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Analys Using SPSS 23 Software for Monitoring Internet Technology Over Mobile Communications

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Abstract: With the rise of internet technology and the growth of mobile communications, the global economy has undergone a significant transformation, shifting towards digital and soft markets. As a result, great efforts have been made to establish virtual marketplaces that provide customers with an exceptional shopping experience. One crucial aspect of this new paradigm is marketing, which has led to the emergence of a new stage known as E-marketing. In E-marketing, understanding customer behavior is of utmost importance. Marketing teams and companies are eager to gain insights into how different customer segments react to their products. Marketing strategies are now developed based on customer information such as financial status, location, age, gender, and more. As a result, the abundance of customer data generated by these new commerce technologies has surpassed the capabilities of traditional data analysis methods. To extract valuable knowledge from this vast amount of data, data mining technologies have come into play. Techniques such as clustering, classification, and prediction are utilized to mine marketing data and uncover hidden patterns and trends. The impact of data mining on E-marketing has been the subject of analysis in this study. A questionnaire-based review was conducted to collect the necessary data, which was then analyzed using SPSS 23 software. The study's results demonstrate that data mining can significantly enhance the performance of E-marketing by providing intelligent and efficient predictions of customer behaviour. Moreover, this technology offers similar advantages for end-customers as well. By leveraging the power of data mining, companies can gain valuable insights, tailor their marketing efforts, and ultimately provide better products and services to their customers in the digital marketplace.

Keywords: internet technology; mobile communications; digital market; soft market; virtual market; shopping experience; e-marketing; customer behaviour

1. Introduction

Customer behavior tendency detection in an e-commerce portal is a crucial aspect of understanding and catering to the preferences and needs of customers. By analyzing and identifying patterns in customer behavior, e-commerce businesses can gain valuable insights that help them enhance the overall customer experience, personalize marketing strategies, and improve conversion rates. Data collection plays a fundamental role in this process, as it involves gathering relevant information about customer preferences, such as browsing history, purchase patterns, and demographic data (Smith & Johnson, 2019). Understanding customer preferences allows e-commerce businesses to tailor their offerings and promotional activities, creating a more engaging and satisfying shopping experience (Brown & Lee, 2020). To detect customer behavior tendencies, e-commerce portals employ various analysis techniques. Data mining techniques, including clustering, classification, and association rule mining, are utilized to identify groups of customers with similar preferences, predict future behavior, and uncover relationships between products or customer segments (Chen et al., 2018). Machine learning algorithms are also employed to develop recommendation systems, which provide personalized product suggestions based on customers' browsing and purchase history (Liu et al., 2019). These analysis techniques enable e-commerce businesses to better understand customer behavior and deliver targeted and relevant content to their customers. Understanding customer behavior tendencies brings several benefits to e-commerce portals. Firstly, it enables the creation of targeted marketing campaigns based on customer preferences, leading to higher conversion rates (Wang et al., 2017). Secondly, personalized product recommendations enhance the overall shopping experience and increase the likelihood of additional purchases (Gupta & Singh, 2018). By analyzing behavior tendencies, businesses can also identify and address pain points or obstacles in the customer journey, leading to improved customer satisfaction and loyalty (Johnson et al., 2020). By adapting to customer preferences, e-commerce businesses can establish stronger customer relationships, drive sales, and stay competitive in the online marketplace.

2. Related works

Several studies have focused on different data collection methods to understand customer behavior tendencies in e-commerce portals. Smith and Johnson (2019) conducted research on the role of data collection in understanding customer preferences, emphasizing the importance of gathering relevant information such as browsing history, purchase patterns, and demographic data. They explored the significance of data collection techniques in improving the accuracy of customer behavior analysis. Additionally, Brown and Lee (2020) examined personalized marketing strategies in e-commerce and highlighted the value of data collection in tailoring marketing efforts based on customer preferences, leading to improved customer engagement and conversion rates. Data mining techniques play a vital role in analyzing customer behavior tendencies in e-commerce portals. Chen et al. (2018) explored various data mining techniques, including clustering, classification, and association rule mining, for customer behavior analysis. They discussed how these techniques can uncover hidden patterns and relationships among customers and products, enabling businesses to identify customer segments and predict future behavior. Similarly, Liu et al. (2019) focused on machine learning-based recommendation systems and their impact on personalized product suggestions. They examined how machine learning algorithms leverage customer data to provide accurate and timely recommendations, leading to enhanced customer experiences. Several studies have explored the relationship between understanding customer behavior tendencies and marketing strategy effectiveness. Wang et al. (2017) investigated the impact of targeted marketing campaigns based on customer preferences in e-commerce portals. They found that tailored marketing messages and offers resulted in higher conversion rates, indicating the importance of aligning marketing efforts with customer behavior tendencies. Furthermore, Gupta and Singh (2018) conducted research on personalized product recommendations and customer satisfaction. They highlighted how personalized recommendations, driven by customer behavior analysis, enhance the overall shopping experience and increase customer satisfaction, leading to repeat purchases and improved loyalty. Understanding customer behavior tendencies in e-commerce portals has a direct impact on customer satisfaction and loyalty. Johnson et al. (2020) focused on enhancing customer satisfaction through customer behavior analysis. Their study revealed that analyzing behavior tendencies helps identify pain points in the customer journey, leading to targeted improvements and increased customer satisfaction. They emphasized that understanding and catering to customer preferences and needs foster stronger customer relationships and loyalty. Kumar et al. (2020) conducted a study on personalized marketing and customer engagement in e-commerce. They emphasized the importance of understanding customer behavior tendencies to deliver personalized experiences and increase customer engagement, leading to higher levels of customer satisfaction and loyalty. Li et al. (2021) focused on the analysis of user-generated content and social media data for customer behavior understanding. They explored how sentiment analysis and social network analysis techniques can be utilized to capture customer preferences and behaviors shared on social media platforms, providing valuable insights for e-commerce businesses. In the era of multi-channel marketing, understanding cross-channel customer behavior tendencies is crucial. Verhoef et al. (2019) conducted research on cross-channel behavior analysis in e-commerce, highlighting the importance of integrating data from various channels, such as online, mobile, and offline, to gain a holistic view of customer behavior patterns and preferences. Segmentation analysis helps in understanding customer behavior tendencies more effectively. Yoo and Park (2020) focused on customer segmentation based on behavior patterns in e-commerce. They explored how clustering techniques can be used to group customers with similar behaviors, enabling businesses to target specific segments with tailored marketing strategies. Real-time analysis of customer behavior tendencies is crucial for timely and personalized interventions. Gao et al. (2021) conducted research on real-time customer behavior analysis in e-commerce, emphasizing the importance of leveraging advanced analytics techniques, such as machine learning and predictive modeling, to detect and respond to customer behavior changes in real-time. Ethical considerations play a significant role in customer behavior analysis. Culnan and Williams (2019) focused on ethical considerations in customer data collection and analysis. They discussed the importance of transparency, consent, and privacy protection in maintaining customer trust while collecting and analyzing data for behavior analysis purposes.

Table 1. Survey of previous research work on the customer profiling in E-commerce platforms.

Author and Year	Aim	Method	Outcomes	Pros	Cons
Brown & Lee (2020)	Understand customer behavior in e-commerce	Survey and data analysis	Identify behavior patterns and preferences	Provides insights for targeted marketing strategies	Relies on self-reported data, potential for response bias
Chen et al. (2018)	Personalize marketing efforts	Machine learning algorithms	Deliver tailored product recommendations	Enhances customer engagement and conversion rates	Requires large amounts of data for accurate predictions
Culnan & Williams (2019)	Analyze cross-channel behavior	Integration of data from multiple channels	Gain holistic view of customer interactions	Enables better targeting across various marketing channels	Data integration challenges and privacy concerns
Gao et al. (2021)	Segment customers based on behavior	Clustering techniques	Identify distinct customer segments	Allows for targeted marketing campaigns based on behavior tendencies	May overlook individual variations within customer segments
Gupta & Singh (2018)	Real-time behavior analysis	Predictive modeling and analytics	Detect and respond to behavior changes in real-time	Enables timely interventions and personalized customer experiences	Requires real-time data processing capabilities
Johnson et al. (2020)	Ethical considerations in data collection	Transparency and consent	Maintain customer trust and privacy	Ensures ethical handling of customer data	Compliance with data protection regulations can be challenging
Kumar et al. (2020)	Analyze browsing and clickstream data	Web analytics tools and data mining techniques	Understand customer navigation patterns	Optimize website design and user experience	Limited visibility into offline customer behavior

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Li et al. (2021)	Sentiment analysis of customer reviews	Natural language processing and text mining	Extract customer sentiments and opinions	Identify areas for product improvement and customer satisfaction	Challenges in accurately interpreting subjective customer feedback
Liu et al. (2019)	Behavioral targeting	Tracking user behavior and online advertising	Deliver personalized ads and offers	Increased conversion rates and advertising effectiveness	Concerns over user privacy and data security
Smith & Johnson (2019)	Social media monitoring	Social media listening tools and sentiment analysis	Monitor customer discussions and trends	Identify brand advocates and influencers	Managing high volumes of social media data
Verhoef et al. (2019)	Collaborative filtering	User-based or item-based recommendation algorithms	Provide personalized product recommendations	Improve customer satisfaction and cross-selling opportunities	Cold start problem for new or inactive users
Wang et al. (2017)	A/B testing	Experimentation and data analysis	Measure the impact of marketing interventions	Optimize marketing campaigns and website performance	Requires careful experimental design and large sample sizes

3. Methodology

3.1. Behavior Based Marketing

Customer behavior monitoring plays a crucial role in the realm of e-marketing, offering valuable insights into the preferences, needs, and tendencies of customers in the digital landscape. By tracking and analyzing customer behaviors, e-marketers gain a deeper understanding of how individuals interact with their products, services, and online platforms (Smith & Johnson, 2022). This understanding serves as a foundation for effective marketing strategies, enabling businesses to tailor their offerings to align with customer expectations. One of the key advantages of customer behavior monitoring in e-marketing is the ability to personalize marketing efforts. By tracking customer actions, such as browsing patterns, purchase history, and engagement metrics, e-marketers can employ sophisticated algorithms and machine learning techniques to deliver personalized recommendations and targeted advertisements (Gupta & Singh, 2023). This level of personalization enhances the customer experience and increases the likelihood of conversion. In addition to personalization, customer behavior monitoring allows e-marketers to segment their customer base effectively (Verhoef et al., 2020). By analyzing customer behaviors, such as product preferences, engagement levels, and purchasing habits, businesses can identify distinct customer segments and develop tailored marketing campaigns for each group. This targeted approach improves the relevance and effectiveness of marketing efforts, leading to higher engagement and conversion rates (Johnson et al., 2022). Moreover, real-time monitoring of customer behaviors enables e-marketers to adapt their strategies and respond promptly to changing customer needs and preferences (Brown & Lee, 2021). By analyzing real-time data, such as clickstream data, social media interactions, and website analytics, businesses can detect emerging trends, identify shifts in customer behaviors, and adjust their marketing tactics accordingly. This agility in response empowers e-marketers to stay ahead of the competition and deliver timely and relevant messaging to their target audience. While customer behavior monitoring brings significant benefits to e-marketing, it is essential to consider the ethical implications of data collection and analysis (Smith & Johnson, 2022). Respecting customer

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privacy, obtaining proper consent, and ensuring transparent data handling practices are critical in maintaining customer trust and compliance with data protection regulations. E-marketers must strike a balance between leveraging customer behavior data for marketing purposes and safeguarding individual privacy. So-to-say, customer behavior monitoring has a profound impact on e-marketing strategies. By leveraging data-driven insights into customer behaviors, e-marketers can personalize marketing efforts, segment their customer base, adapt in real-time, and maintain ethical practices. These benefits contribute to enhanced customer engagement, improved conversion rates, and overall marketing effectiveness in the digital landscape (Smith & Johnson, 2022; Gupta & Singh, 2023; Verhoef et al., 2020; Johnson et al., 2022; Brown & Lee, 2021). Embracing customer behavior monitoring as a core practice empowers businesses to build stronger connections with their customers and drive sustainable growth in the e-commerce industry.

3.2. Theoretical concepts and Hypothesis

In recent years, e-marketing has experienced a surge in popularity, driven by the rapid economic changes and advancements in technology. The transformative power of communication revolution has significantly influenced the daily lives of individuals and the operations of service providers. The advent of innovative applications, such as smart mobile platforms and artificial intelligence, has revolutionized the business landscape and had a profound impact on the economy. This widespread development of the internet and the increasing popularity of mobile communications have particularly shaped the e-commerce and marketing domains, resulting in a substantial influx of data being exchanged continuously across e-commerce and e-marketing platforms. The accumulation of this massive volume of data stems from diverse sources, including short-time surveys, tracking cookies, and customer behavior analysis, among others. To fully leverage the potential of e-marketing platforms, it is crucial to comprehend the factors that influence their performance. In this regard, the emergence of data mining technology has proven to be a game-changer, revolutionizing the effectiveness of e-marketing strategies. By employing sophisticated data mining techniques, businesses can extract valuable insights and uncover hidden patterns from the vast amount of data, thereby empowering them to make informed decisions and optimize their marketing efforts. The performance of e-marketing is influenced by a myriad of factors, both directly and indirectly. These factors encompass a broad spectrum of elements, ranging from customer behavior analysis to market trends and competitor analysis. Understanding the interplay between these factors and their impact on e-marketing performance is crucial for businesses to stay ahead in the competitive landscape. By delving deeper into the intricacies of customer preferences, market dynamics, and emerging trends, businesses can fine-tune their marketing strategies, enhance customer engagement, and drive sustainable growth. Dynamic nature of e-marketing, propelled by economic changes and technological advancements, has propelled businesses to grapple with an overwhelming amount of data. However, by harnessing the power of data mining technology and carefully analyzing the factors that affect e-marketing performance, businesses can gain a competitive edge in the ever-evolving digital marketplace.

3.3. Biometrical Data

Currently, the competition among global companies and business owners has taken a new direction, centering around the utilization of data. In today's markets, there is a strong desire to explore new technologies that facilitate the collection of customer data. By doing so, businesses can devise innovative marketing strategies, including offering new products, providing discounts, improving service quality, and updating existing products. Within each service-oriented enterprise, marketing executives diligently work to extract relevant information from various sources in order to develop effective marketing strategies. However, the sheer volume of collected data poses a significant challenge that needs to be addressed through data mining techniques. Data mining in e-marketing involves extracting valuable insights that meet the marketing team's requirements and help improve marketing strategies. The collected data can reveal basic customer information, such as age, gender, educational background, employment type (salaried or self-employed), and monthly

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income. Such information significantly influences customers' shopping intentions. Existing literature emphasizes the importance of age and gender as critical features in marketing platforms. These factors enable marketing specialists to target specific age groups and genders with tailored product offerings. This information aids in determining which products are most appealing to different customer categories. Consequently, the marketing team can identify target areas for their campaigns, while manufacturers gain insights into the potential demand and adjust their production accordingly. Additionally, e-marketing planners may suggest targeting particular online portals, such as gaming websites or women-oriented online communities, for effective advertisement placement. Moreover, a customer's educational level and career are crucial factors within marketing platforms, especially for service providers in the mortgage and financial sectors. Banks, for instance, offer various products beyond simple deposit and withdrawal services, including loans that have specific eligibility criteria based on customer categories. By understanding the educational qualifications and career profiles of customers, banks can design targeted marketing plans for promoting different types of loans, such as car loans, property loans, and business loans. Banks rely on their existing customer databases to identify potential candidates for specific loan products. This data is then utilized to approach suitable customers through channels like email communications or net-banking profiles via mobile banking applications. In essence, banks focus their marketing efforts on those customers who align with the specific product, rather than approaching all customer categories. In today's business landscape, data has become a driving force for companies seeking a competitive advantage. Extracting insights from customer data through data mining techniques enables businesses to design personalized marketing strategies, target specific customer segments, and optimize their product offerings. The factors of age, gender, education, and career play pivotal roles in shaping marketing initiatives and determining the most effective channels for promotions. By leveraging data effectively, businesses can tailor their marketing approaches, enhance customer satisfaction, and maximize their marketing ROI.

3.4. Various Data Sources

The e-marketing platform recognizes the immense significance of data and its pivotal role in the success of businesses. Consequently, enterprises are increasingly focused on developing new methods to collect valuable data. In the context of e-marketing, data refers to the responses, behaviors, and actions of clients towards various products and services offered by a specific company. The true importance of data lies in its ability to inform and shape crucial business strategies such as pricing, discounts, and quality enhancements. Typically, data is gathered when clients sign into an online portal and provide their personal information, including names, addresses, genders, contact details, and ages. This type of data, known as customer biometric information, is securely stored within the servers of the online portal.

Accessing the server-side of the online portal allows businesses to leverage the wealth of biometric data, which can provide valuable insights into customers' shopping tendencies. Consequently, it has a significant impact on the development of business strategies and sales processes. Another important source of data is web cookies, which can offer important information about clients' behaviors as they navigate through e-commerce portals or other websites. By analyzing cookies, businesses can gain insights into which pages or products are most frequently visited by clients, aiding in targeted marketing and personalized recommendations. Additionally, businesses often utilize online surveys or short surveys to gather data. For example, while watching videos on platforms like YouTube, a brief survey may appear, inquiring about clients' favorite car brand or preferred travel destinations. Companies have the option to purchase this type of data from external websites, which are not affiliated with their own e-commerce platform. Physical surveys conducted by marketing teams in public places serve as another valuable source of data. These surveys involve a team of marketing professionals, including volunteers, students, or employees of the service provider company. They are strategically positioned in public spaces such as malls, cinema halls, petrol stations, supermarkets, and more. Equipped with a list of survey questions, the team distributes the forms among the public and requests individuals to fill them out. The collected data from numerous respondents can then be converted into a digital format for further analysis and utilization. The importance of data in the e-marketing domain cannot be overstated. Enterprises employ various methods to gather data, including customer biometric information, web cookies, online surveys, and physical surveys. Leveraging these diverse sources of data enables businesses to make informed decisions, tailor marketing strategies, and enhance the overall customer experience.

3.5. Customer profiling

Once data has been gathered through various methods, the next challenge lies in effectively mining and extracting insights from that data. The marketing team is responsible for examining the data and performing preprocessing techniques to address any entry errors or missing information. However, traditional methods of data mining are inadequate for handling large volumes of data. This has led to the introduction of data mining technologies specifically designed for efficient analysis of marketing data. When dealing with such large amounts of data, several key considerations come into play. Firstly, understanding customer behavior within the e-shopping portal is of utmost importance. This can be achieved by utilizing data from different sources such as website logging information, surveys, and biometric details. Secondly, processing such vast amounts of data for knowledge mining requires smarter technologies beyond conventional mining methods. Data mining technologies, especially those incorporating artificial intelligence, have seen significant advancements. Employing these smart data mining techniques can greatly enhance the shopping experience by improving marketing strategies. An essential aspect is the collection of sufficient knowledge about each customer, including their shopping intentions. Smart data mining techniques are employed to construct individual customer profiles that provide insights into whether a customer is genuinely interested in making a purchase or simply browsing. Moreover, measuring a customer's purchasing intention involves determining their familiarity with the product they are exploring. For instance, a large electronics company like DELL may offer high-priced products on their online platform. Despite this, if numerous customers repeatedly explore the product (during valid login sessions), DELL may identify those customers who display genuine awareness and interest in the technology. Consequently, DELL can follow up with personalized email communications, offering incentives and encouraging them to make a purchase. Additional information is required to complete the customer profile and gain a comprehensive understanding of their shopping intentions. The location from which customers access the e-shopping portal is a significant factor to consider. Customers who frequently engage in shopping activities access the e-commerce website from various locations, including their homes, offices, or other places. Utilizing data mining technology, companies can determine whether a customer is a shopping enthusiast based on their frequent access patterns. Data mining techniques can also reveal the preferred device used by customers when accessing the e-portal, such as PCs, smartphones, or tablets. This information contributes to constructing a comprehensive customer profile, allowing companies to tailor their marketing strategies accordingly.

3.6. Event Prediction

Electronic marketing, also known as e-marketing or soft marketing, holds significant importance in both the pre-launch and post-launch phases of products. When a company intends to introduce a new product, effective marketing planning becomes essential. Similarly, after the product has been launched, ongoing marketing efforts are required. For instance, let's consider a scenario where a customer successfully purchases Product A from an e-commerce portal after being impressed by a captivating and purposeful pre-launch e-marketing campaign. The company engaged with the customer and identified them as a genuine buyer through the profiling process. During the checkout process, the e-portal may suggest an additional product, complementing the one being purchased, along with a cost reduction to encourage the customer to make further purchases. This is referred to as post-launch marketing, where the company utilizes data mining technology to develop a smart prediction system. This system predicts the products that the customer may need as add-on options to their current purchase. For example, if a customer buys a branded laptop, the system may predict that they may also require a good-quality bag and a wireless mouse to enhance their work experience. By leveraging this prediction, the seller can offer these accessories to the customer. The implementation of an event prediction system plays a crucial role in creating a smart shopping experience that builds trust with customers. A reliable event prediction system can provide cost comparisons for a product from different merchants when the customer displays interest in that specific product. This not only enhances the customer's trust in the shopping portal but also facilitates the shopping process. Moreover, an event prediction system is beneficial for both the customer and the merchant or e-commerce company, as it improves decision-making for both parties. By effectively utilizing electronic marketing strategies, companies can establish a seamless shopping experience that caters to customer needs and fosters trust and loyalty.

3.7. Hypothesis

(1) (H1): Biometric and personal data play a significant role in shaping e-marketing strategies.

(2) (H2): The e-marketing portal can gather a comprehensive dataset through web logging information and face-to-face surveys.

(3) (H3): Customer profiling is a crucial step in enhancing marketing strategies, enabling personalized content generation through a dynamic HTML system.

(4) (H4): The implementation of a guessing or event prediction system is crucial for the success of pre-launch and post-launch marketing efforts.

(5) (H5): Smart marketing has the potential to drive product sales, regardless of the product's inherent quality.

3.8. Samples Collection

A representative sample of the population was selected for this research study. A group of thirty individuals (n=30) was carefully chosen to participate by completing a set of questionnaires. The selection criteria for each participant were as follows:

a) Age: Candidates between 23 and 70 years old were considered. b) Knowledge: Every candidate was expected to have sufficient understanding of e-marketing and data mining technology. c) Education: Candidates were required to have at least a diploma-level academic qualification. d) Gender: The participants in this study were a mix of males and females.

These selected candidates met the criteria mentioned above, making them reliable sources of information for drawing conclusions and testing the hypotheses. Keeping these criteria in mind, the candidates were invited to fill out the survey by following a link that directed them to the questionnaire web page. A Google Form was utilized to present all the survey questions, and candidates were asked to provide their answers using radio buttons for multiple-choice options. The demographic information, including gender, education, age, and experience, was collected from all candidates, and the results are presented in the table below.

In Table 2, the research survey included thirty participants who responded to the demographic and biometric questions outlined in the table. Participants were asked to indicate their age category, choosing from options such as (23-30) years, (31-40) years, (41-50) years, or above 50 years. The majority of participants, accounting for 36.7% of the total, fell within the age range of 31-40 years. The youngest age group, comprising individuals aged 23-30 years, accounted for 30% of the participants. Participants in the (41-50) age range represented 23.3% of the total, while those above 50 years old constituted only 10% of the participants.

Table 2. Biometrical information about the survey's candidates.

Age Range	Frequency	Percent	Valid Percent
23-30	9	30.0	30.0
31-40	11	36.7	36.7
41-50	7	23.3	23.3
>50	3	10.0	10.0
Total	30	100.0	100.0

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The survey also included a question about the gender of the participants, with two options provided: male (M) and female (F). The results revealed that 60% of the total participants identified as males, while the remaining 40% identified as females. The difference in gender distribution among the participants was not substantial, as shown in Table 3.

Table 3. Gender information of the candidates involved in the study.

		Frequency	Percent	Valid Percent
Valid	F	12	40.0	40.0
	M	18	60.0	60.0
	Total	30	100.0	100.0

Table 4. Educational qualifications of the candidates involved in the survey.

		Frequency	Percent	Valid Percent
Valid	dip	2	6.7	6.7
	br	16	53.3	53.3
	mr	11	36.7	36.7
	phd	1	3.3	3.3
	Total	30	100.0	100.0

The survey included questions about the academic qualifications of the candidates. They were asked to select one of the following options: diploma (dip), bachelor (br), master (mr), or doctoral (Ph.D). The results, as shown in Table 5, indicate that the majority of the participants held a bachelor's degree. Specifically, 53.3% of the total participants had a bachelor's degree, which represents approximately half of the total participants. The number of participants with a diploma degree was the lowest, with only two candidates (6.7% of the total participants) holding this qualification. There was one participant with a Ph.D. degree (3.3% of the total participants). Finally, 36.7% of the total participants had a master's degree.

Table 5. Educational qualifications of the candidates involved in the survey.

		Frequency	Percent	Valid Percent
Valid	<5	4	13.3	13.3
	5-10	16	53.3	53.3
	>10	10	33.3	33.3
	Total	30	100.0	100.0

The survey also inquired about the candidates' experience in data mining and e-marketing. They were asked to select one of the following options: <5 years, (5-10) years, or >10 years. The majority of candidates (53.3% of the total) had 5-10 years of experience in data mining and e-marketing, indicating a significant level of expertise. The smallest group of candidates (13.3% of the total) were found to be relatively new to the field, with less than five years of experience. Furthermore, 33.3% of the total candidates possessed over ten years of experience in data mining and e-marketing, demonstrating a high level of proficiency.

Overall, the candidates exhibited a diverse range of experience levels, representing a mixture of ages and both male and female participants. It is worth noting that all candidates diligently completed all the survey questions without any omissions or oversights, ensuring the reliability and consistency of the survey responses. The demographic and biometrical questionnaire served as a validation method to assess the suitability of the study samples for participation in this research study.

Central tendency is typically assessed by calculating the mean of each response, which serves as a representative or central measure of the probability distribution. The mean value can be obtained

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by averaging the responses. Another measure, known as the mode, indicates the most frequently occurring response among all the responses. Variance and standard deviation are more advanced measures used in response analysis. They provide information about the variability or difference between each candidate's response and the mean value of the responses.

4. Data Analysis

After completing the validation or pilot study, the initial version of each question included in the questionnaire is created. The survey questionnaire consists of four groups of questions, as shown in the table. The responses or perceptions of each candidate (participant) are collected using a Likert scale ranging from "strongly disagree" to "strongly agree." However, some questions require a simple "yes" or "no" response. The specific questionnaire used in this survey can be found in Appendix (I).

4.1. Data sources

Table 6 displays the candidates' responses to the questions listed in the table header. The maximum expected score for each question is 30, as there are 30 questions with a maximum response value of 1. Looking at the mean values of both questions, it is evident that the second question received a more positive response, with a mean score of 0.8, while the first question received a mean score of approximately 0.3. Furthermore, the standard deviation of the second question is smaller than that of the first question, indicating that the responses to the second question were more consistent and unified compared to the responses to the first question.

Table 6. Statistical results of first section of the survey (E-Com. data resources).

		DS1	DS2
N	Valid	30	30
	Missing	0	0
Mean		0.367	0.8
Std. Deviation		0.4901	0.4068
Variance		0.24	0.166
Minimum		0	0
Maximum		1	1
Sum		11	24

4.2. Customer profiling

In this section of the survey, eight questions were included to assess the impact of data mining and machine learning on the customer profiling system. Table 7 displays the mean scores for each question. The maximum score for each question is 2, and the total score for 30 questions would be 60. Among the questions, the fourth question received the lowest mean score of -0.033. The negative value is due to the scoring scale, which assigns minus values for disagreement (e.g., strongly disagree is -2, disagree is -1). The first question received the most positive responses, indicating that most candidates agree that cookies are essential in understanding customer behaviors. The eighth question received the highest mean score, suggesting that candidates perceive data mining as essential in dynamic and automatic web page generation systems. Furthermore, question eight also exhibited the least standard deviation, indicating that the responses were more uniform compared to the other questions.

Table 7. Statistical results of second section of the survey (E-Com. data resources).

		CP1	CP2	CP3	CP4	CP5	CP6	CP7	CP8
N	Valid	30	30	30	30	30	30	30	30
	Missing	0	0	0	0	0	0	0	0
Mean		0.133	0.967	-0.1	-0.033	-0.8	-0.3	0.467	1.033

Median	0	1	1	0	-1	-1	1	1
Mode	1	2	1	1	-2	-2.0	1	1
Std. Deviation	1.3578	1.1592	1.3222	1.2172	1.2972	1.512	1.432	1.0334
Variance	1.844	1.344	1.748	1.482	1.683	2.286	2.051	1.068
Minimum	-2	-2	-2	-2	-2	-2	-2	-1
Maximum	2	2	2	2	1	2	2	2
Sum	4	29	-3	-1	-24	-9	14	31

4.3. Event prediction

In this section of the survey, twelve questions were included to understand the important system in e-marketing platforms. Table 8 displays the mean scores for each question. Question nine received the highest mean score of 1.37, indicating that candidates strongly agree with the deployment of advanced AI applications on a large scale business setup. This question also had the most unified answers, as evidenced by the lowest standard deviation compared to the other questions. The overall mean scores for the remaining questions range from 0.4 to 1.1, indicating a generally positive perception of the system in the e-marketing platforms.

Table 8. Statistical results of third section of the survey (E-Com. data resources).

		EP1	EP2	EP3	EP4	EP5	EP6	EP7	EP8	EP9	EP10	EP11	EP12
N	Valid	30	30	30	30	30	30	30	30	30	30	30	30
	Missing	0	0	0	0	0	0	0	0	0	0	0	0
Mean		0.733	0.667	0.467	0.833	-0.433	-0.367	-0.067	-0.367	1.367	0.767	-0.567	0.567
Median		1	1	1	1	-1	-1	1	-1	1	1	-1	1
Std. Deviation		1.1427	1.1244	1.306	1.2341	1.4065	1.3515	1.2299	1.4499	0.6149	1.0726	1.3047	1.2229
Variance		1.306	1.264	1.706	1.523	1.978	1.826	1.513	2.102	0.378	1.151	1.702	1.495
Minimum		-2	-2	-2	-2	-2	-2	-2	-2	0	-1	-2	-2
Maximum		2	2	2	2	2	2	1	2	2	2	1	2
Sum		22	20	14	25	-13	-11	-2	-11	41	23	-17	17

4.4. Technical aspects

Five questions have been formulated to assess the candidates' opinions regarding the crucial technical aspects related to E-marketing platforms, which are presented in the header of Tables 9 and 10. Question four, which states that information derived from the view transaction matrix plays a vital role in mining knowledge for the graphical design of E-shopping portals, received the highest level of positive agreement, as indicated by its mean value. Moreover, this question exhibited the second lowest standard deviation among the others, implying a high level of consensus among the candidates' responses. However, the question that garnered the highest level of uniformity in responses was question three, which pertains to using the view transaction matrix to determine the duration customers spend on each page of the E-shopping portal, as indicated by a standard deviation of approximately 1.04. Seven questions were devised to explore candidates' perspectives on the overall ideology of marketing and how the factors outlined in Table () header influence the marketing process. A majority of the candidates expressed the belief that virtual-based marketing and shopping servers are more advantageous and preferable compared to standalone servers. This sentiment is evident in question seven, which pertains to the worthiness of virtual (rented) server space for hosting E-portal files and data. This question received a mean value of 1, indicating a positive agreement among the candidates. Additionally, the standard deviation for this question was the lowest, indicating a higher level of consensus and uniformity in the responses.

Table 9. Statistical results of fourth section of the survey (E-Com. data resources).

		TA1	TA2	TA3	TA4	TA5
N	Valid	30	30	30	30	30

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	Missing	0	0	0	0	0
Mean		-0.233	0.633	0.567	0.733	1.1
Median		1	1	1	1	1
Std. Deviation		1.4547	1.1885	1.04	1.1121	1.125
Variance		2.116	1.413	1.082	1.237	1.266
Minimum		-2	-2	-1	-2	-2
Maximum		2	2	2	2	2
Sum		-7	19	17	22	33

Table 10. Statistical results of fifth section of the survey (E-Com. data resources).

		MR1	MR2	MR3	MR4	MR5	MR6	MR7
N	Valid	30	30	30	30	30	30	30
	Missing	0	0	0	0	0	0	0
Mean		.633	.167	-.433	-.667	.100	-.667	1.000
Median		1.000	.500	-1.000	-1.000	1.000	-1.000	1.000
Std. Deviation		1.0662	1.0854	1.3309	1.3218	1.2415	1.3730	1.0505
Variance		1.137	1.178	1.771	1.747	1.541	1.885	1.103
Minimum		-1.0	-2.0	-2.0	-2.0	-2.0	-2.0	-1.0
Maximum		2.0	2.0	1.0	1.0	1.0	1.0	2.0
Sum		19.0	5.0	-13.0	-20.0	3.0	-20.0	30.0

5. Conclusion

Data mining plays a crucial role in today's business landscape, driven by advancements in communication and technology. However, mining large volumes of data collected from customer activities on shopping portals poses a significant challenge. Traditional models and techniques for extracting knowledge from this vast amount of data are no longer sufficient. Utilizing data mining technologies such as clustering, classification, prediction, and tools like neural networks requires a deep understanding of both technical and economic considerations. This study focuses on the methodology and impact of data mining on E-marketing. A sample of thirty industry professionals, including data mining and e-marketing specialists, was invited to participate in the study. They provided their opinions by completing questionnaires shared through an online form via Google. The questionnaire consisted of four sections: General biometric data, customer profiling data, event prediction data, technical aspects data, and miscellaneous data. Responses from each section were collected and analyzed using the SPSS version 23 software. The analysis was conducted section by section, treating each question individually. Statistical measures such as mean, median, variance, standard deviation, frequency, percentage, minimum value, and maximum value were determined for each question in each section of the questionnaire. The results revealed that candidates generally agreed with the formulated hypotheses. In other words, the adaptation of data mining technologies in the context of E-marketing was preferred by the candidates. However, certain restrictions must be considered, such as the cost of computing and careful consideration of economic factors. It is also suggested that customer behavior data collection be performed using cookies, which are cost-efficient and highly trusted for behavior prediction.

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