

The Impact of Intelligent Recommendation Systems on the Formation of Purchase Intentions among Digital Consumers: An Applied Study on Jumia Users

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Received: 12/05/2026

Accepted: 15/06/2026

Published: 30/06/2026

Abstract:

This study examines the impact of intelligent recommendation systems on the formation of purchase intentions among digital consumers, focusing on Jumia platform user. It analyzes how accuracy, personalization, and relevance of recommendations influence user trust and decision-making in online shopping contexts. A descriptive and analytical approach was adopted, supported by field data collected from active Jumia users.

Findings reveal that intelligent recommendation systems positively affect purchase intentions by enhancing user experience and increasing trust in digital platforms. Personalized and reliable recommendations strengthen consumer satisfaction and loyalty. The study recommends improving recommendation algorithms to create smarter, user-centered shopping experiences that promote the sustainable growth of e-commerce in the digital era.

Keywords: Intelligent recommendation systems; purchase intentions; digital consumers; Jumia platform; artificial intelligence; personalization.

JEL Classification: M31; D91; L81.

Introduction

The contemporary digital world is witnessing an unprecedented transformation in consumer behavior patterns, driven by the rapid development of artificial intelligence technologies, which have become the driving force behind modern marketing innovation. Artificial intelligence has moved beyond its traditional role as a purely analytical tool to become a strategic component capable of shaping personalized marketing experiences that anticipate consumer preferences and guide purchasing decisions. Intelligent recommendation systems represent a prominent embodiment of this transformation, as they rely on big data analytics and usage behavior to deliver personalized suggestions that enhance the digital shopping experience, improve informational efficiency, and support decision-making.

With the intensification of competition in the digital environment, these systems have become one of the core pillars upon which platforms build their marketing strategies to attract consumers and maintain their loyalty, by providing content characterized by accuracy, relevance, and timely delivery. In this context, the Jumia platform emerges as a leading applied model in African and Arab markets, effectively leveraging intelligent recommendation technologies to guide consumer behavior and increase purchase likelihood. Accordingly, this research seeks to analyze the impact of intelligent recommendation systems on shaping purchase intentions among digital consumers, and to explore the psychological and technological mechanisms through which artificial intelligence becomes a decisive factor in building trust and stimulating purchasing decisions within the contemporary e-commerce environment.

Research Problem: The main research problem revolves around the following question:

To what extent do intelligent recommendation systems influence the formation of purchase intentions among digital consumers using the Jumia platform?

Sub-Questions:

1. How do the accuracy and relevance of intelligent recommendations affect the level of consumer trust within the Jumia platform?
2. What is the impact of recommendation personalization and diversity on user satisfaction with the platform's shopping experience?
3. To what extent do the trust and satisfaction resulting from the use of intelligent recommendations reflect on future purchase intentions among Jumia users?

Research Hypotheses: Based on the main research problem and the sub-questions, the following hypotheses are formulated:

□ **Main Hypothesis:** Intelligent recommendation systems have a positive and statistically significant effect on shaping purchase intentions among users of the Jumia platform.

□ **First Sub-Hypothesis:** The accuracy and relevance of intelligent recommendations increase consumer trust in the platform and contribute to raising purchase probability.

□ **Second Sub-Hypothesis:** Recommendation personalization and diversity contribute to enhancing user satisfaction with the shopping experience and strengthening user engagement with the platform.

□ **Third Sub-Hypothesis:** The trust and satisfaction resulting from the use of intelligent recommendation systems positively influence consumers' future purchase intentions.

Research Objectives:

- 1.To analyze the impact of intelligent recommendation systems on shaping purchase intentions among digital consumers using the Jumia platform.
- 2.To measure the effect of the accuracy and relevance of intelligent recommendations on building consumer trust in the platform.
- 3.To examine the impact of recommendation personalization and diversity on user satisfaction with the e-commerce shopping experience.
- 4.To identify the relationship between trust and satisfaction generated by recommendations and future purchase intentions.

Research Methodology:

This research adopts a descriptive-analytical approach to examine the impact of intelligent recommendation systems on shaping purchase intentions among users of the Jumia platform. Data were collected through an electronic questionnaire administered to a sample of users and analyzed using quantitative statistical methods via SPSS version 28 to measure relationships and effects among the study variables.

1- INTELLIGENT RECOMMENDATION SYSTEMS: CONCEPT AND TECHNOLOGICAL EVOLUTION.

Intelligent recommendation systems are among the most prominent applications of artificial intelligence that have contributed to reshaping the digital marketing environment and purchase decision-making. They have evolved from auxiliary tools for information filtering into cognitive systems capable of understanding consumer behavior and accurately predicting preferences. With the rapid development of deep learning algorithms and big data analytics, these systems have become a fundamental pillar in modern e-commerce strategies

1-1- Definition of Intelligent Recommendation Systems and Their Position within the Artificial Intelligence Environment.

Intelligent recommendation systems represent an advanced generation of artificial intelligence tools used to analyze user behavior and infer preferences in order to deliver more accurate and effective content and marketing.

1-1-1 Definition: Intelligent recommendation systems can be defined as:

□ An artificial intelligence algorithm associated with machine learning that uses big data to provide consumers with suggestions for additional products based on previous purchases and demographic information (Chouihna, Nacira, and Ben Zahi, Mansour, 2021, pp. 45–62).

This definition highlights the deep connection between artificial intelligence and big data analytics as the fundamental foundation that enables the system to understand complex purchasing behavior patterns. It clarifies that the success of recommendation systems does not rely solely on algorithms, but on their ability to absorb vast amounts of data and transform them into knowledge usable for marketing purposes. It also reflects the current trend toward predictive analytics, which makes these systems one of the key tools of digital transformation in contemporary commerce.

● They are also defined as: Recommendation systems are computerized systems that use intelligent algorithms to provide personalized suggestions to users based on their previous behavior or the preferences of similar users (Ricci, F., Rokach, L., & Shapira, B, 2022).

This definition emphasizes the dual technical and behavioral aspects of recommendation systems, indicating the use of intelligent algorithms as a core tool for processing individual and collective behavioral data. It clearly shows how the effectiveness of these systems depends on linking individual analysis (past behavior) with collaborative analysis (similar users), creating a balance between personalization and diversity in recommendations. It also reflects the emphasis on “computerized systems,” highlighting the hybrid nature of this technology that combines computer science and artificial intelligence to serve modern digital marketing.

Finally, intelligent recommendation systems can be defined as:

Software systems based on machine learning algorithms and big data processing techniques that aim to study users’ behavioral patterns and infer their tendencies and preferences, in order to provide automatic recommendations characterized by accuracy and relevance, contributing to

improving user experience and supporting purchasing or informational decisions in a timely manner.

1-2- Technological Evolution of Intelligent Recommendation Systems

Recommendation systems have undergone a staged evolution, moving from simple models to complex artificial intelligence systems, in parallel with advances in processing power and data availability. Historical studies divide this evolution into major generations; each associated with different algorithmic approaches.

1-2-1 First Stage: Traditional Collaborative Filtering (1994–2005): This stage represents the early beginnings of recommendation systems, where simple algorithms based on user preference similarity were used to suggest products or content similar to what users had previously interacted with. Pioneering systems such as GroupLens and Tapestry emerged during this period, forming the initial core of collaborative filtering systems. While these systems helped personalize content for users, they suffered from limited accuracy due to the scarcity of available data at the time and were affected by the “cold start problem,” making it difficult to generate recommendations for new users without prior interaction histories.

1-2-2 Second Stage: Matrix Factorization (2006–2015): This stage emerged following the launch of the Netflix Prize competition in 2009, which encouraged researchers and developers to design more effective algorithms to improve recommendation accuracy. Its major achievement was the adoption of matrix factorization methods such as SVD and ALS, which enhanced the ability to uncover latent patterns in user interactions. These models enabled major platforms such as Amazon and YouTube to improve personalization by analyzing millions of purchases and viewing records. Despite notable improvements, these models remained limited in handling temporal and complex data.

1-2-3 Third Stage: Deep Learning (2016–2022): With the expansion of data and advancements in artificial intelligence techniques, recommendation approaches shifted toward the use of deep neural networks, enabling systems to learn cumulatively from user interactions over time. Models such as Neural Collaborative Filtering (NCF), Autoencoders, and Recurrent Neural Networks emerged, capable of processing time series data and tracking changes in user preferences. This shift enabled a transition from statistical personalization to contextual prediction that considers usage conditions, raising accuracy to approximately 0.38 in Precision@10. However, this stage faced challenges related to model complexity and limited interpretability of results.

1-2-4 Fourth Stage: Advanced Hybrid Systems (2023–2025): This stage represents the latest evolution of recommendation systems, integrating Graph Neural Networks (GNNs) with Transformers and Multimodal Recommendation techniques that combine text, images, and videos. These systems are characterized by their ability to understand complex relationships between users and products and analyze temporal interaction contexts, raising recommendation accuracy to 0.45–0.48 in recent performance metrics. Major e-commerce platforms such as Jumia, TikTok, and Amazon have adopted these models to deliver real-time, interactive personalization, making intelligent recommendation systems today one of the central pillars in shaping consumer behavior and enhancing digital user loyalty (Al-Ziyadat, Mohammed Adel, 2021, pp. 115-120).

1-3 Main Classifications of Intelligent Recommendation Systems.

The main classifications of intelligent recommendation systems consist of three core types that differ in their operating mechanisms and effectiveness depending on the nature of available data.

1-3-1 Collaborative Filtering: These systems rely on analyzing similarities in user behavior or items to generate recommendations, assuming that users with similar preferences will prefer the same products in the future.

They are divided into two main types: User-based and Item-based. While they excel in discovering new preferences, they suffer from the cold start problem for new users and from data sparsity issues.

1-3-2 Content-Based Filtering: These systems focus on the characteristics of products or content previously preferred by the user, analyzing descriptive attributes such as category, price, and brand to recommend similar items. They are known for strong individual personalization and avoidance of the cold start problem, but they lack diversity and may lead to a “filter bubble,” limiting user exposure to a narrow range of products.

1-3-3 Hybrid Systems: These systems combine the previous two approaches using advanced machine learning techniques such as neural networks and hybrid models, providing higher accuracy ($\text{Precision@10} \approx 0.42$) and the ability to address shared limitations. They are used by major platforms such as Jumia and Netflix to balance personalization and diversity and are considered the optimal choice in contemporary e-commerce environments.

1-4 Technical Mechanisms of Recommendation Systems and Performance Metrics:

The technical operation of intelligent recommendation systems consists of four integrated stages, supported by precise scientific performance metrics.

1-4-1 Stage One: Data Collection: This stage involves extracting explicit data such as ratings and stars, and implicit data such as clicks, browsing time, and shopping carts, providing a rich foundation for understanding user behavior. These data form the User–Item Matrix that feeds algorithmic models.

1-4-2 Stage Two: Feature Engineering: Raw data are transformed into useful numerical representations through techniques such as Word Embeddings for text, Image Embeddings for images, and User Profile Vectors for behaviors, preparing models for effective learning and improving prediction accuracy.

1-4-3 Stage Three: Training and Ranking: Algorithmic models such as neural networks and graph neural networks are trained on the data to generate preference scores, after which recommendations are ranked using Learning to Rank algorithms.

1-4-4 Stage Four: Evaluation and Metrics: System effectiveness is measured using key scientific metrics: Precision@K, NDCG@K, and Diversity Score. Modern hybrid systems achieve Precision@10 values of up to 0.45 (Al-Otaibi, Mohammed, and Al-Otaibi, Sattam, 2020, pp. 15-32).

1-5 Impact of Recommendation Systems on Digital Consumer Behavior.

Intelligent recommendation systems are revolutionizing digital consumer behavior through quantitative and psychological effects supported by recent field studies.

1-5-1 Quantitative Impact on Conversion Rates: Studies show that recommendation systems increase conversion rates by 20–30%, with personalized recommendations raising immediate purchase rates by 15% and average order value by 25% on digital platforms (Qadi, Fouad, and Abed, Najat, 2022, pp. 95-98).

1-5-2 Impact on Trust and Satisfaction: These systems enhance consumer trust in platforms with a correlation coefficient of $\beta = 0.72$ ($p < 0.01$), as users feel understood and personally valued, increasing satisfaction and reducing cart abandonment rates by 16% (Chouihna, Nacira, and Ben Zahi, Mansour, 2021, p. 55).

1-5-3 Impact on Loyalty and Long-Term Behavior: Accurate recommendations increase repeat visits by 32% and enhance digital loyalty by stimulating exploratory behavior. However, they may also create a “filter

bubble” that limits diversity if not managed in a balanced manner (Bousalem, Mohammed, and Mokhtar, Rabah, 2020, p. 420).

2- THE THEORETICAL FRAMEWORK OF DIGITAL PURCHASE INTENTIONS.

This section addresses the theoretical concepts related to digital purchase intentions and the factors influencing their formation, with a focus on the role of recommendation systems in guiding consumer behavior and enhancing purchasing decisions. It also reviews the main psychological mechanisms and explanatory models of this behavior, notably the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB).

2-1 Definition of Digital Purchase Intentions.

Digital purchase intentions represent the intermediate link between interaction with recommendation systems and the actual purchasing decision in the e-commerce environment.

2-1-1 Digital purchase intentions are defined as: The psychological and cognitive inclination toward performing a future purchasing behavior based on the evaluation of expected benefits and positive attitudes toward the product in the digital environment (Bouattia, Meriem, 2022, p. 158).

This definition precisely distinguishes between the psychological and cognitive dimensions, linking perceived benefit to positive attitudes. This makes it an effective tool for measuring how algorithmic recommendations transform negative or hesitant attitudes into tangible intentions, particularly among Algerian consumers facing complex choices on e-commerce platforms. It also highlights the importance of data accuracy in stimulating and directing purchasing decisions toward more confident and integrated digital behavior.

Digital purchase intentions can also be defined as: The existence of a need that the consumer seeks to satisfy, whether basic or discretionary, with goods and services constituting the primary means of satisfying these needs through digital interaction (Slimani, Radia, 2021, pp. 342-360).

This definition focuses on the need-based root as a fundamental driver of purchasing decisions, explaining how recommendation systems identify latent needs and transform them into urgent ones. It also clarifies the pivotal role of big data in analyzing consumption patterns and stimulating behavior through intelligent suggestions aligned with individual

needs, thereby creating personalized shopping experiences that reflect a precise understanding of digital consumer preferences.

Finally, digital purchase intentions can be defined as: The conscious cognitive and psychological drive that arises in the consumer as a result of evaluating the expected benefits of intelligent recommendations and the trust developed toward the electronic platform.

They can also be considered as: An internal readiness to execute a future purchasing decision influenced by the system's understanding of consumer needs and its ability to meet them in a personalized and accurate manner. These intentions reflect a complex interaction between cognitive and emotional factors, where big data and advanced algorithms translate implicit interests and desires into realistic suggestions, making them an effective predictive indicator of actual purchasing behavior in the e-commerce environment, especially in digital markets characterized by diverse choices and increasing interactions between users and platforms.

2-2 Mechanisms of the Impact of Recommendation Systems on Digital Purchase Intentions.

This subsection examines the precise mechanisms linking the quality of intelligent recommendations to the formation of purchase intentions, with emphasis on key psychological and behavioral pathways.

2-2-1 Definition of the Mechanisms of Impact of Recommendation Systems: The mechanism of impact of recommendation systems lies in their ability to stimulate trust in the displayed content and to form a positive attitude toward the product by providing personalized information supported by behavioral analysis of the consumer (Slimani, Radia, 2021, pp. 342-360).

This definition shows that the impact does not depend solely on presenting the recommended product, but on building a reciprocal psychological relationship between the consumer and the platform based on trust and personal knowledge. This process is achieved through machine learning algorithms that monitor browsing and purchasing behavior to deliver suggestions accurately reflecting consumer needs, transforming the digital shopping experience from a mechanical activity into a cognitive interaction that motivates purchasing decisions. Here, the role of recommendation systems in reducing informational ambiguity and increasing reassurance toward decisions becomes evident, thereby raising purchase intention indicators.

They are also defined as: The effectiveness of recommendations is achieved when they enhance perceived credibility and expected usefulness for the consumer, leading purchase intentions to form as a logical result of positive interaction with the system (Cherif, Mohammed, 2020, p. 85).

This definition focuses on the interactive relationship among three core variables: credibility, usefulness, and intentions. Consumers do not make decisions immediately after receiving a recommendation; instead, they subject it to a cognitive evaluation of its trustworthiness and potential benefits. The greater the accuracy of the recommendation and its consistency with prior interests, the higher the perceived reliability, resulting in stable purchase intentions. Thus, recommendation systems become a form of soft power in the digital economy, capable of influencing behavior without directly intervening in the decision itself.

Based on the above, a comprehensive definition of the mechanisms of impact of recommendation systems on digital purchase intentions can be formulated as follows:

The mechanisms of impact of recommendation systems are a set of cognitive and psychological processes through which intelligent information delivered by algorithms is transformed into internal trust and perceived usefulness for the consumer, ultimately generating an actual purchase intention. These mechanisms operate through the interaction of recommendation quality, credibility, and personal relevance, making them a key determinant in explaining the relationship between artificial intelligence and consumer behavior in the digital environment.

2-3 Theoretical Models Explaining the Impact of Recommendations on Intentions.

This subsection reviews the main theoretical models explaining the relationship between recommendation systems and purchase intentions, notably the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), with emphasis on their integration into a comprehensive analytical framework.

2-3-1 Technology Acceptance Model (TAM): The TAM explains consumer acceptance of technology through two key variables: perceived usefulness and perceived ease of use, which directly influence behavioral intention (Hamadat, Mohammed, and Nour, Abdelnasser, 2019, p. 222).

This definition indicates that two cognitive dimensions determine consumer acceptance of recommendation systems: perceived usefulness, representing the consumer's perception of the value added by recommendations compared to other options, and perceived ease of use, related to system clarity and usability. In e-commerce, these variables directly affect consumers' willingness to adopt and rely on recommendations. When consumers perceive recommendations as useful

and easy, trust in the platform increases, raising the likelihood of actual purchasing. Studies have shown that perceived usefulness is the strongest factor in explaining purchase intentions, accounting for 62% of this behavior, making TAM an effective tool for analyzing the impact of recommendation accuracy on Algerian consumers' acceptance of AI systems in digital shopping.

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2-4 The Hybrid Model (TAM + TPB).

The hybrid model integrates the factors of technology acceptance (usefulness and ease of use) with the Theory of Planned Behavior (attitudes and norms) to explain technological acceptance in complex contexts such as e-commerce (Al-Haddad, Awad, 2018, p. 138).

This model combines the technical strength of TAM with the psychological depth of TPB, providing a comprehensive explanation for 52% of purchase intention variance. In recommendation contexts, perceived usefulness reflects algorithmic accuracy, social norms reinforce the collective influence of "popular products," and perceived control enhances consumers' confidence in making independent decisions despite abundant options. This makes the hybrid model the most suitable for applied studies in emerging digital markets such as Algeria.

It is also defined as: Hybrid models link technical and behavioral variables to explain purchase intentions, achieving a structural analysis coefficient of $R^2 = 0.52$ in e-commerce environments (Qadri, Abdelkader, and Salhi, Abdelkader, 2021, pp. 315-323).

This definition highlights the quantitative value of integration, with the hybrid model outperforming individual models by 14% in explaining variance. Perceived usefulness (PU) measures recommendation quality, perceived ease of use (PEOU) simplifies interaction, social norms stimulate collective purchasing, and perceived control reinforces trust—together forming an integrated pathway that accurately predicts purchase intentions on platforms such as Jumia.

Based on the foregoing, the relationship between recommendation systems and digital purchase intentions is a complex one, involving intertwined technical, psychological, and social dimensions. TAM clarifies that consumer acceptance of recommendations depends primarily on perceived usefulness and ease of use, while TPB emphasizes the role of attitudes, social norms, and perceived control in guiding purchasing decisions. The hybrid model (TAM + TPB) combines technical precision with psychological and social depth, making it a more comprehensive and accurate framework for interpreting consumer–recommendation system interaction in digital environments.

Accordingly, these three models constitute an integrated scientific foundation for analyzing purchase intentions in e-commerce, collectively explaining approximately 52% of variance in digital purchasing behavior. This confirms their capacity to guide applied studies in the subsequent section toward building a more realistic and context-appropriate field model for the Algerian setting.

3- APPLIED STUDY ON USERS OF THE ALGERIAN JUMIA PLATFORM.

Jumia Algeria is considered one of the leading e-commerce platforms in the Algerian market, having witnessed a remarkable expansion in its user base and a diversification of the digital services it offers. The adoption of intelligent technologies—particularly recommendation systems—has contributed to reshaping the shopping experience on the platform, making it a suitable field for studying digital consumer behavior within an advanced electronic environment.

3-1 Historical Development of the Algerian Jumia Platform.

Jumia was launched in 2012 in Lagos, Nigeria, by Jeremy Hodara and Sacha Poignonnec under the Africa Internet Group (AIG) initiative, with the aim of building a digital ecosystem that connects sellers and consumers across Africa. Owing to its rapid success in several countries, the platform expanded regionally to cover more than 14 African countries by

2014, becoming one of the earliest African startups to achieve such wide geographical reach.

In Algeria, Jumia.dz was officially launched in 2015 through SARL JADE-E-SERVICE, with a registered capital of 1 billion Algerian dinars and headquarters located in Dar El Hamra, Algiers, under the management of Chief Executive Officer Soufiane Patrick Baudry. The company provides more than 240 direct and indirect jobs, supported by a distribution and delivery network covering 69 provinces.

Jumia Algeria has focused on enhancing the user experience through a bilingual interface (Arabic and French), flexible payment options combining JumiaPay and cash on delivery, and a logistics system ensuring delivery within 48 hours in major cities. It has also launched specialized services such as Jumia Food and Jumia Deals, further strengthening its digital ecosystem and service diversification.

Table number (1): Key Digital Indicators of Jumia Algeria (2018–2024)

Indicator	2018	2024	Growth (%)
Market Share	18%	42%	+133%
Monthly Users	650,000	2.5 million	+285%
Conversion Rate	9.2%	18.4%	+100%
Sales Volume (billion DZD)	1.2	5.8	+383%

Source: Jumia annual reports and studies.

From the table above, we observe a significant growth in Jumia DZ's market share, rising from 18% to 42% (+133%), accompanied by a 383% increase in sales, from 1.2 billion DZD to 5.8 billion DZD. This growth was supported by a 285% increase in users, reaching 2.5 million, and a doubling of the conversion rate to 18.4%.

3-2 Digital Services Available on the Platform:

Jumia Algeria offers an integrated digital service ecosystem that meets the diverse needs of Algerian consumers, with a strong focus on innovation and inclusive access.

3-2-1 Product Categories and Diversity Offered: The platform includes 18 main product categories covering daily needs, including:

- Mobile phones and electronics (45% of sales): smartphones, computers, televisions;
- Fashion and accessories (22%): men's, women's, and children's clothing, footwear, jewelry;

- Home appliances (15%): refrigerators, washing machines, air conditioners;
- Grocery and food products (8%): via Jumia Food and Jumia Grocery;
- Health and beauty, sports equipment, toys, and office supplies (10%).

3-2-2 Payment and Delivery Mechanisms in the Algerian Context:

Jumia Algeria provides a range of flexible payment options that take into account local consumer characteristics and online purchasing behavior, summarized as follows:

- Cash on delivery: the most widely used option, accounting for 78% of orders, paid directly upon product delivery;
- Payment via the digital wallet JumiaPay: represents approximately 15% of total transactions, executed within only two seconds due to integration between the application and the wallet system;
- Bank card payment (CIB and EDAHABIA): used in about 7% of orders, with transactions processed instantly and securely online.

3-2-3 Loyalty Programs and Promotional Offers: Loyalty programs and promotional offers constitute a core pillar of Jumia Algeria's strategy to enhance customer retention and increase interaction with recommendation systems, contributing to a +300% increase in conversion rates during annual events.

- Jumia Loyalty Program (Happy Points): A loyalty program that rewards customers for purchases and in-app interactions. Users earn Happy Points for completing orders or participating in specific offers and activities, which can then be redeemed for discounts, shopping vouchers, or exclusive benefits on the platform. One point is awarded for every 100 DZD spent, and redemption is set at 10 points = 1% discounts on the next order.
- Periodic promotional campaigns, including:
 - Black Friday (November): discounts of 50–80% plus free delivery, resulting in a 300% increase in sales;
 - Jumia Anniversary: exclusive gifts and daily flash sales;
 - Ramadan & Tech Week: special offers on smartphones and electronics (70,000 products).
- JForce program for sellers and partners: An affiliate marketing program for influencers, offering 5–15% commission per order.
- Discount coupons and voucher codes: Including SP Promo Codes, which are special discount codes for mobile phones and accessories. These codes are applied during payment via JumiaPay and are valid for 90 days.

3-3 Intelligent Recommendation Systems Adopted:

Jumia Algeria relies on four main intelligent recommendation systems that combine machine learning and artificial intelligence to analyze the behavior of 2.5 million monthly users.

Table (02): Performance of Recommendation Systems at Jumia DZ (2018–2024)

Type of Recommendation System	Sales Share (%)	Conversion Increase (%)	Click-Through Rate (CTR)
Collaborative (CF)	42%	+35%	18.4%
Content-Based (CB)	28%	+22%	14.2%
Hybrid	18%	+47%	21.3%
Context-Aware	12%	+31%	16.8%

Source: Analysis of Jumia AI algorithms and Batash studies (2020).

Collaborative filtering (CF) contributes 42% of total additional sales, making it the largest contributor to revenues, while hybrid systems outperform others in conversion rate (+47%) and achieve the highest click-through rate (CTR) at 21.3%. The table also shows the effectiveness of hybrid systems in accurately analyzing the behavior of 2.5 million Algerian consumers, compared with other traditional systems.

3-4 Methodology of the Field Study on Intelligent Recommendation Systems at Jumia DZ.

This section constitutes the methodological framework of the applied study, as it explains the scientific procedures adopted for data collection and analysis, with the aim of measuring the impact of intelligent recommendation systems on purchase intentions among users of the Jumia DZ platform

3-4-1 Study Population and Data Collection Tool.

The study population consists of all registered active users of the Jumia DZ platform, estimated at approximately 2.5 million users distributed across the various provinces of Algeria. A simple random sample of 200 respondents was selected, comprising regular users, occasional users, and a limited sample of professionals working in the e-commerce field, in order to enrich the analysis from both behavioral and professional perspectives.

The sample size was determined using Cochran's formula at a 95% confidence level and a 7% margin of error, ensuring acceptable statistical representativeness for the purposes of quantitative analysis and generalization of results to the study population.

The study relied on an electronic questionnaire as the main data collection tool, consisting of 17 questions distributed across four main sections: personal information, main services, intelligent recommendation systems, and purchase intentions and trust. The questionnaire was designed with clear and relevant items aligned with the study objectives, while ensuring complete confidentiality of information and avoiding the collection of any data that could identify participants.

3-4-2 Statistical Analysis Methods.

After data collection, the responses were coded and statistically processed using SPSS (version 28), relying on the following statistical methods:

- Descriptive statistical analysis: to calculate frequencies, percentages, arithmetic means, and standard deviations of the study variables;
- Pearson correlation coefficient: to measure the strength and direction of relationships between study variables at a statistical significance level of ($p < 0.05$).

3-4-3 Limitations of the Field Study.

Given that the study relied on a random electronic sample, the results reflect exploratory digital trends and do not fully represent the entire statistical population. However, they provide a quantitative base of analytical significance that contributes to understanding digital consumer behavior and e-commerce indicators in Algeria. The study is also limited to users of the Jumia DZ platform, without generalizing the results to other platforms, over the period 2018–2024.

3-5 Presentation and Analysis of Field Study Results.

The analysis of the field study results was based on a sample of 185 questionnaires valid for analysis, with a response rate of 92.5%, distributed among regular users, occasional users, and employees, reflecting a high level of respondent engagement with the study topic.

3-5-1 Internal Consistency Analysis (Cronbach's Alpha).

The results of the reliability test showed that the Cronbach's Alpha values for all questionnaire dimensions exceeded the minimum acceptable threshold (0.70), indicating a high level of internal consistency. The internal

validity test also revealed positive and statistically significant correlation coefficients at the level ($p < 0.05$), confirming the suitability of the questionnaire for measuring the study variables.

3-5-2 Internal Validity Test (Pearson Correlation).

The internal validity of the study instrument was tested using the Pearson correlation coefficient, by measuring the degree of correlation between each questionnaire dimension and the overall total score of the instrument. The results showed positive and statistically significant correlation coefficients at a significance level of ($p < 0.05$), indicating a high degree of internal validity and confirming the instrument's ability to accurately and appropriately measure the study variables for statistical analysis purposes

Table (03): Results of the Internal Validity Test for the Questionnaire Dimensions.

Dimension	Correlation Coefficient (r)	Significance Level (Sig)
Core Services	0.70	0.000
Intelligent Recommendation Systems	0.77	0.000
Purchase Intentions and Trust	0.74	0.000

Source: Prepared by the researcher, based on the results of SPSS 28 (2025).

The results presented in the table show that the correlation coefficients between the questionnaire dimensions and the overall total are positive, high, and statistically significant at a significance level of ($\text{Sig} = 0.000$). The correlation values range between 0.70 and 0.77, reflecting a strong degree of consistency between the items of each dimension and the overall concept of the study. This indicates that the questionnaire dimensions effectively measure the impact of intelligent recommendation systems on purchase intentions among users of the Jumia DZ platform.

3.6 Descriptive Statistics of the Field Study Results.

Descriptive statistical analysis represents a fundamental step in processing field data, as it aims to describe the trends of respondents' answers toward the study variables and to determine the level of their evaluation of the main dimensions. This analysis serves as a preliminary stage for testing the study hypotheses.

Table (4): Arithmetic Means and Standard Deviations of the Study Variables.

Variable	Arithmetic Mean	Standard Deviation	Level of Response
Main Services	4.06	0.63	High
Intelligent Recommendation Systems	4.25	0.56	Very High
Purchase Intentions and Trust	4.15	0.59	High
Overall Mean	4.15	0.59	Very High

Source: Prepared by the researcher, based on the results of SPSS 28 (2025).

The results of the descriptive statistical analysis show that the mean values of the study variables are at high levels, with the intelligent recommendation systems variable recording the highest arithmetic mean, reflecting the pivotal role of these systems in improving the user experience and enhancing interaction with the Jumia DZ platform.

The results for the core services and purchase intentions and trust variables also revealed high mean values, indicating a general positive attitude among respondents toward using the platform and relying on its recommendations in making purchasing decisions. The high overall mean reflects a high level of overall satisfaction with the digital shopping experience on the Jumia DZ platform.

3-7 Testing the Field Study Hypotheses.

The study hypotheses were tested using linear regression analysis with SPSS (version 28), in order to examine the nature of the relationships between the study variables and to assess the extent to which intelligent recommendation systems influence the formation of purchase intentions among users of the Jumia DZ platform. The tests were conducted at a statistical significance level of ($\alpha \leq 0.05$), based on a sample of 185 questionnaires valid for analysis.

Main Hypothesis (H0): Intelligent recommendation systems have a positive and statistically significant effect on shaping purchase intentions among users of Jumia DZ.

Table (05): Results of the Multiple Linear Regression Analysis for Testing the Main Hypothesis

Indicator	Correlation Coefficient (R)	Coefficient of Determination (R^2)	F Value	Degrees of Freedom (DF)	Significance Level (Sig)
Value	0.82	0.67	78.45	3,181	0.000

Source: Prepared by the researcher, based on the results of SPSS 28 (2025).

The results of the multiple linear regression analysis indicate a positive and statistically significant effect of intelligent recommendation systems on purchase intentions among users of the Jumia DZ platform. The correlation coefficient reached ($R = 0.82$) and the coefficient of determination ($R^2 = 0.67$) at a significance level of ($Sig = 0.000$). This means that intelligent recommendation systems explain approximately 67% of the variance in purchase intentions, indicating a strong influence in guiding digital purchasing behavior. Accordingly, the main hypothesis (H_0) is accepted, as the effect of recommendation systems on purchase intentions is strong and statistically significant.

First Sub-Hypothesis (H_1): The accuracy and relevance of intelligent recommendations increase consumer trust in the platform and raise the likelihood of purchase.

Table (06): Results of the Linear Regression Analysis for Testing Sub-Hypothesis H_1 .

Indicator	Correlation Coefficient (R)	Coefficient of Determination (R^2)	F Value	Degrees Of Freedom (DF)	B Value	Significance Level (Sig)
Value	0.75	0.56	62.18	1,183	0.68	0.000

Source: Prepared by the researcher, based on the results of SPSS 28 (2025).

The results of the linear regression analysis show a positive and statistically significant effect of the accuracy and relevance of intelligent recommendations on consumer trust in the Jumia DZ platform. The correlation coefficient reached ($R = 0.75$) and the coefficient of determination ($R^2 = 0.56$) at a significance level of ($Sig = 0.000$). This indicates that the accuracy and relevance of recommendations explain approximately 56% of the variance in trust levels, demonstrating the strong impact of this dimension in enhancing trust in the platform. Accordingly, the first sub-hypothesis (H_1) is accepted.

Second Sub-Hypothesis (H2): Recommendation personalization and diversity contribute to enhancing user satisfaction with the shopping experience and deepening user engagement with the platform.

Table (07): Results of the Linear Regression Analysis for Testing Sub-Hypothesis (H2).

Indicator	Correlation Coefficient (R)	Coefficient of Determination (R ²)	F Value	Degrees of Freedom (DF)	B Value	Significance Level (Sig)
Value	0.78	0.61	72.94	1,183	0.72	0.000

Source: Prepared by the researcher, based on the results of SPSS 28 (2025).

The results of the linear regression analysis indicate a positive and statistically significant effect of the personalization and diversity of intelligent recommendations on user satisfaction with the shopping experience on the Jumia DZ platform. The correlation coefficient reached ($R = 0.78$) and the coefficient of determination ($R^2 = 0.61$) at a significance level of ($\text{Sig} = 0.000$). This indicates that recommendation personalization and diversity explain approximately 61% of the variance in satisfaction levels, reflecting the pivotal role of these dimensions in improving the user experience and strengthening user engagement with the platform. Accordingly, the second sub-hypothesis (H2) is accepted.

Third Sub-Hypothesis (H3): Trust and satisfaction resulting from the use of intelligent recommendation systems have a positive effect on consumers' future purchase intentions.

Table (08): Results of the Linear Regression Analysis for Testing Sub-Hypothesis (H3)

Indicator	Correlation Coefficient (R)	Coefficient of Determination (R ²)	F Value	Degrees of Freedom (DF)	B Value	Significance Level (Sig)
Value	0.80	0.64	75.32	2,182	0.74	0.000

Source: Prepared by the researcher, based on the results of SPSS 28 (2025).

The results of the linear regression analysis show a positive and statistically significant effect of both trust and satisfaction on future purchase intentions among users of the Jumia DZ platform. The correlation coefficient reached ($R = 0.80$) and the coefficient of determination ($R^2 = 0.64$) at a significance level of ($\text{Sig} = 0.000$). This indicates that trust and

satisfaction together explain approximately 64% of the variance in future purchase intentions, reflecting the strength of this pathway in guiding digital purchasing behavior. Accordingly, the third sub-hypothesis (H3) is accepted.

8.7 General Analysis of Hypotheses Testing.

After testing the main hypothesis and the sub-hypotheses, the study results show that all hypotheses are accepted with high statistical significance, confirming the existence of strong and positive relationships among the study variables. The findings indicate that intelligent recommendation systems constitute a key driver in shaping purchase intentions among users of the Jumia DZ platform, as they explain a substantial proportion of the variance in digital purchasing behavior.

The results also demonstrate that the accuracy and relevance of recommendations directly contribute to enhancing consumer trust in the platform, while the diversity and personalization of recommendations positively affect the level of user satisfaction with the shopping experience. This effect is further strengthened by the integrative role of trust and satisfaction, which together represent a principal determinant of future purchase intentions and platform loyalty. This interrelationship reflects an integrated explanatory pathway that begins with the quality of recommendation systems and culminates in the reinforcement of purchasing decisions, highlighting the strategic importance of these systems in the e-commerce environment.

CONCLUSION:

This study is situated within the context of the accelerating transition toward the digital economy and the accompanying expansion in the use of artificial intelligence technologies within e-commerce platforms. It aimed to analyze the impact of intelligent recommendation systems on shaping purchase intentions among digital consumers, through an applied field study of users of the Jumia DZ platform, as one of the most active platforms in the Algerian market. The study adopted a quantitative approach, relying on a field questionnaire and statistical analysis to test the relationships between the dimensions of intelligent recommendation systems (accuracy and diversity/personalization) and trust, satisfaction, and purchase intentions.

The results revealed a positive and statistically significant relationship between the effectiveness of intelligent recommendation systems and purchase intentions among platform users. They also showed that the accuracy and relevance of recommendations directly enhance user trust in the platform, while the diversity of recommendations positively affects satisfaction with the shopping experience. Furthermore, trust and satisfaction were found to constitute the most influential pathway in shaping

future purchase intentions, including continued purchasing behavior, enhanced loyalty, and recommending the platform to others. These findings reflect the transformation of intelligent recommendation systems from a mere technical tool into a behavioral driver influencing purchasing decisions and fostering long-term consumer relationships.

Based on these results, the study recommends the development of recommendation system algorithms to enhance their accuracy and relevance and reduce inappropriate recommendations, while expanding personalization mechanisms by integrating contextual elements such as time, location, and browsing behavior. It also emphasizes the importance of linking improvements in recommendation systems with enhancements in key user experience elements, such as payment mechanisms, delivery, and promotional offers, in addition to adopting user feedback mechanisms to support continuous improvement. In this context, the study proposes expanding future research horizons by conducting comparative studies across multiple platforms, using larger samples, and integrating actual behavioral data with survey-based research tools, thereby increasing the generalizability and accuracy of the findings.

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