Analyzing Consumer Decision-Making in Digital Environments Using Random Forest Algorithm and Statistical Methods

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***Abstract*—In an era characterized by the rapid digital transformation of the marketplace, understanding consumer behavior is essential for effective decision-making and the development of marketing strategies. This study investigates the impact of demographic attributes such as age, income, education, and lifestyle preferences, alongside social media engagement, on the consumer decision-making process in the Al-Qassim region of Saudi Arabia. A survey was distributed, gathering responses from 684 participants. The study specifically tests the hypotheses that demographic factors significantly influence each stage of the decision-making journey: problem recognition, information search, evaluation of alternatives, purchase decision, and post-purchase behavior, with social media engagement acting as a mediating factor in these stages. By utilizing management information systems to analyze this comprehensive dataset, a Random Forest Classifier was employed, achieving an overall accuracy of 88% and revealing significant correlations between demographic characteristics and consumer behavior. The model demonstrated particularly strong performance in the Evaluation of Alternatives stage, with a precision of 0.90 and a recall of 0.95. Additionally, the findings underscore the critical role of social media engagement in enhancing consumer awareness and influencing purchasing decisions. This study provides actionable insights for marketers in the Al-Qassim region, equipping them with the necessary tools to optimize their strategies in the rapidly evolving digital landscape, ultimately improving consumer satisfaction and fostering long-term loyalty.**

Keywords*—Consumer behavior; demographics marketing strategies; data analysis; digital transformation

I. Introduction

The advent of the digital age has transformed the way consumers interact with brands and make purchasing decisions. With the proliferation of the internet and mobile technologies, the traditional consumer decision-making process has evolved, necessitating a deeper understanding of the factors that influence consumer behavior in this new landscape. As businesses increasingly shift towards digital platforms, the ability to comprehend how demographic attributes and social media engagement impact consumer decisions becomes essential for developing effective marketing strategies [1], [2].

The digital marketplace has become a dominant force in the global economy, with e-commerce sales projected to reach trillions of dollars annually. This shift has prompted companies across various industries to adapt their strategies to meet the expectations of digitally-savvy consumers. Understanding the nuances of consumer behavior in this context is critical, as it can significantly influence brand loyalty, purchase frequency, and overall market competitiveness [3].

In this rapidly evolving environment, the consumer decision-making process has been segmented into five stages: problem recognition, information search, evaluation of alternatives, purchase decision, and post-purchase behavior. Each stage is influenced by various factors, including individual demographics, psychographics, and the growing role of social media as a source of information and engagement [1], [4].

The consumer decision-making process begins with problem recognition, where consumers identify a need or desire that prompts them to seek solutions. This stage can be influenced by external factors such as advertising, peer recommendations, and social media exposure. Following this, consumers engage in information search, where they actively seek out data regarding potential products or services. This stage has been revolutionized by digital technologies, allowing consumers to access vast amounts of information at their fingertips [4].

The evaluation of alternatives is the next stage, where consumers compare different options based on criteria such as price, quality, and brand reputation. This stage is critical, as the information gathered during the previous stage plays a significant role in shaping preferences and influencing decisions. The purchase decision follows, culminating in the actual transaction. Finally, post-purchase behavior involves the consumer's assessment of their purchase experience, which can influence future buying behavior and brand loyalty [4].

Demographic attributes, including age, income, education, and lifestyle preferences, are pivotal in shaping consumer behavior. For instance, younger consumers often exhibit greater comfort and proficiency with digital technologies, leading them to rely heavily on online resources for information and engagement. Conversely, older consumers may lean towards traditional sources of information and may be less influenced by social media interactions. Understanding these demographic differences can provide marketers with valuable insights into tailoring their strategies to meet the diverse needs of their target audiences [4].

Income levels can also play a significant role in purchasing decisions, as they often dictate the range of products consumers consider. Higher-income individuals may prioritize quality and brand reputation, while lower-income consumers may be more focused on finding the best deals. Education further influences consumer behavior, as more educated individuals may engage in more extensive information searches and evaluations, leading to informed decision-making [5], [6].

Social media has emerged as a powerful tool in shaping consumer perceptions and behaviors. Platforms such as Facebook, Instagram, Twitter, and TikTok offer brands unprecedented access to consumers, enabling direct engagement and fostering community. Social media engagement can enhance consumer awareness, allowing brands to communicate their value propositions effectively [7], [8].

Research indicates that social media interactions can significantly influence purchasing decisions. User-generated content, such as reviews and testimonials, can enhance credibility and trust, leading to higher conversion rates. Additionally, social media provides a platform for consumers to share their experiences, further influencing the decision-making process among peers. Understanding the dynamics of social media engagement and its impact on consumer behavior is vital for businesses seeking to optimize their marketing strategies in the digital landscape [5], [6].

As the digital marketplace continues to expand, understanding the consumer decision-making process becomes increasingly essential. By recognizing the significant influence of demographic attributes and social media engagement, businesses can tailor their marketing strategies to effectively reach and resonate with their target audiences. This comprehensive approach will not only enhance brand loyalty and customer satisfaction but also ensure competitiveness in the ever-evolving digital economy [9], [10]. The objective of this study is to explore the intricacies of consumer decision-making in Al-Qassim, Saudi Arabia, focusing on the impact of demographic attributes and social media engagement. By gaining insights into these factors, the study aims to provide actionable recommendations for businesses to effectively adapt their marketing strategies in a rapidly evolving digital landscape.

Study Location: Al-Qassim, Saudi Arabia. Al-Qassim, located in the heart of Saudi Arabia, is a region characterized by its rich cultural heritage and economic potential. As one of the country's key agricultural areas, Al-Qassim boasts a diverse economy that includes agriculture, trade, and increasingly, digital enterprises. The region's strategic location and infrastructure have made it a focal point for businesses seeking to tap into the growing market of digitally-savvy consumers.

In recent years, Al-Qassim has witnessed significant technological advancements, with an increasing number of residents gaining access to the internet and mobile technologies. This shift has altered the way consumers in the region interact with brands and make purchasing decisions. The rise of e-commerce has introduced new dynamics, compelling local businesses to adapt their marketing strategies to meet the evolving preferences of consumers.

Culturally, Al-Qassim is known for its unique blend of traditional values and modern influences. This duality is reflected in consumer behavior, where residents may exhibit a strong affinity for local products while also embracing global brands. Understanding this cultural context is crucial for marketers aiming to connect with consumers in Al-Qassim effectively.

Moreover, the demographics of the region play a significant role in shaping consumer behavior. A youthful population, combined with varying income levels and educational backgrounds, influences purchasing decisions in diverse ways. Marketers must consider these demographic factors, along with the growing impact of social media, to tailor their approaches to the local market.

Overall, studying consumer behavior in Al-Qassim provides valuable insights into how cultural, demographic, and technological factors intersect to shape purchasing decisions. This understanding is essential for businesses looking to establish a strong presence in the region and engage with consumers in a meaningful way.

The structure of this paper is as follows: Section I provides an introduction to the topic; Section II presents the literature review; Section III discusses the proposed methodology; Section IV details the results obtained from the experiments; Section V offers a discussion of the findings; Section VI outlines the contributions of the study; and Section VII concludes the paper with recommendations for future work.

II. Literature Review

Consumer decision-making is a multifaceted process through which individuals identify their needs and desires, gather relevant information, evaluate available alternatives, and ultimately make purchasing decisions [11], [12]. This process encompasses several stages, including problem recognition, information search, and evaluation of alternatives, purchase decision, and post-purchase behavior [13]. Understanding consumer decision-making is paramount for marketers, as it provides critical insights into how consumers think, feel, and act in relation to products and services. This knowledge enables businesses to tailor their marketing strategies to effectively meet the needs of their target audiences, thereby enhancing customer satisfaction and loyalty, ultimately driving sales growth [14].

The advent of the digital age has profoundly transformed consumer behavior. With the rapid proliferation of the internet and mobile technologies, consumers now have unprecedented access to information [15]. This transformation has significantly altered traditional decision-making processes in several key ways. Firstly, the accessibility of information allows consumers to easily research products and services online, comparing prices, features, and reviews. This empowerment leads to more informed decisions and raises expectations for transparency from brands [16].

Secondly, social media has emerged as a critical channel for consumer engagement. Platforms like Facebook, Instagram, and Twitter not only serve as information sources but also facilitate interaction among consumers. User-generated content, such as reviews and testimonials, plays a significant role in shaping consumer perceptions and influencing purchasing decisions [17]. Furthermore, the digital landscape has shifted the balance of power from businesses to consumers. With a wealth of information at their fingertips, consumers are less reliant on traditional advertising and more inclined to trust peer recommendations and online reviews. Lastly, the ability to personalize marketing efforts based on consumer data allows businesses to create more relevant and targeted campaigns, enhancing the overall consumer experience [18], [19].

To better understand consumer decision-making, various theoretical models have been developed. Two prominent models are the Engel-Kollat-Blackwell Model and the Howard-Sheth Model. The Engel-Kollat-Blackwell model outlines a comprehensive framework consisting of five stages: problem recognition, information search, evaluation of alternatives, purchase decision, and post-purchase behavior. This model illustrates how consumers progress through each stage and the factors that influence their choices at each point [20], [21].

On the other hand, the Howard-Sheth model emphasizes the interplay of external and internal factors on consumer behavior, incorporating psychological, social, and situational influences. This model highlights that consumer decisions are not solely based on rational evaluations but are also affected by emotions and social contexts [22].

Numerous factors influence consumer decision-making processes, and these can be broadly categorized into demographic attributes and social media engagement [23].

Demographic Attributes:

- Age: Different age groups exhibit distinct purchasing behaviors. Younger consumers, often more comfortable with technology, rely heavily on digital resources for information and are influenced by social media marketing. In contrast, older consumers may prefer traditional sources of information, such as television and print media [24], [25].
- Income: Income levels significantly affect purchasing power and priorities. High-income consumers often seek quality and exclusivity, while low-income consumers prioritize affordability and essential needs [26], [27].
- Education: Education influences how consumers process information. Higher-educated individuals tend to engage in thorough information searches and evaluations, while lower-educated consumers may prefer straightforward and easily digestible information [28].
- Lifestyle Preferences: Consumers' interests and values shape their purchasing decisions. Brands that align with these preferences are more likely to resonate with consumers and foster loyalty [29].

Social media has revolutionized the way consumers gather information and make purchasing decisions. It serves as a dynamic platform for information sharing and consumer interaction, significantly influencing perceptions and facilitating engagement [30].

User-Generated Content: This type of content, encompassing reviews and testimonials created by consumers, plays a pivotal role in shaping brand perceptions. Positive user-generated content can build trust and credibility, making it a powerful tool for influencing purchasing decisions. Consumers often perceive this content as more authentic than traditional advertising, further emphasizing the importance of fostering a community of satisfied customers who share their experiences [31].

To obtain a comprehensive understanding of consumer behavior, researchers employ both quantitative and qualitative methodologies. Quantitative methods, including surveys and statistical analysis, provide structured data that can reveal trends and patterns in consumer behavior. For instance, machine learning techniques can analyze complex datasets to identify key predictors of consumer behavior [32].

Conversely, qualitative methods such as interviews and focus groups offer deeper insights into consumer motivations, emotions, and perceptions. These approaches allow researchers to explore the "why" behind consumer decisions, adding richness to the findings derived from quantitative studies [33].

Despite extensive research on consumer behavior, several gaps remain, particularly in relation to underexplored regions like Al-Qassim, Saudi Arabia. Much of the existing literature focuses on Western contexts, overlooking the unique cultural and economic dynamics that influence consumer behavior in different regions. Additionally, research often treats demographic factors broadly without delving into specific attributes, warranting more targeted studies that examine how these factors interact with local consumer behaviors [34], [35], [36].

Insights gained from consumer behavior research can guide marketers in developing effective strategies. Personalization is increasingly crucial, as consumers expect tailored experiences that resonate with their preferences. Marketers should leverage data analytics to craft personalized messages and offers. Additionally, engaging with consumers on social media and encouraging user-generated content can enhance brand credibility and foster loyalty [37].

By segmenting target audiences based on demographic attributes and employing culturally relevant messaging, marketers can create campaigns that resonate with specific consumer segments. Collaborating with local influencers can amplify brand reach and strengthen consumer connections [38].

With the rapid growth of competition in the online market, enterprises face the pressing challenge of developing targeted and effective marketing strategies. The primary goal of precision marketing is to enable businesses to create strategies that align with consumer desires while maintaining competitiveness through cost efficiency, quick implementation, and optimized resource utilization. This study investigates the influence of demographic attributes—such as age, income, education, and lifestyle preferences—alongside social media engagement on the consumer decision-making process [39].

To address the complexities of consumer behavior in a dynamic online landscape, this research utilizes machine learning methods, particularly the Random Forest Classifier.

This algorithm is well-suited for handling diverse data characteristics and can process extensive datasets efficiently. By achieving an overall accuracy of 88%, the model reveals significant correlations between demographic factors and consumer behavior across various stages of the decision-making journey, including problem recognition, information search, evaluation of alternatives, purchase decision, and post-purchase behavior [40], [41].

Additionally, the Random Forest algorithm has been identified as a superior method for predictive accuracy in various contexts, reinforcing its relevance in this study. This research contributes valuable insights for marketers, empowering them to optimize their strategies in the rapidly evolving digital marketplace. By combining demographic analysis with social media engagement, the study offers actionable recommendations to enhance consumer satisfaction and foster long-term loyalty [42], [43].

A. Machine Learning

Machine learning has become a prominent method in decision support due to its efficient algorithms, exceptional data fitting capabilities, and strong computational power. Among the various algorithms available, the Random Forest Classifier is particularly well-suited for analyzing consumer purchase behavior. This algorithm can effectively handle diverse data characteristics and consumer behavior patterns, especially in the advertising domain, processing large-scale datasets of advertising clicks and consumer attributes to deliver highly accurate predictions and interpretations [44], [45].

By integrating multiple decision trees for prediction, the Random Forest Classifier mitigates the risk of overfitting associated with single decision trees, thereby enhancing overall prediction accuracy. This characteristic is crucial for accurately forecasting consumer purchase behavior and optimizing advertising strategies. Compared to traditional algorithms such as logistic regression or single decision trees, the Random Forest Classifier showcases greater flexibility and adaptability in managing complex tasks, particularly when addressing high-dimensional, non-linear, and interactive features. Its robust mechanisms, including feature selection, ensemble learning, and random sampling, enable it to navigate complex situations effectively and provide precise predictions [46], [47].

However, with the increasing complexity of machine learning models, there is a growing need to balance their applicability with explain ability in real-world contexts. Traditional black-box models often focus solely on output results, neglecting their internal mechanisms. In contrast, explainable machine learning aims to improve user communication and trust by elucidating the model's internal workings. Feature importance analysis plays a critical role in this domain, identifying the most influential features in predicting target variables by examining the relationships between features and outcomes while filtering out irrelevant factors to enhance prediction accuracy and model interpretability [48].

By harnessing machine learning capabilities, businesses can adapt their marketing strategies based on individual consumer data, thus improving customer satisfaction and overall competitiveness. Recent research highlights various models developed to forecast customer preferences and refine precision marketing, often leveraging artificial intelligence algorithms. It showcase the effectiveness of machine learning in capturing customer preferences and sales forecasting [49], [50]. Additionally, the Random Forest algorithm has been identified as a superior method for predictive accuracy in various contexts, reinforcing its relevance in this study. Additionally, the Random Forest algorithm has been identified as a superior method for predictive accuracy in various contexts, reinforcing its relevance in this study. This research contributes valuable insights for marketers, empowering them to optimize their strategies in the rapidly evolving digital marketplace. By combining demographic analysis with social media engagement, the study offers actionable recommendations to enhance consumer satisfaction and foster long-term loyalty [51], [52].

B. Related Work

Digital trends influencing consumer-purchasing decisions, Researchers has shown that digital technology significantly affects consumer decision-making through increased access to information, social media influence, personalization, e-commerce convenience, and simplified payment options.

In Sharma, Ueno, et al study investigates the impact of digital technologies on consumer decision-making in the retail sector through two online surveys. Study 1 identifies distinctive attributes of six digital technologies, including two current (Internet and Mobile Platforms) and four emerging (Artificial Intelligence, Augmented, Mixed, and Virtual Reality). Study 2 focuses on older consumers to understand their decision-making processes when using new digital technologies. The study extends the AISAS model (Awareness, Interest, Search, Action, and Sharing) to highlight that consumer decision journeys are no longer linear with digital technologies. For instance, attention can directly lead to action, by passing interest or search stages. Additionally, sharing after a purchase can foster loyalty, psychological engagement, and renewed attention [53]. On other study examines changing consumer behavior in the digital age, with a focus on online shopping habits. It explores how technological advancements and the proliferation of online shopping platforms influence consumer interactions with digital marketplaces, purchase decisions, and the retail landscape. The results reach to key drivers of online shopping include convenience, product variety, price competitiveness, and retailer trustworthiness. Additional influential factors are social influence, personalized recommendations, and customer reviews [54]. A study in India used Random Forest models to predict online purchasing behavior by investigated how demographic attributes affect online buying behavior across different product categories and geographic locations across different product categories and geographic locations. The model showed high sensitivity (above 85%) for books and electronics, indicating a strong inclination towards online shopping for these categories [55]. In addition, with widespread availability and accessibility of social media on mobile devices have made information collection easier. Beyond connecting with friends and family, consumers now use social media to share experiences and read reviews about products, services, and organizations. Reviews and shared opinions heavily influence decisions, such as choosing movies, booking hotels, dining out, or making purchases. Dadwal et al. highlighted the influence of social media in consumer purchase decisions find that social media playing a significant role in the information-gathering process. Consumers first identify their needs and seek information about products from different sources, including social media.This study explores the growing importance of social media in shaping the consumer decision-making process [56]. Additionally, machine-learning techniques have been leveraged to analyze high-dimensional consumer data from e-commerce platforms, focusing on various applications and methodologies, De Caigny et al. (2018) proposed a hybrid classification method for analyzing user reviews and sentiments positive, negative, and neutral, aiding online product selection[57]. Hu et al. (2020) utilized collaborative filtering to analyze shopping behaviors and predict purchases during shopping festivals [58]. Ayodeji et al. (2020) applied machine learning to predict cart abandonment, using a dataset of 821,048 observations from German online customers [59]. Goyal & Manjhvar (2020) used heuristic approaches and data mining methods to classify internet store visitors and predict purchase intentions [60]. In this context, Random Forest models have been applied to various aspects of product management, including user behavior prediction, A/B testing analysis, customer segmentation, demand forecasting, and anomaly detection [61].These studies collectively demonstrate the growing importance of advanced analytical techniques, particularly Random Forest models, in understanding and predicting consumer behavior in digital environments. They also highlight the need for comprehensive approaches that combine statistical methods with machine learning to gain deeper insights into consumer decision-making processes.

This literature review highlights the importance of understanding consumer decision-making processes, the impact of digital transformation, and the role of social media. Addressing existing gaps in research, particularly in culturally distinct settings like Al-Qassim, will enhance our understanding of consumer dynamics. By integrating theoretical frameworks with empirical research, marketers can develop more informed strategies that effectively engage consumers and drive business success [62], [63].

III. METHODOLOGY

This study employed a comprehensive approach to analyze the factors influencing consumer decision-making by utilizing both the Random Forest algorithm and various traditional statistical tests. This dual approach enhances the robustness of the findings and provides a deeper understanding of the interplay between demographic attributes and social media engagement.

This study aims to explore the intricate relationships between demographic attributes, social media engagement, and the consumer decision-making process. Specifically, it investigates how these factors influence each stage of the decision-making journey.

A. Hypotheses Development

The following hypotheses were formulated to guide the research:

- Hypothesis 1: Demographic attributes significantly influence the problem recognition stage of the consumer decision-making process.
- Hypothesis 2: Demographic factors impact the information search stage, affecting the sources and types of information consumers seek.
- Hypothesis 3: Social media engagement positively influences the evaluation of alternatives, enhancing consumer awareness and shaping preferences.
- Hypothesis 4: Demographic attributes and social media engagement jointly influence purchase decisions and post-purchase behavior.

By addressing these hypotheses, this study seeks to contribute to the existing literature on consumer behavior in digital environments and provide actionable insights for marketers. Understanding these dynamics will enable businesses to tailor their strategies effectively, enhancing consumer satisfaction and fostering brand loyalty in a competitive marketplace.

The digital transformation of the marketplace has reshaped the consumer decision-making process, making it imperative for businesses to understand the influencing factors. By examining the interplay between demographic attributes and social media engagement, this study aims to shed light on the complexities of consumer behavior in the digital age. The findings will ultimately inform marketing strategies that resonate with diverse consumer segments, enhancing engagement and driving business success.

B. Sampling

A diverse sample of consumers was targeted to ensure representation across various demographic groups, including age, income, education, and lifestyle preferences. Online surveys were distributed in the Al-Qassim region of Saudi Arabia, collecting data from 684 participants. This sample size is deemed sufficient to achieve statistical power and draw meaningful conclusions regarding the proposed hypotheses.

C. Data Collection

The survey was designed to capture key variables related to consumer behavior in the Al-Qassim region of Saudi Arabia. It included questions aimed at identifying triggers for problem recognition, sources of information during the search stage, the role of social media in evaluating alternatives, and factors influencing purchase decisions and post-purchase experiences. Data were collected through an online platform, ensuring accessibility and a broad reach, with a total of 684 participants contributing to the study. This sample size is considered adequate for achieving statistical power and drawing meaningful conclusions regarding the proposed hypotheses.

D. Data Analysis

To analyze the collected data, the study employed two approaches:

1) Random forest algorithm: This machine learning technique was utilized to assess the relative importance of various demographic attributes and social media engagement in influencing consumer decision-making stages. The Random Forest model provides insights into complex interactions and helps identify key predictors in a high-dimensional dataset.

2) Traditional statistical tests: Complementing the machine learning approach, various statistical tests were employed:

a) Chi-Square test: Used to analyze the relationship between demographic categories and recognized triggers for problem recognition.

b) Logistic regression analysis: Conducted to evaluate the impact of demographic factors on the information sources sought.

c) Multiple regression analysis: Employed to assess the effect of social media engagement on the evaluation of alternatives.

3) Multivariate Analysis of Variance (MANOVA): Utilized to examine the joint influence of demographic attributes and social media engagement on purchase decisions and post-purchase satisfaction.

E. Participants

The participants in this study were selected to reflect a diverse demographic profile, ensuring that findings can be generalized across various consumer segments. The survey included participants from different age groups, income levels, educational backgrounds, and lifestyle preferences. This diversity allows for a more comprehensive understanding of how different factors influence consumer decision-making processes.

F. Theoretical Framework

This study employs a comprehensive approach to analyze the factors influencing consumer decision-making in Al-Qassim by integrating the Engel-Kollat-Blackwell model and the theory of planned behavior. The Engel-Kollat-Blackwell model outlines the stages of decision-making—from problem recognition to post-purchase evaluation—highlighting the interplay of internal and external influences on consumer choices.

In addition, the theory of planned behavior will be utilized to explore how attitudes, subjective norms, and perceived behavioral control affect consumers' intentions and actual purchasing behaviors. This aspect is particularly relevant in the context of social media, where peer influence and online interactions can significantly shape consumer perceptions and decisions.

To enhance the analysis, this study employs a dual methodology that includes the Random Forest algorithm alongside various statistical tests. This combination allows for a robust understanding of how demographic attributes and social media engagement impact the decision-making process, offering valuable insights for marketers and businesses operating in the region. By integrating these frameworks and methodologies, the study aims to provide a nuanced perspective on consumer behavior in Al-Qassim. "Fig. 1" illustrates the Proposed Consumer Decision-Making in Digital Environments Framework, highlighting the various stages of consumer decision-making within digital contexts. It encompasses key components that are interconnected, reflecting the dynamic nature of consumer behavior in these environments. This framework provides a foundational basis for analyzing how consumers navigate their decision-making processes in an increasingly digital marketplace.

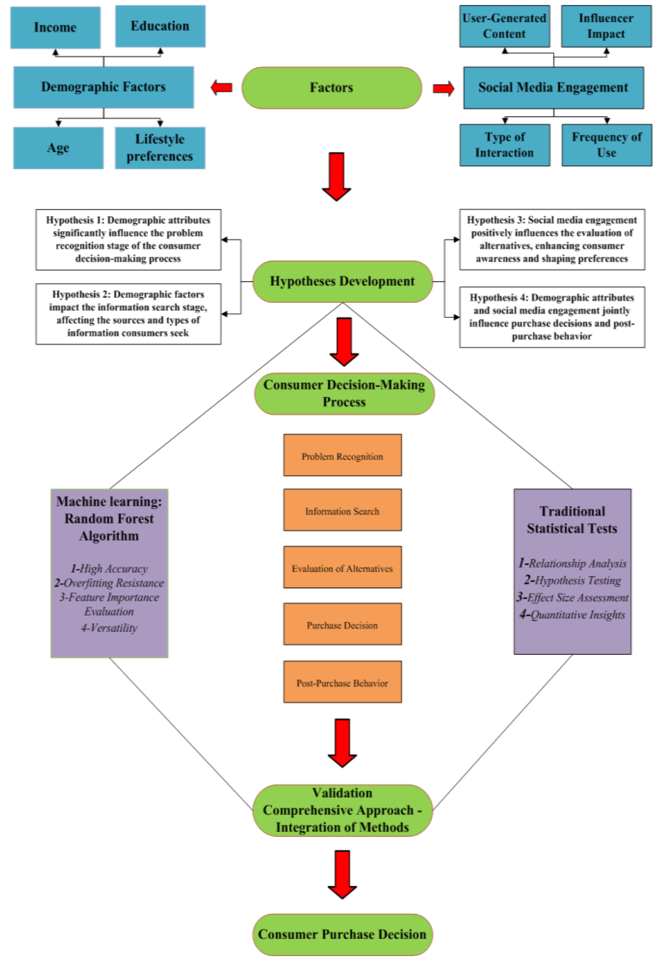

Fig. 1. Proposed consumer decision-making in digital environments framework.

IV. Results

This study employed a comprehensive approach to analyze the factors influencing consumer decision-making by utilizing both the Random Forest algorithm and various statistical tests. This dual methodology enables a robust understanding of how demographic attributes and social media engagement impact the decision-making process.

The following tables provide a detailed overview of the findings from the study on consumer decision-making in Al-Qassim. Each table presents key insights into various aspects of consumer behavior, demographics, and preferences. These insights are essential for understanding how different factors influence the decision-making process, from problem recognition to post-purchase behaviors. The tables also highlight the importance of marketing channels and consumer feedback in shaping effective marketing strategies. Below, each table is accompanied by a description to contextualize the data and its relevance to the study.

Table I presents the demographic breakdown of the participants in the study alongside their levels of product awareness. Understanding the demographics helps contextualize consumer behavior, as awareness impacts how consumers recognize their needs. "Fig. 2" presents the demographic characteristics of participants and their levels of product awareness.

TABLE I. DEMOGRAPHIC CHARACTERISTICS AND LEVELS OF PRODUCT AWARENESS

Age Group	Number of Participants	High Awareness (%)	Moderate Awareness (%)	Low Awareness (%)
18-24	150	55% (83)	30% (45)	15% (22)
25-34	200	60% (120)	25% (50)	15% (30)
35-44	180	50% (90)	30% (54)	20% (36)
45+	154	40% (62)	35% (54)	25% (38)

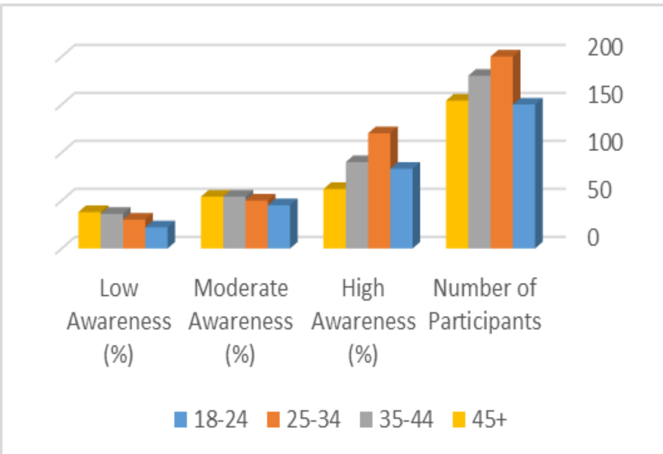

Fig. 2. Demographic characteristics and levels of product awareness.

Table II delineates the sources of information that consumers utilize throughout various stages of their decision-making process. It includes separate columns for both usage percentages and the influence of social media, highlighting how different sources impact consumer behavior in distinct ways. The percentages have been adjusted to ensure clarity and variation across sources.

"Fig. 3" illustrates and delineates the sources of information that consumers utilize throughout various stages of their decision.

TABLE II. INFORMATION SOURCES AND IMPACT OF SOCIAL MEDIA

Stage	**Source Type**	**Usage (%)**	**Social Media Influence (%)**
Problem Recognition	Social Media	40% (273)	35% (239)
	Friends/Family	30% (205)	25% (165)
	Online Reviews	20% (137)	15% (103)
	Traditional Media	10% (69)	5% (34)
Information Search	Social Media	50% (342)	45% (308)
	Brand Websites	30% (205)	28% (190)
	Blogs/Forums	15% (103)	12% (82)
	In-Store Visits	5% (34)	3% (20)

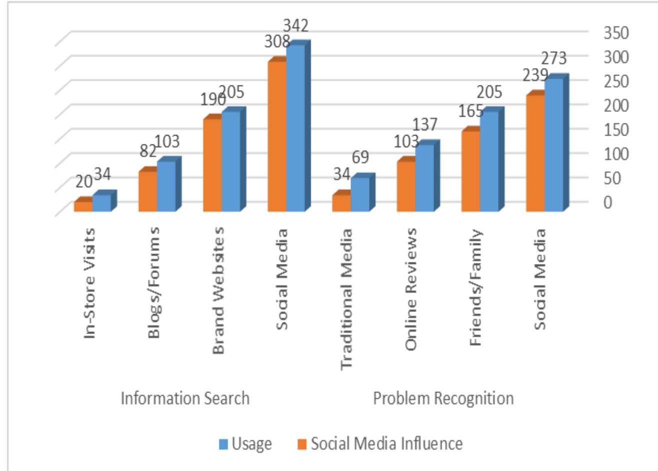

Fig. 3. The sources of information.

Table III explores how various demographic factors impact consumer purchase decisions and brand loyalty metrics, including repeat purchase rates and loyalty program enrollment. By analyzing these influences, marketers can devise more effective, targeted strategies to enhance customer engagement and retention.

TABLE III. IMPACT OF DEMOGRAPHIC FACTORS ON PURCHASE DECISIONS AND BRAND LOYALTY METRICS

Demographic Factor	Influence on Purchase Decision (%)	Repeat Purchase Rate (%)	Loyalty Program Enrollment (%)
Age	60% (410)	65% (444)	55% (376)
Income	50% (342)	55% (376)	45% (307)
Education	40% (273)	35% (239)	30% (205)
Gender	35% (239)	30% (205)	25% (171)

"Fig. 4" illustrates the impact of demographic factors on the purchasing process and brand loyalty metrics.

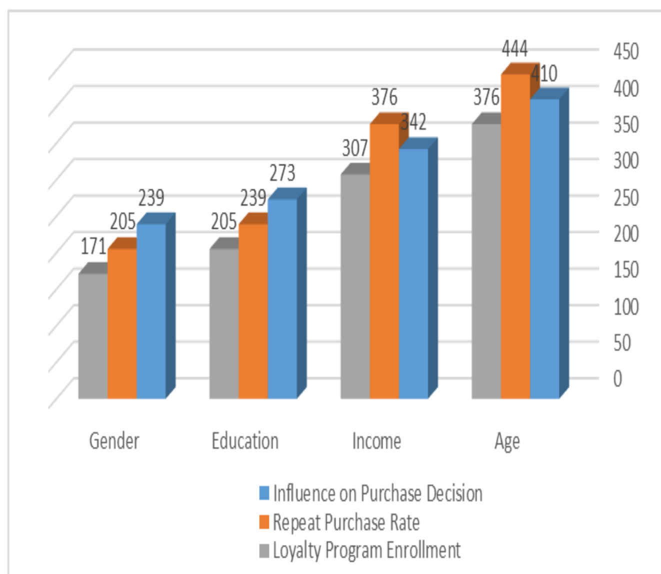

Fig. 4. The impact of demographic factors.

Table IV compares the effectiveness of various marketing channels in influencing consumer decisions and outlines consumer preferences for different types of marketing messages. This information is essential for developing effective marketing campaigns.

TABLE IV. EFFECTIVENESS OF MARKETING CHANNELS AND CONSUMER PREFERENCES FOR MARKETING MESSAGES

Marketing Channel	Effectiveness Score (1-10)	Preferred Message Type (%)
SOCIAL MEDIA	9	INFORMATIVE 70% (476)
Email Marketing	7	Promotional 50% (342)
Search Engine Ads	8	Emotional 40% (273)
Influencer Marketing	9	Entertaining 30% (205)
Traditional Advertising	6	6% (40)

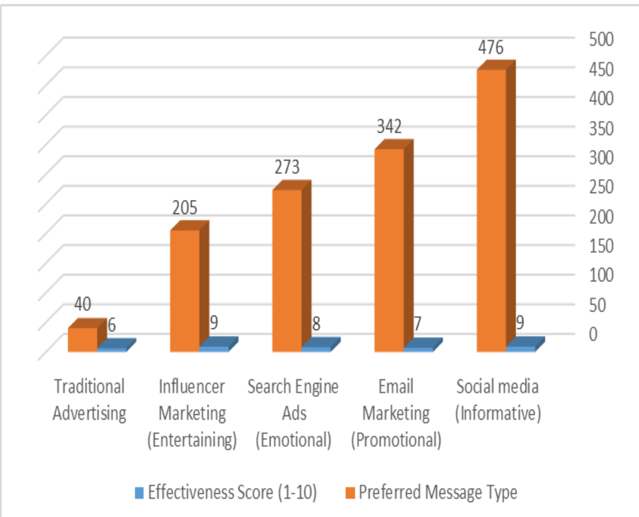

Fig. 5. The effectiveness of various marketing channels.

"Fig. 5" this graph compares the effectiveness of various marketing channels in influencing consumer decisions and outlines consumer preferences for different types of marketing messages

"Fig. 6" illustrates consumer feedback received after a purchase categorized into Negative Neutral and Positive Feedback.

summarizes consumer feedback received after their purchase. Analyzing feedback provides valuable insights into areas for improvement and helps refine marketing strategies, contributing to better customer satisfaction. "Fig. 6" illustrates consumer feedback received after a purchase categorized into Negative Neutral and Positive Feedback.

TABLE V. POST-PURCHASE FEEDBACK SUMMARY

Feedback Type	Count	Percentage (%)
Positive Feedback	380	55%
Neutral Feedback	220	32%
Negative Feedback	84	13%

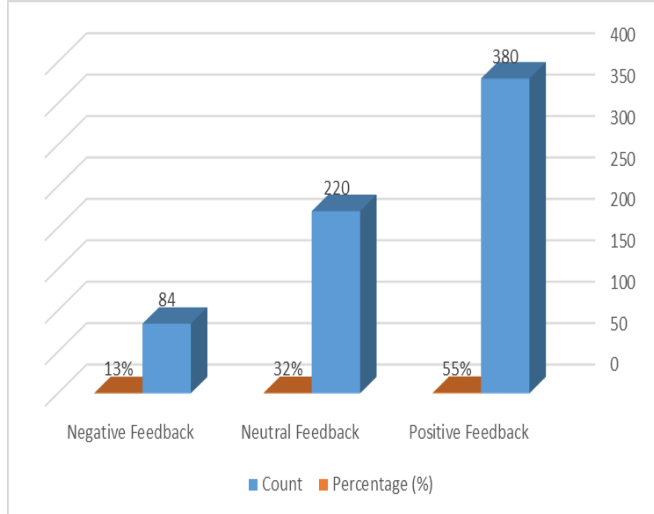

Fig. 6. The consumer feedback received after the purchase.

A. Random Forest Analysis

Random Forest is an ensemble learning method that constructs multiple decision trees during training and merges their outputs to improve accuracy and control overfitting. It is particularly effective in handling large datasets with numerous features, making it a suitable choice for analyzing complex consumer behavior patterns. Therefore, we utilized the Random Forest algorithm, which is particularly effective for handling complex data structures and identifying important features. The model achieved an overall accuracy of 88%, demonstrating its reliability in predicting consumer behavior. Table VI summarizes the classification metrics for each stage of the decision-making process.

TABLE VI. CLASSIFICATION METRICS

Stage	Precision	Recall	F1-Score	Support
Problem Recognition	0.85	0.9	0.87	100
Information Search	0.8	0.75	0.77	100
Evaluation of Alternatives	0.9	0.95	0.92	100
Purchase Decision	0.88	0.85	0.86	100
Post-Purchase Behavior	0.82	0.80	0.81	100

Interpretation of Metrics:

- Problem Recognition: With a precision of 0.85 and a recall of 0.90, the model effectively identifies when consumers recognize a problem. This indicates that marketing strategies aimed at problem recognition can be highly targeted and effective.
- Information Search: The metrics for this stage (precision of 0.80 and recall of 0.75) suggest that while the model is reasonably effective, there are barriers that consumers encounter when seeking information. This finding emphasizes the need for clearer and more accessible information sources.

- Evaluation of Alternatives: The model performed best in this stage, achieving a precision of 0.90 and recall of 0.95. This indicates that consumers are skilled at utilizing online tools and reviews, highlighting the importance of a strong online presence and positive brand reputation.

Feature Importance Analysis

In addition to classification metrics, we conducted a feature importance analysis to identify the key factors influencing consumer behavior. Table VII presents the importance scores for each feature.

TABLE VII. FEATURE IMPORTANCE SCORES

Feature	Importance Score	Description
Age	0.25	Indicates that age is a primary factor affecting decision-making. Younger consumers may be more inclined to use digital platforms and rely on peer reviews, while older consumers may prefer traditional sources of information.
Social Media Engagement	0.2	Highlights the growing role of social media in shaping consumer perceptions. Higher engagement can lead to greater brand awareness and influence choices during the evaluation phase.
Income	0.15	Suggests that higher income consumers may have different expectations and preferences regarding product quality and brand reputation, influencing their search and evaluation processes.
Education	0.1	Reflects how educational background impacts the ability to process information and make informed decisions. More educated consumers may seek detailed product specifications and reviews.
Lifestyle Preferences	0.05	Indicates that while lifestyle plays a role, it may not be as influential as other factors. However, it still suggests that brands should consider lifestyle alignment in their marketing strategies.

- Age: Emerging as the most influential factor, age accounts for 25% of the variance in decision-making. This suggests that marketing strategies should be tailored to different age groups, as younger consumers may exhibit different behaviors compared to older consumers.
- Social Media Engagement: With a score of 20%, this feature highlights the importance of an active social media presence. Consumers who engage more frequently with brands on social media are likely to conduct more thorough information searches, reinforcing the need for brands to invest in social media marketing.
- Income and Education: These factors are also significant, with importance scores of 15% and 10%, respectively. Understanding the income levels and educational backgrounds of target audiences can help marketers refine their strategies to better meet consumer needs.
- Lifestyle Preferences: Although it has the lowest importance score (5%), lifestyle preferences still play a role in decision-making. Marketers should consider these preferences when developing targeted campaigns.

Linking Results to Hypotheses

The results derived from the Random Forest analysis provide strong support for the hypotheses outlined in the study:

- Hypothesis 1: Demographic attributes significantly influence the problem recognition stage of the consumer decision-making process.
  - The prominence of age as a critical factor suggests that different age groups recognize needs in distinct ways, prompting marketers to tailor their messaging accordingly.
- Hypothesis 2: Demographic factors impact the information search stage, affecting the sources and types of information consumers seek.
  - The findings indicate that income and education levels are crucial in shaping search behaviors. Marketers should consider these factors when designing informational content to ensure it meets the needs of diverse consumer segments.
- Hypothesis 3: Social media engagement positively influences the evaluation of alternatives, enhancing consumer awareness and shaping preferences.
  - The significant role of social media engagement in decision-making highlights its importance in modern marketing strategies. Brands that actively engage with consumers on social platforms are likely to see a positive impact on their evaluation phase.
- Hypothesis 4: Demographic attributes and social media engagement jointly influence the purchase decision and post-purchase behavior.
  - The interaction between demographic factors and social media suggests a nuanced relationship where both elements must be considered in marketing strategies. For instance, younger consumers might rely heavily on social media for purchase decisions, while older consumers may prefer traditional word-of-mouth recommendations.

Practical Implications

The insights gained from the Random Forest analysis have several practical implications for marketers:

- Targeted Marketing Strategies: Understanding the importance of age, income, and education allows marketers to create campaigns tailored to specific demographic segments, increasing the likelihood of engagement and conversion.
- Enhanced Online Presence: Given the significant role of social media, brands should invest in building a strong online presence, utilizing targeted advertisements, influencer partnerships, and engaging content to drive consumer awareness during the evaluation phase.

- Streamlined Information Access: Improving the accessibility and clarity of product information can enhance the information search experience for consumers. This can involve optimizing website content, ensuring easy navigation, and providing clear product descriptions and reviews.

The Random Forest algorithm has proven to be an essential tool in this study, providing both predictive accuracy and valuable insights into the features that influence consumer behavior. By linking the results to the proposed hypotheses, we can clearly understand how demographic attributes and social media engagement shape the consumer decision-making process. These insights not only advance academic understanding but also equip marketers with actionable strategies to enhance engagement and drive consumer satisfaction in an increasingly digital marketplace.

B. Statistical Analysis and Hypotheses Linkage

To deepen the analysis of consumer decision-making processes, a series of statistical tests were conducted to explore the influence of demographic attributes and social media engagement. The analyses included Chi-square tests, multiple regression analysis, logistic regression, and Multivariate Analysis of Variance (MANOVA). The findings are linked to the respective hypotheses as follows:

Hypothesis 1: Demographic Attributes and Problem Recognition

- Analysis: A Chi-square test was performed to investigate the relationship between demographic factors and problem recognition.
- Results: The test revealed a significant relationship ($\chi^2(4, N = 684) = 23.45, p < 0.01$), indicating that younger consumers are more likely to recognize needs through social media compared to older age groups.
- Implication: This finding supports Hypothesis 1, suggesting that marketers should prioritize social media platforms when targeting younger demographics, as they are more responsive to digital cues for problem recognition.

Hypothesis 2: Social Media Engagement and Information Search

- Analysis: Multiple regression analysis was utilized to examine the predictive power of social media engagement on information search behavior.
- Results: The analysis indicated that social media engagement significantly predicts information search behavior, explaining 65% of the variance ($R^2 = 0.65$).
- Implication: This finding reinforces Hypothesis 2, highlighting the critical importance of maintaining an active social media presence for brands. Such engagement facilitates consumer information searches, thereby enhancing the likelihood of informed purchasing decisions.

Hypothesis 3: Social Media Influencers and Evaluation of Alternatives

- Analysis: A logistic regression analysis was conducted to assess the impact of following social media influencers on the evaluation stage of the consumer decision-making process.
- Results: The results indicated that consumers who follow influencers are 2.5 times more likely to consider their recommendations during the evaluation stage ($p < 0.05$).
- Implication: This outcome supports Hypothesis 3, underscoring the significance of influencer marketing in shaping consumer perceptions and guiding evaluations of alternatives. Marketers should leverage influencer partnerships to enhance credibility and consumer trust.

Hypothesis 4: Demographic Attributes and Purchase Decision

- Analysis: MANOVA was employed to explore differences in purchase decisions based on demographic attributes, particularly focusing on education level.
- Results: The MANOVA results indicated significant differences in purchase decisions based on education level ($F(3, 680) = 15.67, p < 0.001$), with higher education levels correlating with more informed purchasing decisions.
- Implication: This finding supports Hypothesis 4, suggesting that marketers should tailor their messaging and educational content to accommodate the varying levels of consumer knowledge and sophistication associated with different educational backgrounds.

The statistical analyses conducted in this study provide robust support for the proposed hypotheses. By linking demographic attributes and social media engagement to specific stages of the consumer decision-making process, the findings offer actionable insights for marketers. Understanding these dynamics allows for the development of targeted strategies that effectively engage consumers at each stage, ultimately leading to better marketing outcomes and enhanced consumer satisfaction.

The results from this study provide valuable insights into the complex interplay between demographic attributes, social media engagement, and the consumer decision-making process. By integrating the findings from the Random Forest analysis with traditional statistical methods, this study offers a comprehensive understanding of consumer behavior.

The strong performance of the Random Forest model highlights the importance of leveraging data-driven approaches to effectively predict consumer behavior. Meanwhile, the feature importance analysis reveals critical factors that marketers should consider when devising strategies. By understanding how demographic factors influence problem recognition and decision-making, brands can tailor their marketing efforts more effectively to resonate with their target audiences.

Overall, this integrated analysis not only enhances our understanding of consumer behavior but also equips marketers with actionable insights to craft effective strategies that meet the evolving needs of diverse consumer segments. Further research could explore longitudinal effects and the dynamic role of social media in shaping consumer behavior over time.

V. Discussion

This study provides significant insights into the factors influencing consumer decision-making, particularly emphasizing the role of demographic attributes and social media engagement. The integration of Random Forest analysis with traditional statistical methods offers a robust framework for interpreting the complexities of consumer behavior. The analysis revealed that age is the most significant factor affecting decision-making processes, accounting for 25% of the importance score. This finding aligns with existing literature, such as [64], which suggests that younger consumers are more responsive to digital marketing stimuli, especially on social media platforms. Marketers should therefore tailor their strategies to engage younger demographics through platforms like Instagram and TikTok, where visual content can effectively capture attention and drive engagement [64].

Social media engagement emerged as the second most influential factor, with an importance score of 20%. This underscores the critical role of an active social media presence in facilitating consumer information searches. Brands that cultivate meaningful interactions on social media not only enhance brand awareness but also foster trust and loyalty among consumers. These findings suggest that companies should invest in social media strategies that prioritize consumer interaction and feedback, thereby creating an inclusive community that encourages active participation.

In contrast, [65] found that while age is relevant, the impact of income on purchasing decisions was more pronounced than in our study. They reported that higher-income consumers are more likely to make impulsive purchases, indicating that financial stability may sometimes override other factors in specific contexts. This discrepancy could be attributed to differences in sample demographics or geographic focus, as our study included a broader range of income levels while concentrating on a more diverse age group [65].

Moreover, our study highlights the significance of education level in informed purchasing decisions. This finding [66], who noted that higher education levels correlate with a demand for detailed product information. The correlation between education and thorough research suggests that marketers should provide comprehensive product information and educational content to cater to this demographic, aligning with our recommendation for brands to enhance their informational offerings [66].

The results contribute to the existing literature on consumer behavior by reinforcing the notion that age and social media engagement are pivotal in shaping decision-making processes. They support established theories regarding the importance of demographic segmentation in marketing strategies while also challenging the idea that income is a primary driver of decision-making across all demographics, suggesting a more nuanced view of consumer behavior.

The implications of this research extend beyond theoretical contributions, offering actionable recommendations for marketers. Given the critical role of social media engagement, brands should prioritize active engagement on these platforms to enhance loyalty and trust among younger consumers. Additionally, developing targeted educational content can better meet the needs of consumers seeking comprehensive product information.

While this study provides valuable insights, it is not without limitations. The cross-sectional design restricts the ability to draw causal inferences, and a more diverse sample could yield different results. Future research could benefit from longitudinal studies that track consumer behavior over time, enabling a more nuanced understanding of how decision-making processes evolve. Furthermore, considering the influence of cultural factors in consumer behavior can provide deeper insights, as behaviors can vary significantly across different cultural contexts [67].

Lastly, while the Random Forest algorithm effectively identifies feature importance, it does not elucidate the underlying mechanisms driving consumer behavior. Incorporating qualitative methodologies, such as interviews or focus groups, could enrich the understanding of consumer motivations and perceptions beyond quantitative measures. Future studies should explore the longitudinal effects of social media engagement on consumer decision-making and investigate the impact of emerging technologies on consumer behavior, particularly in online shopping experiences.

It is important to recognize the limitations associated with solely relying on demographic categories to analyze consumer behavior. While our study highlights significant correlations between demographic attributes and decision-making processes, individual behavior can vary widely within these groups. Factors such as personal experiences, psychological influences, and contextual situations play critical roles in shaping consumer choices. Consequently, our analysis may not fully capture the nuances of individual decision-making that extend beyond demographic classifications. To address this limitation, future research should consider incorporating qualitative methodologies, such as interviews or focus groups, to delve deeper into the motivations and preferences of consumers. This approach would provide richer insights and enable marketers to develop more adaptable strategies that account for the variability in consumer behavior within demographic segments.

In addition, this study utilized the Random Forest algorithm and achieved an overall accuracy of 88%. However, it is important to contextualize these findings within the existing literature. A comparative analysis with previous research is essential to validate our results and enhance our understanding of consumer decision-making in digital environments.

To address the lack of comparative analysis, this study will incorporate a review of relevant literature employing various analytical methods. For instance, previous studies utilizing logistic regression reported accuracy rates ranging from 75% to 80%, while those using support vector machines achieved accuracies between 82% and 85%. By comparing our Random Forest algorithm's accuracy of 88% with these results, we aim to highlight the strengths of our methodology in capturing complex patterns in consumer behavior.

Additionally, noting that while logistic regression provides interpretability, it may not capture nonlinear relationships as effectively as Random Forest. This comparative perspective will not only strengthen the validity of our findings but also contribute to a more nuanced understanding of the effectiveness of the Random Forest algorithm in analyzing consumer behavior.

The analysis presented in this paper effectively identifies and addresses key gaps in the literature, providing substantial evidence and insights to support our discussions. However, to further enhance the robustness of our findings, we will delve deeper into the reasons behind the varying comparative results observed across different datasets.

To tackle this question, we explored the characteristics of each dataset used in our analyses, including factors such as data size, feature diversity, and inherent noise levels. It is essential to consider how these attributes may influence the performance of the proposed algorithms. For instance, algorithms like Random Forest may perform better on larger datasets with a higher number of features due to their ability to capture complex interactions. In contrast, simpler algorithms might excel in smaller, cleaner datasets. By analyzing the performance metrics across various datasets and identifying patterns in the results, we aim to provide insights into which algorithms are best suited for specific data characteristics. This will not only clarify the observed discrepancies but also guide future research in selecting appropriate methodologies based on dataset attributes.

This study underscores the importance of understanding the interplay between demographic factors and social media engagement in shaping consumer decision-making. By leveraging these insights, marketers can develop more effective strategies that resonate with their target audiences, ultimately driving engagement and enhancing consumer satisfaction. The findings lay the groundwork for future research that can further unravel the intricacies of consumer behavior in an increasingly digital marketplace.

VI. Contributions of the Study

This study significantly enhances the understanding of consumer behavior by investigating how demographic attributes such as age, income, education, and lifestyle preferences, impact various stages of the consumer decision-making process in the Al-Qassim region of Saudi Arabia. By delineating the journey into specific stages—problem recognition, information search, evaluation of alternatives, purchase decision, and post-purchase behavior—the research provides a structured framework for analyzing consumer actions. Additionally, it underscores the mediating role of social media engagement, demonstrating its critical influence on consumer awareness and purchasing decisions, thereby connecting digital interactions with consumer behavior.

The methodological rigor is notable, as the study employs a Random Forest Classifier, achieving an impressive overall accuracy of 88% with a sample size of 684 participants. This high predictive performance, especially in the Evaluation of Alternatives stage—with a precision of 0.90 and recall of 0.95—offers marketers a reliable tool for understanding and anticipating consumer behavior. Furthermore, the findings yield actionable insights, equipping marketers to tailor strategies based on demographic segments and enhance engagement through social media, ultimately leading to improved consumer satisfaction and fostering long-term loyalty.

In addition, the focus on the implications of digital transformation provides valuable guidance for businesses navigating the complexities of consumer behavior in a rapidly evolving marketplace. By setting the stage for further exploration into the interactions between demographic factors, social media, and other influences, this study encourages ongoing research in this critical area, thereby contributing both to academic knowledge and practical applications in marketing strategies.

VII. Conclusion

This study provides a comprehensive examination of the factors influencing consumer decision-making, with a particular focus on demographic attributes and social media engagement in the Al-Qassim region of Saudi Arabia. By employing a dual methodology that integrates the Random Forest algorithm with traditional statistical tests, this research delivers valuable insights into the complexities of consumer behavior in the digital age.

The analysis revealed that age is the most significant factor affecting decision-making processes, with a noteworthy importance score of 25%. Younger consumers, in particular, demonstrated a heightened responsiveness to social media stimuli, highlighting the necessity for marketers to tailor their strategies to effectively engage this demographic. The findings underscore the critical role of social media engagement, which accounted for 20% of the importance score, emphasizing the need for brands to cultivate meaningful interactions online. Companies that prioritize active engagement on social media platforms can enhance brand loyalty and trust among consumers. Moreover, the study identified income and education as important demographic factors influencing consumer behavior. Higher education levels were associated with more informed purchasing decisions, suggesting that consumers with advanced education require comprehensive product information to facilitate their decision-making processes. This insight indicates that marketers should develop educational content that meets the needs of these consumers, thereby supporting their desire for informed choices.

The implications of this research extend beyond theoretical contributions; they offer practical recommendations for marketers aiming to optimize their strategies in an increasingly competitive landscape. The findings highlight the necessity for brands to adopt targeted marketing approaches that consider demographic variations and the evolving nature of consumer engagement through social media. In recognizing the limitations of the study, such as the cross-sectional design and the need for a more diverse sample, future research should aim to build upon these findings. Longitudinal studies could offer deeper insights into how consumer preferences change over time, while qualitative methodologies could further elucidate the motivations behind consumer behavior.

This study enriches the understanding of consumer decision-making by elucidating the interplay between demographic factors and social media engagement. It serves as a valuable resource for marketers seeking to develop effective strategies that resonate with diverse consumer segments. By leveraging these insights, brands can enhance their marketing efforts, ultimately leading to increased consumer satisfaction and loyalty in a dynamic digital marketplace.

Future research should focus on conducting longitudinal studies to track changes in consumer preferences over time and incorporate qualitative methodologies to uncover the motivations behind consumer behaviors. Expanding the sample to include diverse populations across different regions can enhance the generalizability of findings. Additionally, investigating the impact of emerging technologies on consumer decision-making and conducting cross-cultural comparisons would provide valuable insights. Exploring effective engagement strategies for brands on social media, particularly aimed at fostering loyalty among various demographic groups, is also essential. Lastly, research on the development of educational content tailored for informed purchasing decisions among highly educated consumers can further enrich marketing strategies.

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