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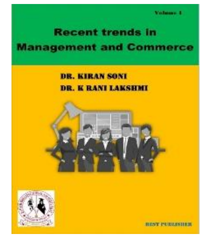

Understanding Age-Driven Preferences: A Weighted Sum Analysis of Consumer Behavior in E-commerce

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Abstract: *Consumer activity in online commerce plays a crucial role in modern business functions, impacting market trends and guiding approaches for digital merchants. This research utilizes the weighted sum technique to assess consumer actions among different age brackets, emphasizing significant indicators like Average Order Value, Satisfaction with Customer Support, Timeliness of Delivery, and Rate of Product Returns. The results underscore unique preferences and performance patterns across age segments, offering actionable intelligence for e-commerce enterprises aiming to refine their tactics. The examination indicates that individuals aged 45-54 stand out as the leading performers across every metric, showcasing the highest expenditure, most satisfactory customer support ratings, swiftest delivery times, and minimal product return rates. Conversely, the 35-44 age bracket displays the lowest overall performance, marked by comparatively lower spending, moderate satisfaction with customer support, extended delivery durations, and elevated rates of product returns. Intermediate groups include the 18-24 and 55-65 age groups, with the former showing strong overall performance and the latter displaying good customer support satisfaction and reasonable delivery times but lower spending and slightly higher return rates compared to the top performers. Additionally, the 25-34 age group performs moderately well, with decent customer support satisfaction and delivery times but lower spending and higher product return rates. These findings provide invaluable direction for e-commerce enterprises aiming to customize their strategies adeptly for diverse age segments. By comprehending the unique preferences and actions of each demographic, businesses can refine their online shopping offerings, elevate customer contentment, bolster retention figures, and foster comprehensive advancement within the competitive e-commerce.*

Keywords: *Mean Order Value, Client Assistance Contentment, Shipment Duration, Merchandise Return Frequency, and MCDM (Multi-Criteria Decision Making).*

1. INTRODUCTION

This paper aims to explore the perceived uncertainties faced by the new generation of online shoppers by analyzing their current consumer behavior. It seeks to identify the sources of uncertainty among this demographic by examining the internal factors influencing their purchasing decisions. Following this, a comparative analysis will be conducted to highlight differences in the identification variables of the new generation of consumers across various aspects of consumer behavior.[1] However, an increasing number of companies have recognized the inevitability of the shift in consumer behavior and consequently adapted their marketing strategies. Recent studies have revealed a significant surge in online shopping, especially in the business-to-consumer (B2C) sector, making it increasingly popular among consumers. Several factors contribute to this rapid growth in internet shopping, primarily driven by the conveniences offered by the internet. [2] The influence of consumer behavior on e-commerce businesses is prompting widespread adoption of consumer behavior analysis to attract more shoppers and enhance their shopping experiences. A significant shift in consumer attitudes and purchasing habits has been observed, with many expected to persist beyond the pandemic. The lockdown measures have compelled consumers to reassess their shopping practices, including increased cost consciousness, a preference for local products, and a notable shift towards e-commerce. To what extent the pandemic has altered consumer purchasing behavior towards online transactions is a crucial question. [3] Consumer behavior's impact on e-commerce enterprises is driving the widespread adoption of consumer behavior analysis to draw in more shoppers and elevate their shopping experiences. A notable transformation in consumer mindsets and purchasing patterns has emerged, with many anticipated to endure post-pandemic. Lockdown measures have prompted consumers to reevaluate their shopping behaviors, leading to heightened cost awareness, a preference for locally sourced goods, and a significant transition towards e-commerce.[4] Hence, it's crucial to employ the appropriate strategy when constructing consumer behavior models. Once a prediction model is established, it becomes challenging for marketers to precisely determine the marketing actions to take for individual customers or customer groups. This is because once the model is created, altering the variables within it is not feasible. Despite the complexity of this formulation, many customer models in practice are relatively straightforward. Consequently, due to this limitation, numerous essential elements are often overlooked in customer behavior models, rendering the forecasts unreliable. The aim of this study is to present various research endeavors that have explored the analysis of consumer behavior through diverse machine learning and data mining approaches.[5] Consumers to Administration or C2A operates bidirectionally, encompassing both C2A and A2C interactions. In the C2A model, various applications are involved, including e-democracy, e-voting, and access to public service information. Through these applications, consumers can communicate concerns, requests, feedback, and information to their local governments and administrations. Conversely, in the A2C model, a direct link is established between the government and consumers, facilitating activities such as timely and location-specific tax return filing for individuals.[6] Consumer behavior is regarded as one of the most effective and straightforward approaches worldwide, particularly in India, where it plays a significant role in trading and fostering substantial growth. India stands out as a thriving hub where consumer behavior is continually improving and flourishing in our region.[7] In the realm of research, consumer segmentation studies are frequently encountered. Customer segmentation involves dividing an existing or potential customer base into groups of individuals with similar characteristics from a marketing perspective. This segmentation process marks the initial stage of a three-step consecutive process, followed by targeting and positioning stages. During the targeting stage, companies make decisions regarding which segments to prioritize. Ultimately, in the positioning stage, companies refine or develop their products and services tailored to the chosen segments and devise a marketing strategy for each segment. Effective customer segmentation strategies empower companies to identify their most and least profitable customers, concentrate their marketing endeavors on the most lucrative customers, enhance relationships with existing customers, refine their products and services, improve customer service, and utilize company resources more efficiently [8]. Therefore, considering the sequence of actions taken by users during a session can be valuable for detecting more intricate behavioral patterns. To tackle this issue, this study suggests employing a linear-temporal logic model for analyzing structured e-commerce web logs. By establishing a standard method for mapping log records based on the e-commerce framework, web logs can be readily transformed into event logs that capture user behavior. Subsequently, various predefined queries can be executed to uncover different behavioral patterns, taking into account the diverse actions performed by a user within a session. Ultimately, the effectiveness of this approach has been evaluated through its application to a real case study involving a Spanish e-commerce website. The findings have revealed insightful discoveries, facilitating the proposal of enhancements to the website [9]. Based on the preceding discussion, it can be inferred that consumer behavior is subject to various influences, particularly during crises like the ongoing pandemic. Given the evolving nature of the pandemic and the fluctuating data, ongoing research is necessary. Nonetheless, current data suggest that consumer purchasing patterns and overall behavior have been impacted by the restrictions on physical store visits imposed during lockdowns. Consumers have shifted towards purchasing essential items such as food and vegetables, while reducing spending on non-essential items due to financial constraints [10]. The implementation of restrictions such as self-quarantine and social distancing naturally led to changes in consumers' shopping behaviors. However, the lasting impact of these changes on e-commerce is significant and unprecedented [11,12,13].

2. METHODOLOGY

Although it may have limitations in accurately representing the Pareto optimal set, the weighted sum method remains widely utilized in multi-objective optimization (MOO). This method is favored not only for generating multiple solution points by adjusting weights consistently but also for yielding a single solution point that aligns with preferences supposedly embedded in the selection of a specific set of weights [14]. This implies that the visible part of the feasible criterion space from within the feasible space, when observed from the direction of "p", only needs to be convex. Consequently, it is only essential for the Pareto optimal hypersurface to be convex for the weighted sum method to offer a prerequisite condition for Pareto optimality. Presently, the authors are unaware of any method to forecast whether the Pareto optimal hypersurface is convex or not [15]. We aim to establish precise conditions for the weighted coefficients in order to ensure that every solution obtained through the linear weighted sum method is Pareto optimal. Our objective is to devise practical criteria for determining these weighted coefficients, facilitating the efficient generation of the Pareto set. To achieve this, we intend to leverage the capabilities of symbolic computation in MATHEMATICA to visualize both the generated Pareto set and the feasible design space [16]. Our goal is to define exact criteria for the weighted coefficients to guarantee that every solution derived from the linear weighted sum approach is Pareto optimal. We aim to develop practical guidelines for selecting these coefficients, streamlining the process of generating the Pareto set efficiently [17]. Hence, the multi-objective optimization problem (MOP) is indirectly converted into one or several single-objective optimization problems, enabling the acquisition of one or more optimal solutions through the straightforward resolution of these single-objective optimization problems. In multi-load cases of topological optimization, key solution approaches encompass the weighted sum method, hierarchical sequence method, and evolutionary algorithms [18]. These criteria are readily accessible for any commercially available turbine, thereby streamlining the proposed approach. Unlike numerous prior studies that employed intricate and time-consuming methods, the weighted sum method is straightforward and yields solutions efficiently within linear time, enhancing computational efficiency. Furthermore, the study incorporates 18 turbines sourced from various manufacturers, contributing to the comprehensiveness of the findings. It is worth noting that the proposed scheme is both scalable and robust; additional criteria or turbine types can be incorporated or removed effortlessly to meet designer requirements without compromising computational efficiency [19]. The multi-objective adaptive weighted sum method efficiently addresses multi-objective optimization problems featuring more than two objective functions. In contrast, the bi-objective adaptive weighted sum method is designed for optimizations with only two objective functions, utilizing inequality constraints to define regions for subsequent refinement. Conversely, the multi-objective adaptive weighted sum method employs equality constraints and is adaptable to problems of any dimensionality. These equality constraints guide the selection of additional solutions, resulting in a well-conditioned mesh of the Pareto front [20]. The multi-objective adaptive weighted sum method is adept at managing optimization problems involving multiple objective functions, while the bi-objective adaptive weighted sum method is designed for scenarios with only two objective functions. In the bi-objective method, inequality constraints are employed to identify regions for refinement. In contrast, the multi-objective approach utilizes equality constraints and can be adjusted to handle problems of varying dimensionality. These equality constraints are pivotal in determining the acquisition of additional solutions, contributing to a well-organized mesh of the Pareto front [21].

3. ANALYSIS AND DISCUSSION

TABLE 1

	Average Order Value £	Customer Support Satisfaction	Delivery Time	Product Return Rate
Age Group (18-24)	150	4.7	5	0.05
Age Group (25-34)	120	4.5	6	0.1
Age Group (35-44)	80	4.2	7	0.08
Age Group (45-54)	200	4.8	4	0.03
Age Group (55-65)	110	4.6	5	0.07

The multi-objective adaptive weighted sum method effectively manages optimization problems with multiple objective functions, while the bi-objective adaptive weighted sum method is specifically tailored for scenarios with only two objective functions. In the bi-objective approach, inequality constraints are used to identify areas for further improvement. Conversely, the multi-objective method employs equality constraints and can be adjusted to handle problems of varying dimensionality. These equality constraints play a critical role in determining the acquisition of additional solutions, resulting in a well-structured mesh of the Pareto front. As for consumer behavior analysis, the 45-54 age group stands out with the highest Average Order Value of £200, indicating their propensity to spend the most per order. Moreover, they exhibit the highest Customer Support Satisfaction rating of 4.8, along with the shortest Delivery Time of 4 days and the lowest Product Return Rate at 0.03. These findings suggest a high level of satisfaction and fewer issues with their purchases. he multi-objective adaptive weighted sum method effectively manages optimization problems involving multiple objective functions, while the bi-objective adaptive weighted sum method is specifically designed for cases with only two objective functions. In the bi-objective approach, inequality constraints are employed to identify areas for further improvement. In contrast, the multi-objective method utilizes equality constraints and can be adjusted to handle problems of varying dimensionality. These equality constraints are crucial in determining the acquisition of additional solutions, resulting in a well-structured mesh of the Pareto front. In terms of consumer behavior analysis, the 45-54 age bracket demonstrates distinct attributes. They show the highest Average Order Value of £200, suggesting a tendency to make higher-value purchases per order. Furthermore, they report the highest Customer Support Satisfaction rating of 4.8, along with the shortest Delivery Time of 4 days and the lowest

Product Return Rate at 0.03. These observations suggest a high level of contentment and fewer concerns with their purchases. Conversely, the 35-44 age group spends the least, with an Average Order Value of £80, has a moderate Customer Support Satisfaction of 4.2, the longest Delivery Time of 7 days, and a slightly higher Product Return Rate of 0.08. The age groups of 25-34 and 55-65 exhibit moderate figures across all metrics. Their Average Order Values are £120 and £110, respectively, with comparable Customer Support Satisfaction scores of 4.5 and 4.6. Delivery Times stand at 6 days for the 25-34 group and 5 days for the 55-65 group, while Product Return Rates are 0.1 and 0.07, respectively.

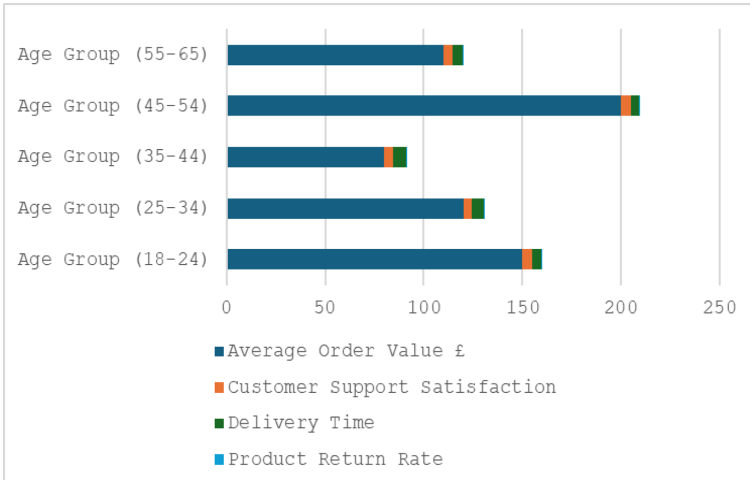

FIGURE 1

Figure 1 illustrates diverse metrics for distinct age groups, presumably in the context of online shopping or retail. These metrics encompass Average Order Value (in £), Customer Support Satisfaction (rated on a 5-point scale), Delivery Time (in days), and Product Return Rate. The age group of 18-24 demonstrates a relatively elevated Average Order Value of £150, a Customer Support Satisfaction rating of 4.7, a swift Delivery Time of 5 days, and a minimal Product Return Rate of 0.05. In contrast, the 35-44 age group has the lowest spending with an Average Order Value of £80, a moderate Customer Support Satisfaction of 4.2, the longest Delivery Time of 7 days, and a slightly higher Product Return Rate of 0.08. The age groups of 25-34 and 55-65 exhibit moderate metrics across the board. They have Average Order Values of £120 and £110, respectively, along with comparable Customer Support Satisfaction scores of 4.5 and 4.6. Delivery Times are 6 days for the 25-34 group and 5 days for the 55-65 group, with Product Return Rates of 0.1 and 0.07, respectively.

TABLE 2

0.7500	0.9792	0.8000	0.6000
0.6000	0.9375	0.6667	0.3000
0.4000	0.8750	0.5714	0.3750
1.0000	1.0000	1.0000	1.0000
0.5500	0.9583	0.8000	0.4286

The 45-54 age group consistently achieves a perfect score of 1.0000 across all metrics, signaling that they boast the highest Average Order Value, the most exceptional Customer Support Satisfaction, the swiftest Delivery Time, and the lowest Product Return Rate. This indicates that this group excels the most comprehensively. The 18-24 age group achieves scores of 0.7500 in Average Order Value, 0.9792 in Customer Support Satisfaction, 0.8000 in Delivery Time, and 0.6000 in Product Return Rate, indicating high satisfaction levels and efficient delivery, albeit with a relatively higher rate of returns. The 25-34 age group has normalized scores of 0.6000 in Average Order Value, 0.9375 in Customer Support Satisfaction, 0.6667 in Delivery Time, and 0.3000 in Product Return Rate, indicating moderate performance in spending and delivery time but a notably lower return rate. The 55-65 age group has intermediate scores, with 0.5500 in Average Order Value, 0.9583 in Customer Support Satisfaction, 0.8000 in Delivery Time, and 0.4286 in Product Return Rate, showing good satisfaction and moderate return rates.

TABLE 3. Weight

0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

Table 3 presents the assigned weights for different metrics across various age groups, presumably within the realm of online shopping or retail. The metrics comprise Average Order Value (£), Customer Support Satisfaction, Delivery Time, and Product Return Rate. Each metric is uniformly allocated a weight of 0.25 across all age groups. The uniform weighting (0.25) across all metrics signifies that each factor is deemed equally significant when assessing the performance or behavior of the various age groups. This equitable approach guarantees that no single metric unduly impacts the overall evaluation. Across the age brackets of 18-24, 25-34, 35-44, 45-54, and 55-65, the consistent weights imply a comprehensive assessment approach. This indicates that Average Order Value, Customer Support Satisfaction, Delivery Time, and Product Return Rate are all regarded as equally essential factors in gauging the overall performance or satisfaction level of each age group. Using these uniform weights allows for a well-rounded evaluation of each age group's performance, preventing the dominance of high performance in one aspect (such as Customer Support Satisfaction) over lower performance in another (like Delivery Time). This approach fosters a thorough assessment, facilitating equitable comparisons across various metrics and age groups.

Table 4. Weighted Normalized Matrix

0.1875	0.2448	0.2000	0.1500
0.1500	0.2344	0.1667	0.0750
0.1000	0.2188	0.1429	0.0938
0.2500	0.2500	0.2500	0.2500
0.1375	0.2396	0.2000	0.1071

Table 4 showcases the weighted normalized values for diverse metrics utilizing the weighted sum method, reflecting the equal significance of each metric across different age groups. The metrics encompass Average Order Value (£), Customer Support Satisfaction, Delivery Time, and Product Return Rate. In the 18-24 age group, the normalized values are 0.1875 for Average Order Value, 0.2448 for Customer Support Satisfaction, 0.2000 for Delivery Time, and 0.1500 for Product Return Rate. This suggests a balanced emphasis across all metrics, albeit with a slightly lower priority placed on Product Return Rate compared to the other metrics. The 25-34 age group exhibits values of 0.1500 for Average Order Value, 0.2344 for Customer Support Satisfaction, 0.1667 for Delivery Time, and 0.0750 for Product Return Rate. The group's lowest score in Product Return Rate implies fewer return-related issues, albeit with lower spending and slightly diminished satisfaction compared to the 18-24 group. In the 35-44 age group, the ratings are 0.1000 for Average Order Value, 0.2188 for Customer Support Satisfaction, 0.1429 for Delivery Time, and 0.0938 for Product Return Rate. This group displays the lowest values across most metrics, suggesting lower overall performance. The 45-54 age group achieves the highest possible normalized values of 0.2500 across all metrics, reflecting top performance in spending, satisfaction, delivery efficiency, and minimal returns. The 55-65 age group demonstrates moderate values, with 0.1375 for Average Order Value, 0.2396 for Customer Support Satisfaction, 0.2000 for Delivery Time, and 0.1071 for Product Return Rate. These scores suggest satisfactory levels of satisfaction and moderate performance across other metrics.

Table 5. Preference score

Alternate Parameters	Preference Score
Age Group (18-24)	0.78229
Age Group (25-34)	0.62604
Age Group (35-44)	0.55536
Age Group (45-54)	1.00000
Age Group (55-65)	0.68423

Table 5 presents the preference scores for various age groups utilizing the weighted sum method. These scores amalgamate the performance across different metrics, including Average Order Value, Customer Support Satisfaction, Delivery Time, and Product Return Rate, with each metric being equally weighted. The 45-54 age group attains the highest preference score of 1.00000, signifying that they are the top-performing group across all metrics. This score mirrors their elevated spending, superior customer support satisfaction, shortest delivery times, and minimal product return rates. The 18-24 age group has the second-highest preference score at 0.78229. This suggests that they perform well in most areas, showing a balanced but slightly lower performance compared to the 45-54 age group. The 55-65 age group achieves a score of 0.68423, positioning them in the middle range. They exhibit commendable customer support satisfaction and reasonable delivery times, although their spending is lower and their return rates slightly higher compared to the top-performing group. The 25-34 age group obtains a preference score of 0.62604, suggesting a moderate level of performance. While they demonstrate satisfactory customer support satisfaction and delivery times, their spending is lower, and their return rates are higher. The 35-44 age group records the lowest preference score of 0.55536, indicating their generally inferior performance across most metrics. They exhibit the lowest spending, moderate customer support satisfaction, longer delivery times, and higher return rates.

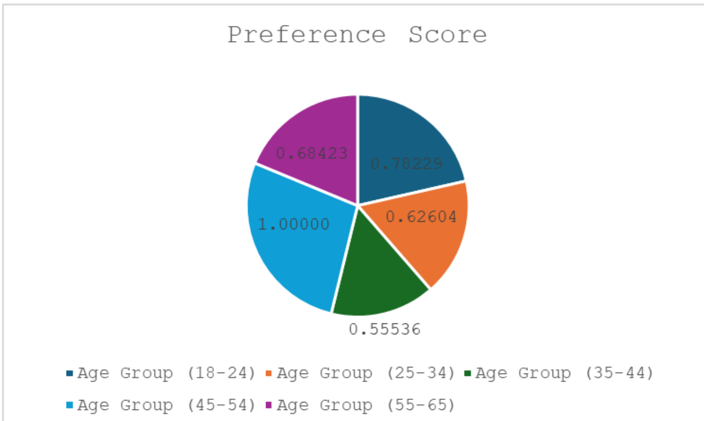

FIGURE 2

Figure 2 depicts the preference scores for various age groups employing the weighted sum method. These scores amalgamate the performance across metrics such as Average Order Value, Customer Support Satisfaction, Delivery Time, and Product Return Rate, with each metric assigned equal weight. The 45-54 age group achieves the highest preference score of 1.00000, positioning them as the top-performing group overall. This underscores their elevated spending, outstanding customer support satisfaction, shortest delivery times, and minimal product return rates. The 18-24 age group trails closely behind, securing a preference score of 0.78229. This indicates robust performance across various areas, although it falls slightly short of the 45-54 group's stellar performance. It's akin to a talented runner-up in a competition, showcasing commendable skills and effort but just missing the top spot. Scoring 0.68423, the 55-65 age group occupies a middle position. While they demonstrate commendable customer support satisfaction and reasonable delivery times, their spending is lower and their return rates are slightly higher compared to the top-performing group. The 25-34 age group achieves a score of 0.62604, indicating moderate performance. While they exhibit satisfactory customer support satisfaction and delivery times, their spending is lower and their return rates are higher. The 35-44 age group secures the lowest preference score, standing at 0.55536, indicating an overall inferior performance. They exhibit the lowest spending, moderate customer support satisfaction, longer delivery times, and higher return rates.

TABLE 6. Rank

Alternate Parameters	Rank
Age Group (18-24)	2
Age Group (25-34)	4
Age Group (35-44)	5
Age Group (45-54)	1
Age Group (55-65)	3

Table 6 displays the rankings of various age groups determined by their preference scores utilizing the weighted sum method. This assessment incorporates metrics such as Average Order Value, Customer Support Satisfaction, Delivery Time, and Product Return Rate, with each metric being assigned equal weight. The 45-54 age group secures the top position, underscoring their outstanding performance across all metrics. They demonstrate the highest spending, excellent customer support satisfaction, shortest delivery times, and lowest product return rates. The 18-24 age group holds the second position, suggesting commendable performance in most aspects, albeit slightly trailing behind the 45-54 group. This demographic displays robust overall performance with commendable scores across all assessed metrics. Ranked third, the 55-65 age group indicates a mid-level performance. While they exhibit good customer support satisfaction and reasonable delivery times, they display lower spending and higher return rates compared to the top-ranked group. The 25-34 age group secures the fourth position, indicating a moderate level of performance. While they demonstrate satisfactory customer support satisfaction and delivery times, their spending is lower, and they experience higher product return rates. customer support satisfaction, longer The 25-34 age group secures the fourth position, indicating a moderate level of performance. While they demonstrate satisfactory customer support satisfaction and delivery times, their spending is lower, and they experience higher product return rates.

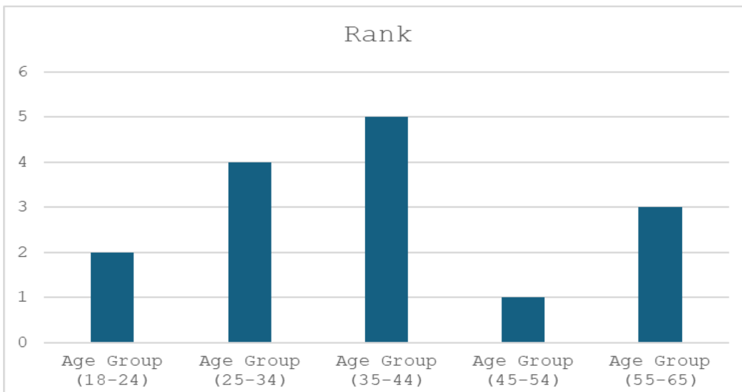

FIGURE 3

Figure 3 displays the ranks of different age groups based on their preference scores using the weighted sum method, which considers metrics like Average Order Value, Customer Support Satisfaction, Delivery Time, and Product Return Rate, all equally weighted. The 45-54 age group holds the top position, demonstrating their exceptional performance across all metrics. They exhibit the highest spending, finest customer support satisfaction, swiftest delivery times, and lowest product return rates. The 18-24 age group secures the second position, excelling in most areas, albeit slightly trailing behind the 45-54 group. They display robust overall performance with commendable scores across all evaluated metrics. Coming in third, the 55-65 age group embodies a mid-level performer. While they showcase satisfactory customer support satisfaction and reasonable delivery times, they display lower spending and higher return rates in comparison to the top-performing group. The 35-44 age group ranks fifth, reflecting the lowest overall performance. They have the least spending, moderate customer support satisfaction, longer delivery times, and higher return rates, making them the least preferred group according to the weighted sum method.

4. CONCLUSION

Consumer behavior in e-commerce refers to how individuals make decisions and navigate online shopping. As technology rapidly advances and internet access becomes ubiquitous, e-commerce plays a pivotal role in the global economy. Understanding consumer behavior is essential for businesses to tailor strategies effectively and enhance the online shopping experience. Key factors influencing consumer behavior include convenience, product variety, pricing, and the ease of comparing products. Trust and security are also critical, with consumers preferring websites that prioritize data protection and feature reliable customer reviews. Social media and digital marketing further impact consumer decisions by providing platforms for recommendations and advertisements. By analyzing these behaviors, e-commerce businesses can optimize their websites, enhance customer engagement, and ultimately boost sales. The analysis using the weighted sum method reveals distinct preferences among various age groups in e-commerce consumer behavior. The 45-54 age group emerges as the top performer across all metrics, displaying the highest spending, superior customer support satisfaction, shortest delivery times, and lowest product return rates. Close behind, the 18-24 age group demonstrates robust overall performance, albeit slightly trailing the 45-54 group.

Meanwhile, the 55-65 age group falls in the middle, exhibiting satisfactory customer support satisfaction and reasonable delivery times, but lower spending and slightly elevated return rates compared to the top performers. In a moderate position, the 25-34 age group showcases decent customer support satisfaction and delivery times, yet lower spending and higher product return rates. Conversely, the 35-44 age group lags behind, characterized by the lowest overall performance marked by minimal spending, moderate customer support satisfaction, longer delivery times, and higher return rates. These insights offer valuable guidance for e-commerce businesses in tailoring strategies to effectively target diverse age demographics and optimize the online shopping experience.

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