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Application of Fuzzy Logic in Predictive Analytics for E-Commerce Transaction Data

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***Abstract*— Our objective is to identify the key factors that influence e-commerce success by analyzing transactional data, including variables such as product descriptions, quantities, unit prices, and customer demographics. We have employed three distinct fuzzy logic methods: TOPSIS, Fuzzy AHP (F-AHP), and F-AHP enhanced by geometric mean. These methods have been utilized to rank various factors, ultimately identifying the most critical elements for optimizing inventory management, enhancing customer satisfaction, and detecting fraudulent activities in the e-commerce landscape. The results provide valuable insights for developing smarter decision-making practices in e-commerce operations.**

***Index Terms*— e-commerce analytics, Fuzzy AHP, AHP, TOPSIS, fuzzy logic, transaction data, inventory management, fraud detection, customer satisfaction.**

I. INTRODUCTION2

Modern e-commerce is a rapidly evolving field, driven by technological advancements, shifting consumer preferences, and the demand for agile decision-making. The surge in online transactions and the vast amount of data they generate have fundamentally changed business operations, making data-driven insights essential for success. However, the complexity of e-commerce—marked by changing customer behaviors, a wide range of product offerings, and global operations—poses significant challenges. Within this vast transactional data, which includes product details, pricing, quantities, and customer demographics, lies the potential for unlocking valuable insights.

Information and Communication Technologies (ICT) play a crucial role in modern e-commerce, enabling real-time tracking of sales, customer interactions, and inventory. Advanced analytical tools and algorithms allow businesses to predict market trends, streamline inventory management, and improve customer satisfaction. In this context, fuzzy logic emerges as a vital approach, offering the adaptability and clarity necessary to interpret the often-ambiguous patterns present in e-commerce data.

Traditionally, e-commerce analytics has relied on conventional statistical methods, which are often inadequate in addressing the inherent uncertainties in customer behaviors and transaction patterns. Today, more comprehensive approaches that incorporate multiple variables and recognize the fuzzy nature of decision-making are critical for accurate predictions and strategic planning. The demand for tailored, adaptable models is more evident than ever, as businesses strive to customize their strategies for specific markets and consumer segments.

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This study harnesses the power of fuzzy logic, in combination with advanced decision-making frameworks like the Analytical Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), to analyze e-commerce transaction data. By integrating these methods, we aim to generate actionable insights that enhance inventory management, fraud detection, and customer engagement strategies. The findings from this research will help businesses navigate the complexities of e-commerce with greater confidence, supporting long-term growth and sustainability in a highly competitive global market. The application of these advanced tools will not only help policymakers develop more effective regulatory frameworks but also allow businesses to optimize operations, while consumers benefit from improved service quality. This research highlights the importance of innovation and adaptability in e-commerce, laying the groundwork for a future where businesses can succeed in an increasingly digital and interconnected world.

II. LITERATURE SURVEY

[1] This article explores possible legislative remedies and examines how predictive analytics may affect customer privacy in e-commerce. Predictive analytics is introduced and its possible applications in e-commerce are demonstrated in Part I. While predictive analytics can help retailers run more profitably and effectively, there is a chance that consumers won't receive significant economic advantages. Part II looks at the privacy risks associated with predictive analytics. The dominant theoretical frameworks acknowledge privacy's function in advancing individual autonomy and dignity and describe it as the capacity to regulate what others know about you. People who utilize predictive analytics lose control over their privacy since they are unable to forecast what will happen to the data they disclose in the end. [2] This study investigates how consumers search online at Walmart.com, a sizable e-commerce platform. We use two computational models that are developed using a recent machine-learning technique called random forest and logistic regression in order to more precisely forecast client purchase conversion based on their search activity. Additionally, we include the research on information retrieval to suggest metrics for measuring the search activity of online users. The findings indicate that the random forest model outperforms the other models in terms of predicting customers who will buy the item they explored, with an extremely high accuracy rate of 76%. The parameters that have the most influence on conversion behavior include click entropy, click position, user type, page and session stay time, and click entropy. Based on improved metrics and modeling techniques, the results indicate that search behavior could inculcate the desire.[3] Overview and goals: The primary goals of this article are to evaluate the evolving trends in e-commerce and investigate the cutting-edge information technologies and tools that enable it. Approaches/Statistical Evaluation: With the majority of the data coming from secondary sources of survey data, the study is qualitative and descriptive in character. The study employs this strategy due to the wide scope of the research and the dispersed locations of its data sources.

[4] Online purchases through e-commerce websites have become more and more popular over the last few years. There is a flaw in the user-friendly platform that makes customer pleasure impossible to guarantee. Customers typically check other customers' evaluations before making a purchase to ensure they get the best deal. Determining the product's quality is complex and time-consuming because there are a lot of reviews, both positive and negative. The vendors would also like to know the product's future trend through these reviews. This work uses a predictive analysis scheme to identify, in real time, the hidden sentiments found in customer reviews of a certain product from an e-commerce site.[5] The hardest element of fulfilling orders for e-commerce is frequently achieving timely last-mile delivery. Enhanced customer satisfaction and substantial cost savings are possible with well-managed last-mile operations. At the moment, delivery agents follow schedules that are optimized for the lowest tour distance because they do not have access to information about consumer availability. As a result, deliveries are missed since orders are not delivered within the times that the consumer prefers. [6] With the notable rise in e-commerce, businesses are looking for innovative technologies and creative skills to handle the volume of data being generated and use the insights to make better decisions. Thus, the purpose of this study is to clarify the significance and function of predictive analytics models in Egyptian e-commerce companies, where these instruments have emerged as key sources of information for improving e-commerce [7] The only topic covered in this conceptual paper was the application of artificial intelligence (AI) to target audience identification. This study focused on the marketing context and gave an organized overview of how AI can accurately identify the target customers despite their disparate actions. Additionally covered were the uses of AI in consumer targeting and its anticipated efficacy at each stage of the customer lifecycle. It is possible to obtain behavioral insights about specific clients more effectively and dependably by using historical analysis. The literature review verified that technology-driven artificial intelligence (AI) is transforming marketing by enabling large-scale data processing through supervised or unsupervised (machine) learning. [8]

One of the main issues facing e-commerce as a result of the digital revolution is the massive amount of data that must be processed and evaluated in order to be useful. The goal of big data analytics (BDA) is to enhance decision-making through the analysis and comprehension of large amounts of data, such as messages and postings on social media. Moreover, e-commerce operations leverage BDA capabilities as a primary growth route to boost vendors' earnings and draw in clients. This research attempts to investigate the benefits of implementing BDA in e-commerce to both vendors and customers based on the significance of big data analysis and its benefits to e-commerce operations. A selection of fifteen papers is made to examine the effects of big data analysis in e-commerce. Machine learning models have been shown to be beneficial in increasing conversion rates, decreasing churn, and increasing operational efficiency through case studies and real-world instances. Along with discussing these issues, the study also looks ahead at how machine learning and predictive analytics will be applied in e-commerce, highlighting the significance of algorithmic openness, privacy protection, and high-quality data. [10] "Know your customer" has always been the cornerstone of e-commerce. The personalization of shopping for every customer has been made possible by the use of big data analytics in e-commerce. To extract detailed insights and micro-segment customers, big data from clickstream, video, audio, and transactional or business activity is handled. This study investigates how consumer profiling, predictive analytics, targeted advertising, enhancing user experience, and price personalization are used to achieve this kind of personalization.

[11] Big Data has become a significant topic of study and research interest for academics and practitioners alike. The internet and digital gadgets are growing exponentially, which drives the exponential growth of data. Large-scale data analysis and storage are now economically possible because to technological advancements. Big Data is a collection of real-time, structured, semi-structured, and unstructured data from many sources. The mechanism for extracting intelligence from massive data sets is provided by predictive analytics. Numerous forward-thinking businesses, like Google, Amazon, and others, have discovered how big data and analytics may be used to obtain a competitive edge. These methods offer many advantages, such as finding patterns or improving optimization algorithms. There are a few obstacles in managing and evaluating big data, which include reliability, quality, and scale. [12] As e-commerce platforms generate more data, new avenues and opportunities present themselves for utilizing this data to apply predictive analytics solutions and, as a result, obtain a competitive edge. The majority of current solutions address the difficulties and constraints posed by massive amounts of data. Research on the challenges of handling small-scale data, which is accessible through DIY shopping cart software used by micro and tiny enterprises like start-ups, is, nevertheless, scant or non-existent. [13] As a result of customers finding it more convenient to purchase products online, digital retailers are witnessing a rise in the volume of online transactions from their clientele. These exchanges result in intricate behavioral patterns that can be examined using predictive analytics to help companies better understand the demands of their customers. The dearth of huge data and potential analysis tools begs for a rigorous evaluation of the literature. Consequently, a thorough assessment of the literature on client purchase prediction in the context of e-commerce is presented in this work. The primary contributions consist of an innovative framework for analysis and a research agenda for the topic. In this review, the framework highlights three primary tasks: predicting client intents, buying sessions, and purchase decisions.

[14] One way to approach business through the integration of information and communication technologies, more specifically data analytics, is to use vast data to outperform competitors. This article details the creation of a web application that uses predictive analytics to help stakeholders enhance customer relations and sales. Via effective product predictive analytics, having an online system that keeps track of stock levels and product availability gives stakeholders a competitive advantage over rivals. The evaluation's findings demonstrate how well-liked the program is by end users. According to the study's findings, predictive analytics is pertinent to current advancements in e-commerce platforms. Additionally, this study offers research and practical advice. [15] The study looks at the potential and prospects that come with big data in retailing, especially in relation to five main data dimensions: time, place, channel, customers, and items. A combination of new data sources, clever statistical tool use, domain expertise coupled with theoretical insights, and increased data quality and application opportunities are largely responsible for these developments. Even as the role of Big Data and predictive analytics in retailing is expected to grow, supported by newer data sources and large-scale correlational techniques, the significance of theory in directing any systematic search for answers to retailing questions and in streamlining analysis remains undiminished. Among the statistical concerns addressed is the applicability and relevance of Bayesian analysis techniques. Singh et al. [15] used ML and DL approaches for predicting stock market price and all the visualizations were shown using Tableau software. Lochan et al. [16] used ML methods for online payment fraud prediction. Charitha et al. [17] used ML techniques for detecting

fraud in online transactions. Khushi et al. [18] used computational models for detection of frauds in online payments and transactions. Akshitha et al. [19] used machine learning methods for prediction of stock price.

III. METHODOLOGY

In order to evaluate and prioritize the important elements in e-commerce operations, this study uses three different decision-making techniques: The Analytical Hierarchy Process (AHP), Fuzzy AHP, and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). These techniques will be applied to evaluate the significance of various factors found in the dataset, including consumer demographics, product descriptions, quantities, and unit prices, as well as their impact on fraud detection, inventory control, and sales trends.

A. Analytic Hierarchy Process

Step 1: Pairwise Comparison Matrix
For each criterion and sub-criterion, a pairwise comparison matrix $A=[a_{ij}]$ is created, where a_{ij} represents the relative importance of criterion i compared to criterion j.

$$a_{ij} = \frac{Importance\ of\ i}{Importance\ of\ j} \tag{1}$$

Step 2: Normalizing the Matrix
The next step involves normalizing the pairwise comparison matrix to ensure that the values are on a consistent scale. This is done by dividing each element a_{ij} in the matrix by the sum of its column:

$$\text{Normalized matrix element} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{2}$$

Step 3: Calculate the Priority Vector (Eigenvector)
Compute the priority vector w=[w1,w2,…,wn] by averagingthe rows of the normalized matrix.

$$w_i = \frac{1}{n}\sum_{j=1}^{n} \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{3}$$

Step 4: Consistency Check
Calculate the Consistency Index (CI):

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{4}$$

where λ_{max} is the principal eigenvalue of the matrix.
Calculate the Consistency Ratio (CR):

$$CR = \frac{CI}{RI} \tag{5}$$

where RI is the Random Consistency Index for the given matrix size n.

B. TOPSIS

A multi-criteria decision-making technique called the Technique for Order Preference by Similarity to Ideal answer (TOPSIS) is used to order options according to how near they are to the ideal answer. A thorough technique and the formulas needed to apply TOPSIS to your dataset are provided below.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{6}$$

Step 1: Construct the Decision Matrix
The first step is to organize the data into a decision matrix X=[xij]X = [x_{ij}]X=[xij], where each row represents an alternative (e.g., different transactions or products), and each column represents a criterion (e.g., price, quantity, customer demographics).
Step 2: Normalize the Decision Matrix
Normalize the decision matrix to eliminate the impact of different measurement units among criteria. The normalized value r_{ij} is calculated as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{7}$$

where:

- ➢ X_{ij} is the original value of the i-th alternative for the j-th criterion.
- ➢ m is the total number of alternatives.

Step 3: Calculate the Weighted Normalized Matrix

Multiply the normalized decision matrix by the weights wjw_jwj of the respective criteria to obtain the weighted normalized decision matrix $V=[v_{ij}]$:

$$V_{ij} = w_j \times r_{ij} \tag{8}$$

Step 4: Determine the Ideal and Negative-Ideal Solutions

The next step is to identify the ideal solution (A^+) and the negative-ideal solution (A^-). The ideal solution represents the best possible values, while the negative-ideal solution represents the worst:

$A^+=(\max(v_{ij})|$benefit criteria,$\min(v_{ij})|j\in$cost criteria)

$A^-=(\min(v_{ij})|j\in$benefit criteria,max

$(v_{ij})|j\in$cost criteria)

Step 5: Calculate the Separation Measures

The separation measures Si^+ and Si^- for each alternative from the ideal and negative-ideal solutions, respectively, are calculated using the Euclidean distance:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (V_{ij} - A_j^+)^2} \tag{9}$$

Step 6: Calculate the Relative Closeness to the Ideal Solution

The relative closeness C_i* of each alternative to the ideal solution is computed as:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{10}$$

Step 7: Rank the Alternatives

Finally, the alternatives are ranked based on their relative closeness C_i* , with higher values is considered as the best option according to the TOPSIS method.

C. Fuzzy-Analytic Hierarchy Process Enhanced by Geometric Mean

The Fuzzy Analytic Hierarchy Process (F-AHP) enhanced by the geometric mean method is a refined decision-making approach used for Quantity, Unit price, Revenue, Fraud detection, Inventory, etc.. The following steps outline the methodology:

Step 1: Define Fuzzy Pairwise Comparison Matrices

Triangular Fuzzy Numbers (TFNs): Each pairwise comparison is represented by a triangular fuzzy number a~ij=(lij,mij,uij)

where:

- ➢ lij is the lower bound.
- ➢ mij is the most likely value (modal value).
- ➢ uij is the upper bound.

$$\tilde{A} = \begin{bmatrix} (1,1,1) & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & (1,1,1) & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{m1} & \tilde{a}x_{m2} & \cdots & (1,1,1) \end{bmatrix} \tag{11}$$

Step 2: Fuzzy Synthetic Extent Calculation

Calculate the fuzzy synthetic extent Si for each criterion using the formula:

$$S_i = \left(\sum_{j=1}^{n} \tilde{a}_{ij}\right) \times \left(\sum_{k=1}^{m} \sum_{j=1}^{n} \tilde{a}_{kj}\right)^{-1} \tag{12}$$

Where:

- ➢ ∑j=1na~ij is the fuzzy sum of the i-th row (fuzzy multiplication of TFNs).

- ∑k=1m∑j=1na~kj is the fuzzy sum of all elements in the pairwise comparison matrix (also a fuzzy multiplication).

Step 3: Degree of Possibility V(Si ≥ Sj)

The degree of possibility of Si being greater than or equal to Sj is calculated as:

$$(S_i \geq S_j) = \begin{cases} 1 & if\ m_i \geq m_j \\ \frac{l_j - w_i}{(m_i - v_i) + (m_j - l_j)} & if\, l_j \leq u_i \\ 0 & otherwise \end{cases} \quad (13)$$

Where:

- Li, mi , ui are the lower, middle, and upper values of Si
- lj , mj , uj are the corresponding values for Sj .

Step 4: Weight Calculation (Fuzzy Weights)

The fuzzy weight w~I for each criterion is obtained by comparing the degree of possibility:

$$\widetilde{w}_i = minV(S_i \geq S_j)\ for\ all\ j \neq i \quad (14)$$

This is repeated for all criteria.

Step 5: Defuzzification (Conversion of Fuzzy Weights to Crisp Values)

The fuzzy weights are defuzzified to obtain crisp weights wi using the centroid method:

$$\widetilde{w}_i = \frac{l_i + 4m_i + v_i}{6} \quad (15)$$

This converts the triangular fuzzy numbers into a single crisp value for decision-making.

Step 6: Normalization of Weights

Normalize the defuzzified weights to ensure that the sum of all weights equals 1:

$$W_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \quad (16)$$

IV. Results

The obtained results are as follows:

A. AHP

TABLE I. AHP RESULTS

RANK	INVOICE NO	DESCRIPTION	QUANTITY	UNIT PRICE	SCORE
1	555200	HANGING JAM JAR T-LIGHT HOLDER	24	0.85	0.7065
2	546157	RETROSPOT LAMP	2	9.95	0.3000
3	554974	GOLD FISHING GNOME	4	6.95	0.2669
4	576652	PACK 3 BOXES CHRISTMAS PENETTONE	3	1.95	0.0738
5	550972	SET/6 RED SPOTTY PAPER CUPS	4	0.65	0.0636

In this study, we utilized the Fuzzy AHP method to rank five randomly selected items from an e-commerce dataset based on two criteria: ‘Quantity’ and ‘UnitPrice’. With greater emphasis placed on Quantity, we computed weighted scores for each item. The "HANGING JAM JAR T-LIGHT HOLDER," with the highest quantity (24 units) and a moderate unit price (0.85), achieved the top rank, highlighting the influence of higher quantities in the decision-making process.

Despite its higher unit price, the "RETROSPOT LAMP" ranked second due to its lower quantity. Items with both lower quantities and unit prices, like "SET/6 RED SPOTTY PAPER CUPS," ranked lower, illustrating their lesser importance under the selected criteria weights.

This analysis showcases the flexibility of the Fuzzy AHP method in aligning with decision-makers' priorities and evaluating the importance of different criteria. It proves to be a valuable tool in complex decision-making scenarios such as inventory management or product prioritization in e-commerce, effectively identifying the most favorable option based on specific criteria and providing insights for optimizing inventory or sales strategies.

B. TOPSIS

TABLE II. TOPSIS RESULTS

QUANTITY	UNIT PRICE	TOPSIS SCORE	TOPSIS RANK
24	0.85	0.505493	1
4	0.65	0.063028	2
2	9.95	0.500000	3
3	1.95	0.102650	4
4	6.95	0.414710	5

Based on the TOPSIS method applied to the five randomly selected data points, we can draw the following conclusions:

Most Preferred Option: The data point with a quantity of 24 and a unit price of 0.85 received the highest TOPSIS score, making it the most favorable choice among the five based on the criteria of Quantity and UnitPrice. This indicates that a higher quantity combined with a relatively lower price makes this option the most desirable.

Rank Interpretation: The TOPSIS method effectively balances the trade-offs between criteria. For instance, although one option has a very low unit price (0.65), it ranks 2nd due to its lower quantity (4). Conversely, an option with a significantly higher unit price (9.95) ranks 3rd despite having the lowest quantity, demonstrating that both criteria must be optimized to achieve a higher rank.

Decision Guidance: This analysis helps decision-makers prioritize options that offer the best combination of quantity and price. In this case, an option with a moderate price and higher quantity is favored.

Overall, TOPSIS offers a structured approach to evaluating and ranking alternatives, aiding in making informed decisions based on multiple criteria.

C. Fuzzy AHP

TABLE III. FUZZY AHP RESULTS

INVOICE NO	DESCRIPTION	QUANTITY	F-AHP Score	F-AHP Rank
581483	PAPER CRAFT, LITTLE BRIEDIE	80995	0.895	1
581482	BANKING SET 9 PIECE	24	0.253	2
581482	GARDENERS KNEELING PAD	48	0.032	3
581482	KINGS CHOICE MUG	36	0.002	4
581482	VINTAGE RED TRIM MUG	96	0.0004	5

The data element with InvoiceNo 581483 and StockCode 23843 ("PAPER CRAFT, LITTLE BIRDIE") achieves the highest aggregate score of 0.895. According to the AHP method, which considers the criteria of Quantity, Unit Price, and Total Revenue, this product emerges as the most significant among the five evaluated. The other products are ranked in descending order based on their respective scores.

This ranking is valuable for decision-making, as it takes into account multiple factors to determine the overall importance of each product, including the quantity sold, unit price, and total revenue generated.

V. CONCLUSION

The Fuzzy AHP method emerges as the most suitable approach for your dataset, offering a robust solution that effectively integrates the hierarchical decision-making framework of AHP with the flexibility to manage uncertainty and subjective judgments. This method is particularly advantageous in complex decision-making scenarios, such as ranking products based on multiple criteria like Quantity, Unit Price, and Total Revenue. By incorporating fuzzy logic, Fuzzy AHP enhances the traditional AHP model, enabling it to handle imprecise and ambiguous information, which is often inherent in real-world data. This makes Fuzzy AHP a more versatile and resilient method, as it not only accounts for the relative importance of each criterion but also adjusts for the uncertainties that can arise during the decision-making process. If your research prioritizes a balance between methodological complexity and practical applicability, Fuzzy AHP is the optimal choice for deriving accurate and meaningful rankings from your dataset. However, if the focus is on simplicity and ease of implementation, and if the dataset is relatively straightforward without significant uncertainties, the traditional AHP method could be sufficient. On the other hand, if computational efficiency and the ability to clearly distinguish between alternatives are more critical, the TOPSIS method may be considered, particularly in situations where the primary goal is to rank alternatives based on their proximity to an ideal solution. Ultimately, the choice of method should align with the specific objectives and constraints of your research, but Fuzzy AHP offers a compelling balance of rigor and flexibility that makes it particularly well-suited for complex, multi-criteria decision-making tasks.

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