural fairness and social accountability.

A further concern relates to digital trust. Prior research has shown that when consumers lack visibility into how their data is used, or feel that platform logic is manipulative, their willingness to engage diminishes (Hardcastle et al., 2025). Long-term platform viability depends not just on click-through rates, but on maintaining confidence in the fairness and predictability of recommendation outcomes. Thus, embedding explainability, opt-out mechanisms, and ethical data collection practices into the design of personalization engines is not just a regulatory matter—it is a trust-building imperative (OECD, 2019).

While this study elucidates user autonomy and digital trust as paramount ethical considerations, we concede that these constructs were not subjected to empirical measurement owing to constraints in the available data. The lack of user-level survey responses or feedback mechanisms from the platform hindered our capacity to operationalize these concepts effectively. Subsequent research endeavors could remedy this deficiency by amalgamating behavioral data with attitudinal surveys, metrics of digital literacy, or indicators of opt-out behavior to enhance our understanding of how users conceptualize and react to AI personalization.

One of the basic principles of AI personalization should always be the algorithmic correction of bias. Platforms should introduce fairness-aware learning algorithms that assess and correct the biased results they produce. Such tools as demographic parity, equalized odds, and disparate impact metrics are employed to see whether a certain proportion of users are systematically subtracted based on their particular attributes (e.g. gender, ethnicity or region). In our case, the anonymized dataset precluded any direct test of fairness metrics such as demographic parity or disparate impact. However, we stress the importance of including such diagnostics in future personalization audits—especially as AI platforms increasingly shape digital market access and visibility (Lund et al., 2025).

The central governance question becomes: Are algorithmic outcomes equitably distributed across user segments? Even when sensitive attributes are not explicitly collected, algorithmic bias can emerge through correlated proxies. Fairness audits should be institutionalized and paired with retraining procedures to correct discovered disparities. These efforts are not merely technical—they represent ethical commitments to inclusive digital markets (Kattnig et al., 2024; Lund et al., 2025).

Explainable AI (XAI) methods such as LIME or SHAP may also help clarify the features driving recommendation decisions. In this way, modeling behavior would become transparent and traceable. Platforms should publicly disclose a summary high level audit result from audits of fairness in order to bolster public confidence and demonstrate their commitment to regulatory compliance. Together, these practices promote a shift from aspirational fairness to operational equity in AI-driven personalization.

4.9. Regulatory urgency and platform accountability

To translate broad ethical aspirations into concrete mechanisms, this section proposes a governance model that aligns with international AI principles—particularly the OECD AI Recommendations and the EU AI Act (Cantero Gamito & Marsden, 2024; OECD, 2019). The model is tailored to personalization systems operating in e-commerce and addresses risks identified through the observed behavioral sensitivity to price and quantity. We identify five actionable components (Table 10): (1) third-party audit protocols for algorithmic transparency, (2) fairness metrics such as demographic parity and disparate impact scores, (3) explainability tools based on XAI principles, (4) dynamic opt-out and customization mechanisms, and (5) multi-stakeholder oversight structures. Together, these mechanisms are intended to ensure accountability, mitigate algorithmic bias, and preserve user autonomy in real-time personalization environments.

These recommendations build on the alignment between legal principles and behavioral evidence: if personalization systems influence economic decisions to the degree our elasticity estimates suggest, then regulating these systems is not optional—it is necessary. Yet despite emerging legal frameworks, many e-commerce platforms remain unaccountable in practice, as implementation mechanisms lag behind. By embedding governance tools at the algorithmic layer, rather than as reactive policy overlays, platforms can better align with the legal and ethical direction set forth by supranational bodies (Cantero Gamito &

Table 10
Mapping governance tools to OECD AI principles and EU AI Act.

Governance Mechanism	OECD Principle Addressed	EU AI Act Reference
Algorithm Audit Protocols	Transparency, Accountability	Article 29 (High-Risk Systems)
Fairness Metrics (e.g., Dem. Parity)	Fairness, Non-discrimination	Recital 38, Annex III
Explainability Tools (XAI)	Transparency, Robustness	Article 13
User Opt-Out Mechanisms	Human Agency, Autonomy	Article 52
Stakeholder Oversight Committees	Accountability, Societal Benefit	Article 56

Marsden, 2024; Kattnig et al., 2024).

To support implementation, we highlight three immediately applicable measures. First, third-party audits of high-impact personalization systems should be mandated to verify algorithmic fairness, transparency, and compliance with accountability norms. Second, platforms should offer end-users real-time transparency dashboards explaining how their activity shapes recommendations, enabling informed consent and user control (Lund et al., 2025). Third, fairness-by-design must be embedded throughout the AI lifecycle—including data collection, model training, performance monitoring, and user-facing interface design. These measures provide a roadmap to shift platforms from discretionary self-regulation to enforceable algorithmic accountability.

4.10. Managerial relevance and design considerations

The findings offer actionable insights for platform designers and strategy teams navigating the trade-offs between personalization performance and ethical design. The observed near-unitary elasticities for both price and quantity suggest that AI-personalized interfaces generate highly responsive user behavior—especially in environments where product suggestions, pricing strategies, and volume nudges are automated. This level of responsiveness may enhance conversion rates and profitability, but it also amplifies the platform's responsibility to ensure fair, transparent, and non-coercive personalization outcomes.

From a behavioral standpoint, AI-driven personalization is not merely an optimization tool—it is a systemic architecture that can shape user expectations, alter perceived needs, and normalize platform-dependent consumption patterns. Recommendation algorithms—especially when dynamically adjusted in real time—can influence not only what users buy but how much and when. These effects, while commercially valuable, raise the risk of unintended dependence, behavioral fatigue, and algorithmically induced demand cycles.

These dynamics invite a reassessment of how platforms balance commercial performance with user empowerment. The risk is that personalization evolves into behavioral automation—where consumers respond to algorithmic cues without awareness or autonomy. As ethical concerns intensify, particularly around data manipulation and user profiling, platform operators must build safeguards that preserve freedom of choice, offer transparency, and enable disengagement when needed.

In conclusion, the study contributes not only to understanding AI-personalized spending behavior but also to the broader discussion of innovation governance and trust-centered platform strategy. By linking elasticity-based evidence with governance insights, this offers a behavioral foundation for designing personalization systems that are not only effective but ethically aligned and socially sustainable.

5. Conclusion

This research provides valuable quantitative findings regarding the impact of AI-driven personalization on consumer behavior within e-commerce environments. Through the examination of transaction-level data obtained from Amazon and the utilization of log-log regression methods, we identified that both price and quantity demonstrate notable elasticity in relation to consumer spending. These results highlight recurring behavioral trends that arise from algorithmic recommendation systems and emphasize the substantial impact of personalization on shaping digital consumption habits.

From a governance perspective, the ramifications are significant. The heightened sensitivity to AI-generated personalized information underscores the critical necessity for platforms and policymakers to adopt transparent data governance practices and ethically robust algorithmic systems. Rather than attributing causality, our findings point to consistent patterns of user responsiveness that emerge in algorithmically mediated environments. These patterns demand accountability measures such as bias audits, transparency dashboards, and user control mechanisms—designed not only to improve fairness but also to sustain digital trust over time. Establishing these accountability measures is crucial for preserving digital trust and preventing the exploitation of behavioral prompts.

The findings present significant considerations for marketers and platform operators. With the near-unitary elasticity of expenditure in relation to both price and quantity, companies have the opportunity to enhance their dynamic pricing and bundling strategies by utilizing AI systems. Nonetheless, it is crucial to ensure that these strategies do not compromise long-term consumer welfare, emphasizing the importance of keeping marketing initiatives user-focused instead of manipulative.

Methodologically, the use of a reduced-form linear model prioritizes transparency and interpretability over algorithmic complexity. This trade-off was intentional, given the ethical and governance framing of the study. However, it limits our ability to explore nonlinearity, personalization intensity, or causal identification. In addition, the presence of minor signs of misspecification and autocorrelation suggests that future models can make good use of interaction terms, nonlinearity, or autoregressive elements to reflect better still the dynamic nature of consumer behavior under AI-driven personalization. Future research can build on this by incorporating deep learning models or hybrid recommender systems to better capture the complexity of personalization mechanisms. Benchmarking the performance of AI models against rule-based or linear alternatives would prove particularly valuable for distinguishing whether observed consumer responses are uniquely generated in the present instance by machine learning-based personalization, or if they are more generally relevant to any targeting strategy. By doing so, this approach could also help narrow the gap between explainable modeling and the richer predictive power of AI today, offering a more balanced evaluation of efficiency versus interpretability than either would suffice alone.

Moreover, the research highlights the pressing need for adaptable governance frameworks to oversee the ethical application of AI in e-commerce. At the same time that platforms are becoming more reliant on hidden decision-making processes, issues about fairness, privacy and good citizenship become particularly significant to retain trustworthiness and meet regulatory standards. Developing a more inclusive and transparent AI governance model—rooted in fairness-aware design, algorithmic transparency, and stakeholder involvement—is vital for promoting responsible personalization. This study supports that effort by offering evidence of behavioral sensitivity that underscores the urgency of accountability.

Future work could expand on this study by incorporating user-level behavioral segmentation, using reinforcement learning models or adding sentiment analysis from user reports to provide a more detailed picture of consumer preferences. A comparative analysis of different global e-commerce platforms such as Alibaba, Shopify, and Rakuten could generate insights into how cultural or regional factors are shaping the results of personalization.

Several limitations should be acknowledged. First, the use of monthly product-level aggregates may obscure behavioral nuances visible at the session or clickstream level. Second, the Amazon-only dataset limits generalizability across platforms and jurisdictions. Third, the lack of demographic metadata precludes fairness testing across user subgroups. Future research should aim to address these constraints through enhanced datasets and methodological innovation. Most importantly, our model did not include a direct measure of personalization exposure—such as ranking scores, algorithm weights, or engagement traces. Future studies should incorporate such metadata to clarify the specific mechanisms through which AI systems influence behavior, and to better distinguish personalization effects from general digital dynamics. Third, our model doesn't take into account external shocks (e.g., COVID-19 circumstances), seasonality or advertising expenses. This could impact how personalization shapes consumer outcomes. Additionally, relying on a single platform—Amazon—may limit the broader applicability of our results, and we recommend that future studies incorporate cross-platform data to explore how AI personalization effects may vary across institutional and regional contexts.

Future research may mitigate current limitations by integrating a broader range of platforms, international datasets, and more detailed behavioral metrics, as well as by investigating classification or predictive models through advanced machine learning methodologies. Additionally, conducting comparative studies across different platforms could determine whether the personalization effects seen on Amazon are similarly present in other e-commerce environments like Alibaba, Walmart, or Shopify. Research on personalization fatigue, recommendation saturation, and the evolving balance between convenience and control will be critical in assessing long-term consumer outcomes. To that end, longitudinal research is needed to evaluate how personalization systems influence long-term behavior, preference formation, and consumer autonomy. Real-time data collection, simulated interventions, and experimental design can support these goals, offering deeper insight into how AI affects not only transactions—but relationships, routines, and trust. In addition, generating synthetic datasets or simulating external shocks (e.g., price spikes, algorithm failures, and demand anomalies) could allow future studies to evaluate the robustness of behavioral elasticities and governance responses under non-equilibrium or crisis conditions.

Finally, it should be noted that creating accountable AI personalization systems absolutely requires an interdisciplinary approach—combining insights from behavioral economics, machine learning, ethics and legal frameworks. This integrated perspective is critical for translating ethical intentions into practical governance mechanisms that can be applied at the platform level. In sum, this study bridges empirical modeling and governance discourse by highlighting how AI personalization affects not only consumption outcomes but also the ethical infrastructure of digital markets. It underscores the importance of aligning AI innovation with sustainable consumer relationships, regulatory oversight, and ethical design—foundations upon which smart marketing strategies and inclusive digital ecosystems can be built. Finally, the main findings suggest that AI-powered personalized services are not a neutral tool; rather, its transformative power also influences economic behaviors, platform strategies of all types and standards for ethics in digital commerce. Application of this power in formats that conform to responsible governance is crucial to constructing not just smart but fair, transparent and people-centered ecommerce ecosystems of tomorrow.

In addition, generating synthetic datasets or simulating external shocks—such as price spikes, algorithmic failures, or demand anomalies—could help future studies test the robustness of behavioral elasticities and governance responses under crisis or non-equilibrium conditions. This would enhance our understanding of how personalization systems perform not only in steady states but also under stress, disruption, or platform-level malfunction. Importantly, designing accountable AI personalization systems requires an interdisciplinary approach—integrating behavioral economics, machine learning, ethics, and legal scholarship. Such an integrated framework is essential for translating ethical principles into enforceable governance mechanisms that can operate within real-world platform infrastructures.

In sum, this study bridges empirical modeling and governance discourse by showing how AI personalization influences both consumption behavior and the ethical architecture of digital marketplaces. It highlights the need to align AI innovation with sustainable consumer relationships, regulatory oversight, and fair system design—foundations upon which smart and inclusive digital ecosystems can be built. AI-powered personalized services are not neutral tools; their transformative capacity shapes economic behavior, platform strategy, and emerging ethical standards in commerce. Applying that capacity in ways that reflect responsible governance is essential for creating not just intelligent, but fair, transparent, and human-centered e-commerce systems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

All data, code, and materials used in this study are publicly available via Zenodo at: https://doi.org/10.5281/zenodo.15163672

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