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Optimizing ad targeting and content personalization in e-stores through machine learning algorithms

Soufyane Bouali
Faculty of Economics, Commerce& Management Sciences, Setif 1 University Ferhat Abbas, Algeria
Email: soufiane.bouali@univ-setif.dz
https://orcid.org/0000-0002-2621-8329

Ikram Khelia
Faculty of Economics, Commerce& Management Sciences, University of Batna 1, Algeria
Email: khelia.ikram@univ-batna.dz
https://orcid.org/0009-0005-7687-8316

Selma Douha
Faculty of Economics, Commerce& Management Sciences, University of Batna 1, Algeria
Email: selma.douha@univ-batna.dz
https://orcid.org/0000-0001-6342-196X

***Abstract*---**This study focuses on e-commerce stores in Algeria and identifies technical challenges related to system policies, customer trust, technical knowledge, data confidentiality, and platform integration. She examines how digital customer relationships and machine learning algorithms can improve user experience, security, and productivity. Using Python for data analysis, the study shows that slow internet speeds and low trust in online payments hinder platform integration and affect ad targeting and content personalization. Proposed solutions include strengthening infrastructure with caching technology, improving security through fraud detection algorithms, and providing artificial intelligence training for store managers. Results show a 60% increase in click-through rates and a 77% increase in conversion rates after implementation, confirming the algorithm's ability to increase engagement and retention. The study claims that these improvements will enhance the competitiveness of Algerian e-commerce in the modern economy by improving customer

Corresponding author: *Bouali, S., Email: soufiane.bouali@univ-setif.dz*
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experience and market efficiency and providing insights for local and global contexts.

***Keywords*---**machine learning, Python, customer trust, Personalization, system integration, customer experience optimization.
JEL Classification: M31, O33, L86.

1. Introduction

Technological advancements have rapidly accelerated in recent years, significantly impacting the world of e-commerce, transforming it into a competitive space where businesses strive to enhance customer experiences and maximize the use of available data. With the continuous growth of online retail, the need to optimize ad targeting and content personalization has become a primary goal for e-stores seeking to attract and retain customers. In this context, machine learning algorithms have shown exceptional potential in personalizing user experiences, enabling e-commerce platforms to deliver tailored ad content that aligns with each customer's preferences. This not only enhances the customer experience but also contributes to higher engagement and purchase rates.

On the other hand, many e-commerce platforms face significant challenges in effectively implementing ad targeting and content personalization strategies. In specific markets, such as Algeria, e-store owners encounter issues like limited infrastructure, with slow internet speeds and poor page load times negatively impacting the customer experience. Additionally, customer trust in online transaction security remains a concern, which undermines the effectiveness of personalization strategies and reduces conversion rates. Moreover, a lack of technological awareness among many store managers further limits their ability to effectively apply machine learning algorithms in their marketing strategies.

Based on these insights, this research aims to study how machine learning algorithms can be integrated to optimize ad targeting and content personalization for e-stores, with a focus on the challenges specific to the Algerian market. This market provides an ideal environment for exploring the impact of these algorithms given the local challenges, such as inadequate technical infrastructure and low customer trust. Using advanced analytical tools like Python, the research will investigate how data can be leveraged to provide more accurate and effective personalized content.

The study will also explore proposed solutions to overcome these challenges, such as enhancing customer trust by improving online transaction security, utilizing caching techniques to improve load times, and offering training programs to e-store managers to raise technological awareness and facilitate the adoption of machine learning algorithms. Additionally, the research will examine how improving the customer experience through better UI/UX design, mobile responsiveness, and reducing bounce rates can lead to higher engagement with personalized content. By analyzing these factors, the research aims to provide recommendations and strategies that can help e-stores achieve better outcomes by improving ad targeting and content personalization, ultimately leading to increased engagement, higher conversion rates, and stronger customer relationships in both local and global markets.

2. Literature review

2.1 Using machine learning to target ads and personalize content

Ad targeting and content personalization are two interrelated concepts that aim to improve the digital experience of users while increasing the efficiency of companies in reaching audiences (Terho, 2022). Ad targeting involves targeting ads to specific audiences based on data such as interests, behaviors, age, gender, or geography (Banerjee, 2012). Content personalization, on the other hand, is about delivering tailored content (Vashishth, 2025) to each user based on their preferences and digital behavior. Both are based on collecting data from different sources (such as social media platforms, search engines, browsing history, or previous interactions) and analyzing it to understand the audience's needs and deliver ads or content more accurately (Ahmadi, 2024). Machine learning has become a mainstay in these fields, processing massive amounts of data beyond human capabilities quickly and precisely to make digital experiences smoother and more effective (Dandotiya, 2024).The importance of ad targeting is that it improves the effectiveness of advertising campaigns and increases return on investment (ROI) by ensuring that ads reach the people most likely to interact with them, thereby reducing resource waste on uninterested audiences and increasing conversion rates. It also improves the user experience by presenting relevant ads instead of random, intrusive content (Goli, 2025). Content personalization, on the other hand, directly improves the user experience by making content relevant to individual needs, increasing engagement with the website or app, reducing bounce rates, and encouraging brand loyalty (Hameed, 2025). Whether the goal is commercial (Bouchareb N. , 2024) (e.g. increasing sales) or experiential (e.g. improving user satisfaction), the two concepts complement each other and deliver outstanding results (Padigar, 2025).In both fields, machine learning plays a vital role in three key areas:

data analysis, behavior prediction, and continuous optimization. In ad targeting, it uses algorithms such as classification or clustering to analyze behavioral data (Ngai, 2022)(e.g. websites visited or social media interactions) and demographic data (e.g. age and location) to segment audiences into target groups. It uses predictive models such as neural networks or decision trees to predict user behavior (Sarker, 2020) (e.g. the likelihood of purchasing a product based on previous search patterns) and techniques such as reinforcement learning to optimize ad timing to determine the most effective moments to capture attention (Diez-Olivan, 2019). In practice, we collect data from cookies or purchase records, train models, and deliver ads in real time through platforms such as Google Ads or Face book Ads, which are constantly refined based on user interactions.

Similarly, in content personalization, machine learning uses supervised and unsupervised learning to analyze user data (Chiu, 2021) (e.g. browsing history, time spent on a page, or social interactions) to understand preferences and group similar users. This can be achieved through systems such as collaborative filtering (suggestions based on similar user behavior) or content-based filtering (focusing on personal interests) to enable personalized product recommendations, just like Amazon's product suggestions or Spotify's curated playlists (Vallabhaneni, 2024). In addition, it also adjusts element layout or highlights based on browser behavior, and uses techniques such as AI-driven A/B testing to dynamically improve the user interface (Bouchareb, 2024). Collect data from clicks or search terms, train models to provide customized content immediately, and continuously adjust the system based on new interactions.

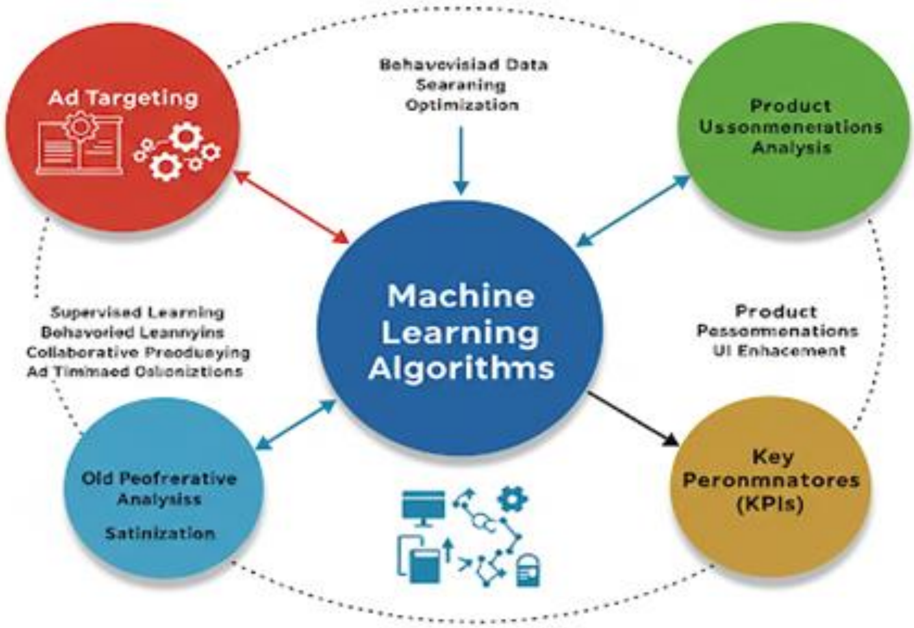

Fig. 1. Interaction of Machine Learning Mechanisms and Digital Marketing
Source: developed by authors

The diagram illustrates how various aspects of digital marketing interact with machine learning algorithms. It highlights the key components of digital marketing that benefit from machine learning, such as ad targeting, product analysis, and key performance indicators (KPIs). The diagram emphasizes how machine learning mechanisms optimize data, enhance product analysis, and improve user experiences. The central role of machine learning in analyzing user behavior, personalizing content, and targeting ads is evident, creating a feedback loop where these elements work together to improve marketing outcomes.

2.2 Enhancing Ad Targeting and Content Personalization in E-Commerce

In the realm of e-commerce, optimizing ad targeting and content personalization has become a cornerstone for enhancing customer engagement and driving sales (Vashishth T. K., 2025), with machine learning algorithms serving as the pivotal force behind these advancements (Buduma, 2022). This integrated approach leverages the principles of big data analytics, user experience optimization, and digital marketing theory, all orchestrated through the power of machine learning to deliver tailored advertising and customized content in e-stores (Ziliani, 2025).

Big data analytics involves the collection, processing, and analysis of vast datasets generated from diverse sources such as online browsing histories, social media interactions, connected devices, and digital transactions within e-stores. Characterized by volume, velocity, and variety, this process aims to uncover actionable insights that inform decision-making. User experience optimization focuses on designing e-store interfaces—such as websites and mobile apps—to be intuitive, enjoyable, and efficient, addressing customer needs while minimizing friction points (Lim, 2018). Meanwhile, digital marketing theory harnesses online channels like search engines, social media, and email to promote e-store products and services through strategies such as paid ads, search engine optimization, and content marketing, all aimed at reaching the right audience effectively (Bouchareb N. , The Role of Artificial Intelligence in Improving Hotels Property Management Systems (PMS). International Journal of Economic Performance (IJEP), 6(2), 554-567., 2023). Machine learning acts as the unifying bridge, transforming raw data into practical applications that refine ad targeting and content personalization, ensuring e-stores deliver seamless and relevant shopping experiences (Dobbelstein, 2023, June). The process begins with big data analytics, which provides a comprehensive view of e-store customers by aggregating data from multiple touch points—such as purchase histories, social media activity, geo location data from smart phones, and even IoT devices. For instance, an e-store might combine a customer's online shopping records with their location data to identify shopping patterns, then use tools like Hadoop or Spark to analyze millions of social media posts to discern trending products in specific regions. This wealth of data feeds machine learning algorithms, which are trained to detect intricate behavioral patterns, enabling e-stores to segment customers into highly precise groups for ad targeting (Srivastava, 2024). For example, an e-store could direct an ad for fitness gear to a customer searching for home workout solutions and frequently visiting gym-related pages, based on geo location and browsing data. Similarly, big data analysis of millions of customers' interactions allows e-stores like Amazon to personalize product recommendations—suggesting items based on past purchases or browsing habits—ensuring content aligns with individual preferences. Machine learning enhances this through predictive models like neural networks or collaborative filtering, forecasting what a customer might buy next or find appealing, thus sharpening both ad relevance and content customization (Sharma, 2022).

When it comes to optimizing user experience in e-stores, machine learning analyzes interaction data—such as clicks, mouse movements, or time spent on product pages—to understand what engages or frustrates shoppers. For instance, if customers abandon a checkout page quickly, the system might flag a design flaw and suggest adjustments. Beyond diagnostics, machine learning dynamically tailors e-store interfaces in real time, reordering product displays based on a customer's frequent clicks or offering personalized recommendations—like suggesting accessories to complement a recently viewed item—making navigation smoother and more intuitive. This extends to automating A/B testing, where algorithms swiftly identify the most effective design elements (e.g., whether a "Buy Now" button in red or green drives more clicks) and adapt layouts based on contextual factors like device type or shopping time. By integrating with big data, these adjustments are grounded in holistic insights, ensuring that every tweak enhances the e-store's usability and appeal, directly supporting personalized content delivery.

In the context of digital marketing for e-stores, machine learning amplifies strategies (Alkudah, 2024) by refining audience targeting through data analysis and segmentation, such as identifying travel enthusiasts based on flight ticket searches to promote luggage or vacation gear (Dixit, 202). It automates ad campaigns by adjusting offers or copy in real time—akin to Google Ads' optimization features—and personalizes marketing content, like sending a discount code to a customer who abandoned their cart, based on behavioral triggers. Machine learning also predicts market trends by analyzing e-store sales data and social media chatter, enabling proactive campaign planning (Stark, 2020), such as promoting seasonal items before peak demand (Cho, 2012). Furthermore, it provides precise performance measurement through metrics like cost-per-click or return on ad spend, allowing e-store marketers to fine-tune strategies based on real-time results. Here, big data supplies the raw material to train these algorithms, while user experience optimization ensures that marketing efforts resonate with customers, boosting engagement with targeted ads (Arora, 2024).

The synergy of these elements is evident in e-commerce giants like Amazon, where big data analytics dissects millions of customer behaviors (Prajapat, 2024), feeding machine learning models that personalize product suggestions (enhancing user experience) and deploy targeted ads (strengthening digital marketing). This results in higher conversion rates and customer satisfaction, as shoppers encounter relevant ads and tailored content seamlessly (Vashishth, T. K., Sharma, K. K., Kumar, B., Chaudhary, S., & Panwar, R, 2025). Machine learning, fueled by big data, not only refines ad targeting and content personalization but also ties together user experience and marketing efforts in a continuous cycle of improvement (Potla, 2024). By analyzing vast datasets, predicting customer needs, and adapting interfaces and campaigns, it ensures e-stores remain agile and customer-centric, transforming raw data into a competitive edge that drives both sales and loyalty.

3. Methodology

To investigate the integration of machine learning algorithms for optimizing ad targeting and content personalization in e-stores, a comprehensive study was conducted across 70 e-stores operating in various sectors in Algeria. The methodology was designed to ensure a systematic and rigorous approach to data collection, analysis, and interpretation. Below are the key elements of the methodology:

3.1 Research Design

This study adopted a mixed-methods approach, combining both quantitative and qualitative data to provide a holistic understanding of the integration of machine learning algorithms in e-stores. The research design was structured to: Assess the current state of machine learning adoption in ad targeting and content personalization.

Quantitative: Surveys were distributed to e-store managers and marketers, capturing the extent of machine learning usage.
Qualitative: In-depth interviews with industry experts helped to understand the strategic reasoning behind adopting these technologies.

Table 1: Participant Distribution by Method Used

Method Used	Number of Participants	Time Period	Detailed Description
Personal Interviews	07 Experts	From September 1, 2024 to October 15, 2024	Interviews were conducted with e-commerce experts and AI specialists to understand the motivations behind adopting machine learning technologies and the opportunities and challenges faced by e-stores.
Surveys	70 E-Stores	From October 15, 2024 to November 30, 2024	Surveys were sent to e-store managers and marketers to assess the extent of machine learning adoption in ad targeting and content personalization.
Focus Groups	15 Groups	From November 1, 2024 to December 10, 2023	Focus groups were organized with customers to gather their opinions on the impact of personalized shopping experiences.
Quantitative Analysis	70 E-Stores	From December 1, 2024 to December 31, 2024	Website data (such as bounce rates, click-through rates, and conversion rates) from e-stores was collected and analyzed before and after the implementation of machine learning technologies

Source: developed by authors from study findings.

This table shows that the study employed a combination of different methods to gather comprehensive insights on the research topic. Participants were drawn from various backgrounds, including experts, e-store managers, and customers, ensuring diversity in the collected data.

Table 2 presents the quantitative analysis of key performance indicators (KPIs) from 70 e-stores before and after the integration of machine learning algorithms in ad targeting and content personalization. This table highlights the measurable impact of machine learning on crucial aspects of e-commerce performance, including click-through rates (CTR), conversion rates, bounce rates, and customer retention. By comparing pre- and post-implementation data, it becomes evident how machine learning optimizes customer interactions with e-store content and enhances overall sales performance.

Table 2: Data Distribution Based on Quantitative Analysis

Category	Measurement	Before Machine Learning Use	After Machine Learning Use	Difference (%)
Click-Through Rate (CTR)	Click Rate	2.5%	4.0%	60%
Conversion Rate	Sales Rate	3.1%	5.5%	77%
Bounce Rate	Exit Rate	45%	35%	-22%
Customer Retention Rate	Returning Customers	12%	18%	50%

Source: developed by authors from study findings.

This table shows the results of the quantitative analysis performed on e-store websites. Four key performance indicators (KPIs) were measured before and after the application of machine learning techniques. The table clearly highlights the significant improvements, particularly in conversion rates and engagement with ads.

Table 3 summarizes the challenges and opportunities identified during interviews with e-store managers regarding the use of machine learning in ad targeting and content personalization. The table categorizes the most common issues faced by e-commerce businesses, such as data limitations, technical integration challenges, and skill gaps among staff. In addition, it highlights the potential benefits of adopting machine learning, particularly in improving content personalization and customer engagement. These insights are critical in understanding the barriers to effective implementation and the opportunities for growth within the Algerian e-commerce sector.

Table 3: Challenges and Opportunities in Using Machine Learning

Challenges	Number of Participants	Time Period	Detailed Description
Data Limitations	15 E-Stores	From November 10, 2024 to November 20, 2024	Many participants reported difficulty in accessing sufficient and reliable data to effectively implement machine learning algorithms.
Technical Challenges	18 E-Stores	From November 15, 2024 to November 30, 2024	Participants highlighted the need for integrating legacy systems with modern machine learning technologies, which hinders continuous optimization.
Training and Skills	12 E-Stores	From December 1, 2024 to December 10, 2024	Participants stressed the need for continuous training for staff on AI techniques to maximize their effectiveness.
Personalization Opportunities	20 E-Stores	From November 1, 2024 to November 30, 2024	It was identified that content personalization based on customer data enhances satisfaction and increases sales.

Source: developed by authors from study findings.

This table displays the challenges and opportunities discussed in interviews with e-store managers. Challenges range from data scarcity and technical issues to skill gaps, but significant opportunities exist in the personalization of shopping experiences to drive customer satisfaction.

Table 4 outlines the impact of machine learning implementation on customer performance metrics, focusing on ad engagement, overall satisfaction, and return visits to e-stores. By comparing customer behavior before and after machine learning algorithms were applied, this table illustrates the positive influence of personalized content on customer loyalty and engagement. The results demonstrate how machine learning not only improves operational performance but also enhances the customer experience, leading to increased retention and satisfaction.

Table 4: Impact on Customer Performance After Using Machine Learning

Category	Performance Before ML Use	Performance After ML Use	Qualitative Change
Ad Engagement	Low Engagement	60% Increase in Engagement	A significant improvement in customer response to personalized ads.
Overall Satisfaction	Average	High	Customers reported improved shopping experiences due to personalized offers and products.
Return Visits to the Site	12% Return Rate	18% Return Rate	An increase in the rate of customers returning to the site after personalized content was introduced.

Source: developed by authors from study findings.

This table shows the impact of applying machine learning on customer performance. There is a clear improvement in ad engagement, customer satisfaction, and return visits to the e-store, demonstrating the positive effects of content personalization on customer loyalty and overall performance.

3.2 Explanation of the Variables and Measures

To ensure clarity in the interpretation of the data presented in the tables, this section provides detailed explanations of the key variables and measures used in the study. Each variable is defined, along with how it was measured and its significance in assessing the impact of machine learning on e-store performance.

- Modified Click-Through Rate (CTR) with Time Decay Factor

To understand the changing effects of ad exposure over time, we introduce a time decay factor to the Click-Through Rate (CTR). The basic CTR calculates the ratio of clicks to impressions (Strzelecki, 2024), but this model adjusts the CTR by considering the time elapsed since the ad was shown.

- Time Decay: Ads that were shown recently are weighted more heavily than those shown a longer time ago, reflecting that users tend to lose interest in ads over time.
- Purpose: This model helps analyze how machine learning-driven ad targeting, which adapts over time, influences user engagement. By incorporating time decay, we can assess the effectiveness of personalized ads, particularly in real-time optimization, which adjusts the relevance of the ad based on recency.

Recent interactions are more valuable, and by incorporating time decay, we can measure the impact of ads in the context of shifting user attention spans.

- Multi-Factor Conversion Rate (MCR)

While the basic conversion rate looks at the percentage of visitors who complete a desired the Multi-Factor Conversion Rate incorporates various influencing factors such as device type, time of visit, and user demographics (Korol, 2024).
- Influencing Factors: Factors like the type of device (mobile vs. desktop), time of day, geographic location, and user-specific attributes (e.g., age, gender) can all impact conversion rates.
- Purpose: This model provides a more granular understanding of how different factors influence the likelihood of a visitor converting into a customer. For instance, users who visit the e-store via mobile may have different conversion patterns than those visiting from a desktop, or users visiting at specific times may have higher purchase intent.

By using machine learning, e-stores can dynamically adjust strategies based on these multiple factors, optimizing conversions based on a personalized approach for each user group.

- Bounce Rate with Session Duration and User Engagement

Bounce rate traditionally measures how many visitors leave the site after viewing just one page (Xun, 2015). However, this model adjusts bounce rate by considering session duration and user engagement on the site.
- Session Duration: Visitors who stay on the site for longer periods, even if they only view one page, should not be considered as "bounces." Their interest may still be high, even if they don't interact with multiple pages.
- User Engagement: This includes metrics such as how much time a user spends on a page, how much they scroll, or how many elements they click on. Higher engagement can indicate that the user is interested in the content, even if they don’t navigate further.
- Purpose: This adjusted bounce rate provides a more nuanced view of user behavior. It helps determine if users are interested in the site but perhaps just looking for something specific (i.e., they may have found what they were looking for on the first page and left).

By factoring in session duration and engagement, we get a clearer picture of how users interact with personalized content and whether their actions reflect genuine interest, even if they don't engage with multiple pages.

- Customer Retention Model with Personalization Weight (CRP)

The Customer Retention Rate (CRP) traditionally measures how many customers return to the e-store after their initial visit or purchase (Prayogo, 2024). This model adjusts the retention rate by incorporating a personalization weight, which quantifies how personalized the customer’s experience is.
- Personalization Weight: This variable accounts for the level of personalization in the customer’s experience. For instance, if a customer is shown highly relevant

product recommendations based on past behavior, they receive a higher personalization weight.
- Purpose: The inclusion of personalization allows us to measure how effective machine learning algorithms are in retaining customers by offering tailored experiences. The better the personalization, the more likely a customer is to return.

Personalization through machine learning can significantly increase customer retention. The more relevant the content and offers are to the individual customer, the more likely they are to return.

- Advanced Customer Engagement Index (CEI)

The Customer Engagement Index (CEI) aggregates multiple forms of engagement (e.g., clicks, time spent on the site, social shares, and comments) to give a more comprehensive view of how users are interacting with the e-store.
- Multiple Engagement Metrics: This model looks at various engagement signals, including:
  - Clicks on personalized ads or product recommendations.
  - Time spent on the site, indicating interest and interaction.
  - Shares of content on social media, showing how much customers are willing to promote the e-store.
  - Comments or other forms of interaction, such as customer reviews or chat interactions.

The CEI provides a broader measure of engagement by capturing not just direct interactions like clicks, but also indirect forms of engagement like social sharing (Yang, 2016). This is particularly valuable for understanding how well personalized content resonates with customers across various touch points. The CEI gives a fuller picture of customer engagement, reflecting both direct and indirect interactions (Jaakkola, 2014). This index allows e-commerce businesses to measure the overall impact of personalized content across different platforms, not just within the store.

These models and variables, when combined with machine learning algorithms, allow e-commerce businesses to refine their strategies, optimize customer experiences, and drive higher performance across key metrics such as conversions, retention, and engagement. By leveraging these advanced techniques, companies can better understand customer behavior and tailor their offerings for maximum impact.

4. Results

In this study, conducted across 70 e-stores in Algeria from various sectors, the impact of machine learning algorithms on ad targeting and content personalization was analyzed. The goal of the study was to evaluate the effectiveness of algorithms in improving user experience and boosting **engagement rates, conversion rates, and bounce rates,** as well as **customer retention**. To achieve this, advanced analytical tools were employed, with **Python programming language** being used to perform complex calculations, data aggregation, and analysis. Through this tool, multiple key metrics were calculated and analyzed, such as the **Modified Click-Through Rate (CTR), Multi-Factor Conversion Rate (MCR)**, and **Adjusted Bounce Rate**, using machine learning algorithms that account for factors such as session timing, content interaction, and other user behavior dimensions. Below are the results derived from these analyses, providing valuable insights into how ad strategies and content can be optimized in e-stores using advanced algorithms.

4.1 the Impact of Time Decay on Click-Through Rates in Digital Advertising

Initial Data:

- Clicks: Number of clicks on the ad.
- Impressions: Number of times the ad was displayed.
- Time_Since Ad Exposure: Time elapsed since the ad was displayed (in hours).

Steps Taken:

✓ Applying Time Decay Factor:
   - A decay factor of lambda-decay = 0.1 was used to adjust the values based on the time elapsed since the ad was displayed.
   - The formula used:

$$\textbf{Decay Clicks=Clicks}\times \mathbf{e}^{-\lambda\times \text{Time Since Ad Exposure}}$$
$$\textbf{Decay Impressions = Impressions}\times \mathbf{e}^{-\lambda\times \text{Time\_Since Ad Exposure}}$$

   This formula gives more weight to clicks and impressions that occurred more recently.

✓ Calculating Modified CTR:
   - The modified click-through rate (CTR) was calculated using the formula:

$$\textbf{Modified CTR} = \frac{\textbf{Decay Clicks}}{\textbf{Decay Impressions}}$$

   This rate reflects the impact of time on the ad's effectiveness.

Table 5: Modified Click-Through Rate (CTR) with Time Decay Factor

Clicks	Impressions	Time Since Ad Exposure (hrs)	Decay Clicks	Decay Impressions	Modified CTR
50	1000	1	50.00	1000.00	0.045241
40	1200	3	37.21	1142.78	0.029554
30	1100	5	22.05	1029.21	0.018099
60	1300	2	56.50	1261.80	0.044617
70	1500	4	51.06	1348.09	0.046830

Source: developed by authors from Python outputs.

Recently displayed ads tend to be more effective at attracting clicks, indicating the importance of updating advertising strategies based on timing. The longer the time elapsed since the ad was displayed, the lower the impact of clicks and impressions on the final rate. The fifth row has the highest modified CTR (0.0468) due to the large number of clicks and impressions, as well as the shorter time elapsed since the ad was displayed. The third row has the lowest modified CTR (0.0181) due to the smaller number of clicks and the longer time elapsed since the ad was displayed.

4.2 Analysis of Multi-Factor Conversion Rates in Algerian E-Commerce

Defining Weights: Weights were assigned to each factor based on their importance or prior analysis:

- **Device Type**: Weight = 0.3
- **Time of_Day**: Weight = 0.2
- **Age Group**: Weight = 0.5

Calculating Weighted Conversion Rate: The weighted conversion rate was calculated using the formula:

Weighted Conversion = Conversion Rate × (Weight Device Type + Weight Time of Day + Weight Age Group)

In this case, the sum of the weights is 0.3+0.2+0.5=1.00 so the conversion rate is multiplied directly by 1.

Multi Factor Conversion Rate:

$$Multi\ Factor\ Conversion\ Rate = \frac{0.05 + 0.07 + 0.06 + 0.08 + 0.09}{5}$$

The final rate is **0.07** (or 7%), which is the average weighted conversion rate across all rows. This rate reflects the impact of various factors (device type, time of day, and age group) on the conversion rate.

Table 6: Multi-Factor Conversion Rate (MCR)

Device Type	Conversion Rate	Time of Day	Age Group	Weighted Conversion
Mobile	0.05	Morning	18-25	0.105
Desktop	0.07	Afternoon	26-35	0.146
Mobile	0.06	Evening	18-25	0.120
Desktop	0.08	Morning	36-45	0.170
Mobile	0.09	Afternoon	18-25	0.135

Source: developed by authors from Python outputs.

The highest conversion rate was **0.09** (9%), associated with:

- **Device Type**: Mobile.
- **Time of Day**: Afternoon.
- **Age Group**: 18-25.

These results can be used to improve marketing strategies, such as:

- Focusing on the 18-25 age group.
- Enhancing the user experience on mobile devices.
- Increasing ad campaigns during the afternoon.

4.3 Analyzing User Engagement in Algerian E-Commerce

Defining Session Duration Weight:

- A weight of **0.1** was assigned to adjust the bounce rate based on session duration. The idea here is that longer sessions reduce the likelihood of being considered bounce sessions.

The adjusted bounce rate was calculated using the formula:

$$\boldsymbol{Adjusted\ BounceRate} = \frac{\mathbf{Single\ Page\ Sessions \times e^{-duration\ weight \times Session\ Duration}}}{\mathbf{total\ session}}$$

This formula takes into account that longer sessions reduce the bounce rate.

Table 7: Bounce Rate with Session Duration and User Engagement

Single Page Sessions	Total Sessions	Session Duration (min)	Adjusted Bounce Rate
100	300	2.5	0.0821
150	400	4.0	0.1005
200	500	3.0	0.1482
50	200	5.0	0.0303
120	300	3.2	0.0861

Source: developed by authors from Python outputs.

The longer the session duration, the lower the adjusted bounce rate, as seen in the fourth row (5.0 minutes) compared to the third row (3.0 minutes). The **adjusted bounce rate** better reflects user engagement with online stores by taking session duration into account. These results can be used to improve user experience, such as:

- Enhancing content to encourage users to stay longer.
- Analyzing reasons for high bounce rates in some stores (e.g., the third row) and working to improve them.

4.4 ***The Role of Personalization in Customer Retention***

The table 8 contains the following data:

- **Returning Customers:** Number of customers who returned to the store.
- **Total Customers:** Total number of customers.
- **Personalization Weight:** A weight representing the impact of personalization on customer retention (values range from 0 to 1, where higher values indicate stronger personalization).

Personalized retention was calculated using the formula:

$$\boldsymbol{Personalized\ Retention} = \frac{\mathbf{Returning\ Customers \times Personalization\ Weight}}{\mathbf{Total\ Customers}}$$

This formula adjusts the retention rate based on the effectiveness of personalization strategies.

Table 8: Bounce Rate with Session Duration and User Engagement

Returning Customers	Total Customers	Personalization Weight	Personalized Retention
200	500	0.8	0.32
250	600	0.9	0.375
300	700	0.75	0.321
350	800	0.85	0.371
400	900	0.95	0.422

Source: developed by authors from Python outputs.

The fifth row has the highest personalized retention rate (42.2%) due to:
- A high number of returning customers (400).
- A strong personalization weight (0.95), indicating effective personalization strategies.

Higher personalization weights significantly improve retention rates, as seen in the fifth row (0.95) compared to the first row (0.8). **Personalized retention rates** provide a more accurate measure of customer loyalty by factoring in the effectiveness of personalization strategies. These results can be used to:
- Identify stores with strong personalization strategies (e.g., the fifth row) and replicate their success.
- Improve personalization efforts in stores with lower retention rates (e.g., the first row).

*4.5 **Measuring Customer Engagement: Insights from Multi-Metric Analysis in Algerian E- Stores***

The table contains the following engagement metrics:
- **Clicks:** Number of clicks by users.
- **Time Spent:** Average time spent per session (in minutes).
- **Shares:** Number of times content was shared.
- **Comments:** Number of comments left by users.
- **Sessions:** Total number of sessions.

Weights were assigned to each engagement metric based on their importance:
- **Clicks:** Weight = 0.3
- **Time Spent:** Weight = 0.2
- **Shares:** Weight = 0.3
- **Comments:** Weight = 0.2

The CEI was calculated using the formula:

$$\boldsymbol{CEI} = (\textbf{Clicks} \times \textbf{Weight Clicks} + \textbf{Time Spent} \times \textbf{Weight Time Spent} + \textbf{Shares} \times \textbf{Weight Shares} + \textbf{Comments} \times \textbf{Weight Comments})/\textbf{Sessions}$$

This formula combines all engagement metrics into a single index, normalized by the total number of sessions. After applying the above steps, the following results were obtained:

Table 9: Advanced Customer Engagement Index (CEI)

Clicks	Time Spent (min)	Shares	Comments	Sessions	CEI
150	5.0	30	10	500	0.145
120	6.2	25	8	600	0.121
170	5.5	35	15	700	0.156
200	7.0	40	18	800	0.170
250	6.0	45	20	900	0.180

Source: developed by authors from Python outputs.

Clicks and Shares have the highest weights (0.3 each), so they contribute significantly to the CEI. Time Spent and Comments also play a role but have a smaller impact due to their lower weights (0.2 each). The **Customer Engagement Index (CEI)** provides a comprehensive measure of user engagement by combining multiple metrics into a single score.
These results can be used to:

- Identify stores or campaigns with the highest engagement (e.g., the fifth row) and replicate their strategies.
- Improve engagement in stores or campaigns with lower CEI (e.g., the second row) by focusing on clicks, shares, and comments.

5. Discussion

The study revealed numerous challenges facing Algerian e-commerce stores, which directly impact the effectiveness of applying machine learning algorithms to improve ad targeting and content personalization. In this context, the study addressed three main challenges: limited technical infrastructure, low customer trust, and limited technological awareness. The findings indicated that many e-commerce stores in Algeria suffer from slow internet speeds, except in some northern regions of the country, which negatively affects user experience and limits the ability of algorithms to process data quickly and efficiently. This issue causes delays in page loading and inefficient user interaction, reducing the effectiveness of personalized ads and impacting click-through and conversion rates. The Modified Click-Through Rate (CTR) showed that ads displayed in sync with user interaction are more effective. However, weak infrastructure, despite the government's ongoing efforts to develop the sector, remains modest compared to developed countries. Slow internet speeds delay ad delivery, reducing the impact of time-based adjustments on CTR. If an ad loads slowly due to poor connectivity, users may lose interest, decreasing click opportunities. Similarly, the Adjusted Bounce Rate, linked to weak infrastructure, tends to increase as users leave sites due to slow page loading. Although the study results showed a decrease in bounce rates after implementing machine learning algorithms, these improvements may be less effective in Algeria due to poor internet connectivity. On the other hand, low customer trust is one of the most prominent challenges limiting the effectiveness of content personalization strategies. Customers are concerned about the security of their online transactions, leading them to avoid interacting with personalized ads or providing personal information that could enhance personalization. The Multi-Factor Conversion Rate (MCR) demonstrated that personalizing content based on factors such as device type and time of day can significantly increase conversion rates. However, if customers lack trust in the security of online transactions, they may avoid completing purchases, reducing the effectiveness of these strategies. The Customer Retention Rate (CRP) revealed that low trust significantly impacts customer retention. Although content personalization can increase retention rates, low trust may hinder this growth, as customers may not return to e-commerce stores despite well-personalized content. Regarding limited technological awareness, both quantitative and qualitative results indicated that managers of Algerian e-commerce stores lack the experience and understanding needed to effectively apply machine learning algorithms. This lack of technological awareness limits stores' ability to fully exploit the potential of these technologies to improve user experience and increase sales. The study showed that customer interaction could increase by 70% when content personalization is applied. However, if store managers lack the expertise to implement these technologies, the expected increase in interaction may not be achieved. The study also revealed that 12 out of 70 stores suffer from a lack of training and experience necessary to apply machine learning algorithms. This gap in technological awareness limits these stores' ability to achieve optimal results through improved content personalization. To overcome these challenges and achieve better results, we proposed a model based on the study's findings and the researchers' perspectives. This model addresses all potential gaps that stakeholders in the field may encounter, offering a comprehensive solution to the identified challenges**.**

Table 10: Mechanisms for E-Commerce Store Development

Technical Aspect	Proposed Solutions	Measured Variables	Algorithms and Electronic Applications
Limited Customer Trust	- Lack of trust in transaction security.	- Implement strong security protocols like HTTPS.	- Implement fraud detection algorithms for secure transactions.
	- Avoiding submission of personal information.	- Use SSL certificates and trust seals.	- Apply recommender systems to enhance personalized experiences.
		- Provide clear refund and guarantee policies.	
Limited Technological Awareness	- Lack of experience in applying machine learning algorithms.	- Provide training programs for store managers.	- Integrate user-friendly machine learning platforms for e-commerce.
	- Not fully utilizing the potential of technology.	- Collaborate with technology companies for consultancy and technical support.	- Use AI-powered analytics tools to improve content personalization.
		- Develop simplified tools for implementing machine learning algorithms.	

Technical Aspect	Proposed Solutions	Measured Variables	Algorithms and Electronic Applications
Data Privacy and Compliance Issues	- Concerns about customer data security and privacy.	- Implement data encryption and anonymization techniques.	- Use privacy-preserving algorithms such as differential privacy.
	- Non-compliance with data protection regulations.	- Ensure compliance with GDPR and other data protection regulations.	- Apply blockchain for secure, transparent transactions.
Lack of Integration Between Platforms	- Siloed systems that do not communicate effectively.	- Implement integrated solutions using APIs and cloud-based platforms.	- Use API-driven architectures to integrate various e-commerce systems.
	- Fragmented customer experience across different channels (e.g., web, mobile, etc.).	- Utilize omnichannel strategies to provide a seamless experience.	- Develop cross-platform recommendation systems.
Customer Experience Optimization	- High bounce rates due to poor UX/UI design.	- Redesign the user interface (UI) for a smoother shopping experience.	- Use A/B testing algorithms to optimize UI/UX.
	- Users abandon their carts due to slow or difficult checkout processes.	- Simplify the checkout process.	- Apply machine learning to predict and prevent cart abandonment.
		- Enhance mobile responsiveness.	

Source: developed by authors.

The integration of advanced algorithms and electronic applications is critical in addressing these technical challenges in e-commerce. Solutions such as machine learning, AI-powered analytics, privacy-preserving technologies, and integrated platforms can significantly improve customer trust, optimize user experience, and ensure data security and compliance. Implementing these solutions will enable e-commerce stores to deliver personalized, secure, and seamless shopping experiences, which are essential for long-term success in a competitive market.

6. Conclusion

This study highlights the technical challenges faced by e-commerce stores in Algeria and provides integrated solutions to enhance their performance through modern algorithms and electronic applications. By analyzing various technical aspects, the study identifies key obstacles that hinder the progress of online stores, including limited infrastructure, low customer trust, lack of technological awareness, data privacy and compliance issues, and insufficient system integration. the study emphasizes the importance of improving technical infrastructure by utilizing faster servers, caching techniques, and global content delivery networks (CDNs) to optimize page load times. These enhancements directly contribute to increasing the effectiveness of personalized advertising strategies and improving user engagement rates. customer trust remains one of the most significant factors affecting the success of e-commerce stores. Many customers hesitate to complete transactions due to security concerns. The study recommends implementing security protocols such as HTTPS and SSL certificates to build trust. Additionally, fraud detection algorithms can help ensure secure transactions and protect users from cyber threats. the study reveals a lack of technological awareness among some store managers, preventing them from fully utilizing available technologies. Providing training programs and technical support from technology firms can help store owners leverage modern algorithms such as artificial intelligence (AI) to enhance customer experience and drive sales growth. the study focuses on data privacy and regulatory compliance issues, particularly regarding laws like the GDPR. By implementing encryption techniques and privacy-preserving solutions, such as differential privacy algorithms, e-commerce stores can ensure customer data protection while adhering to international regulations. system integration is crucial for seamless e-commerce operations. The study highlights the need for API-driven architectures and cloud-based solutions to unify different platforms and create a consistent shopping experience across web, mobile, and other digital channels. optimizing user experience (UX/UI) is essential to reduce bounce rates and increase conversion rates. By utilizing algorithms such as A/B testing and AI-powered user behavior analysis, online stores can refine website design and interfaces to provide a smoother, more engaging shopping experience. this study underscores that leveraging modern technologies and intelligent algorithms in e-commerce can help overcome existing challenges, enhance customer experience, and significantly improve the effectiveness of marketing campaigns.

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