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Evaluating the Effectiveness of Recommendation Engines on Customer Experience Across Product Categories

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ABSTRACT

Artificial intelligence (AI)-powered tools such as recommendation engines are widely used in online marketing and e-commerce; however, online retailers often deploy these tools without understanding which human factors play a role in which products and at which stage of the customer journey. Understanding the interaction between AI-powered tools and humans can help practitioners create more effective online marketing platforms and improve human interaction with e-commerce tools. This paper examines customers' reliance on recommendation engines when purchasing fashion goods, electronics, and media content such as video and music. This paper also discusses the potential for improvement in recommendation engines in online marketing and e-commerce.

KEYWORDS

AI-Powered Tools, Correlation Analysis, Customer Journey, Online Marketing, Recommendation Engine, Similarity Analysis

INTRODUCTION

Artificial intelligence (AI) was established as a field of research at a conference at Dartmouth College in 1956 (Russell & Norvig, 2016). Since then, AI has greatly impacted day-to-day activities and has become a key technology in business. Among various business fields, Verma et al. (2021) suggest that AI will continue to revolutionize the field of marketing. In fact, we observe many AI-powered tools that significantly impact customers throughout all purchase stages of their customer journeys (He & Zhang, 2023). Tools like chatbots, recommendation engines, and virtual assistance also help companies improve their brand awareness and customer relationships (Rana et al., 2022). Polisetty et al. (2023) also investigated the factors that impact a company's readiness for AI implementation.

As previous studies have shown, AI tools can increase product sales through e-commerce, and thus, firms have incentives to adopt AI tools for their business; however, the effectiveness of AI tools may depend on specific products and their corresponding categories. In particular, the current literature lacks research on how AI tools affect customers differently when purchasing products from distinctly different categories. This study fills the gap between what is known—the fact that AI tools are effective—and our expectation that the effectiveness of AI tools may depend on product

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categories. To understand how effective AI tools are for each product category, we conducted a survey to examine the basic statistics and performed descriptive analysis on the collected data using machine learning techniques such as similarity analysis and correlation analysis. The study aims to identify the differences, if any, in the performance of AI tools when used for different product categories. Specifically, we evaluate the effectiveness of recommendation engines when customers purchase items from three different product categories: fashion goods, media content (such as music and videos), and consumer electronics products. We also evaluated customer perceptions when interacting with recommendation engines. This research addresses the following research questions (RQs):

RQ 1: In which product category do consumers use recommendation engines more?
RQ 2: In which product category do consumers find recommendation engines more effective?
RQ 3: How do satisfaction levels change at different stages of the customer journey for different product categories?
RQ 4: What is the area where AI recommendation engines are less effective and need human support?

The rest of this paper presents a literature review and explains the survey design. It then discusses practical insights and considerations, followed by sections on the survey results and data analysis. Finally, we conclude with a summary of this article and a plan for future research.

LITERATURE REVIEW

Recommendation Engines in Marketing

Big data combined with AI offers new opportunities for companies that take advantage of it. For example, companies can implement customer-centric marketing initiatives by analyzing and interpreting customer data (Rosário & Dias, 2023); as another example, companies can find new marketing opportunities in the metaverse as the number of users who socialize virtually (especially among Generation Z) increases (Chakraborty, Polisetty, et al., 2023). Many companies have increased sales and improved marketing processes by using AI-powered tools and software applications that use AI instead of human intervention. It is observed that deploying AI technologies has a positive relationship with user engagement and conversion (Bag et al., 2022), and AI even impacts the consumption value of over-the-top platforms (Chakraborty, Siddiqui, et al., 2023). AI has also been used to gain insights into customer purchase behavior (D'Arco et al., 2019), help customers find the products or brands they are looking for and make purchase decisions (Libai et al., 2020), and improve the quality of interactions on digital business platforms (DBPs), thereby enabling value creation and appropriation on DBPs (Rangaswamy et al., 2020).

Among the various AI-powered tools available, recommendation engines are one of the most effective tools in e-commerce to boost sales. By identifying customer preferences from their shopping behavior, recommendation engines can suggest additional items for customers to add to their shopping carts, resulting in higher average cart value and increased customer engagement with the seller (Behera et al., 2020). Recommendation engines also help businesses develop effective marketing strategies by analyzing customer search behavior (Dzyabura & Hauser, 2019). AI also makes it possible to effectively provide customized offers to customers by identifying their needs and preferences (e.g., Verma, 2014; Tripathi & Verma, 2018; Kumar et al., 2019; and Verma & Yadav, 2021).

Recommendation Engines and Product Type

Recommendation engines have become increasingly prevalent in recent years and are used for a variety of product categories, including movies, music, news, books, and general merchandise. In fact, recommendation engines benefit the retail industry (Chandrashekhara et al., 2023). They are not only utilized for tangible products such as fashion (Hurrah et al., 2023) but also pose emerging considerations in the travel product sector (Zhu et al., 2017). Other examples include recommendation engines adopted in the life insurance industry (Vij & Preethi, 2021) and the movie industry (Khadse et al., 2018). The food and medical industries also use AI in delivery applications; however, they face barriers related to customer psychology and behavior when adopting such delivery apps (Verma et al., 2023; Chakraborty, Singu, et al., 2023).

In marketing, one common classification of products distinguishes between hedonic and utilitarian products (Hirschman & Holbrook, 1982). Hedonic products deliver multisensory, experiential, and joyful benefits, while utilitarian products provide practical and instrumental benefits (Dhar & Wertenbroch, 2000). Hedonic consumption is primarily driven by affect, emphasizing sensory or experiential pleasure, and reflects emotional benefits, while utilitarian consumption is more cognition-driven, focusing on functional and instrumental goals (Botti & McGill, 2011). Consumers typically buy hedonic products to achieve pleasure-related outcomes and utilitarian products to fulfill functional or practical needs (Chitturi et al., 2008).

There is some research comparing the effectiveness of human and AI recommendations for different types of products. Human recommenders are more effective than AI recommenders in eliciting favorable consumer responses, such as attitudes and purchase intentions, in the hedonic domain but not in the utilitarian domain (Wien & Peluso, 2021). AI recommenders outperform human recommenders in assessing utilitarian attribute value and generating utilitarian-focused recommendations, but they exhibit less competence in assessing hedonic attribute value and generating hedonic-focused recommendations (Longoni & Cian, 2022).

In summary, extant research findings related to recommendation engines and product types are as follows: (a) Studies of recommendation engines exist for specific product categories; (b) emphasis is placed on broad comparisons, such as hedonic versus utilitarian products, rather than focusing on specific product categories; and (c) the focus is on comparing AI recommenders with human recommenders.

Recommendation Engines and the Customer Journey

A customer journey is a roadmap of a customer's interactions with a brand when purchasing a product or receiving a service. This journey has three stages: prepurchase, purchase, and post-purchase (Lemon & Verhoef, 2016). Customer behaviors in these three stages involve the following elements: The *prepurchase* stage includes need awareness, consideration, and search; the *purchase* stage includes choice, ordering, and payment; and the *post-purchase* stage includes consumption, usage, engagement, service requests, and recommendations. Clarifying customer behaviors and experiences helps us understand a customer journey (Meyer & Schwager, 2007). Customer journeys are not only important in the business-to-consumer (B2C) sector but are also increasingly prevalent in the digital spaces of the business-to-business (B2B) sector (Rusthollkarhu et al., 2022).

To understand the impact of AI-powered technologies such as recommendation engines, we need to examine their impact on each stage of the customer journey, as the impact of recommendation engines on pre-purchase and purchase stages may be highly correlated. As an example of the customer journey in the food service industry, Mende et al. (2019) revealed strong correlations between customer interactions with (AI-powered) robots, customer satisfaction levels, and the amount of their food consumption. Similarly, an AI-powered recommendation engine may influence customers' experience of online purchases.

D'Arco et al. (2019) presented a framework that outlines the several types of information that researchers and practitioners can collect at each stage of the customer journey. With this information, they can better understand and improve customer experience at each stage. The framework encompasses several specific tasks to improve customer journeys and has the potential for significant improvements through big data and AI. Developing effective customer journeys is widely recognized as a critical element in securing a competitive advantage; however, the impact of recommendation engines on various products throughout different stages of the customer journey has not been clarified yet.

AI and the Human

As companies continue to amass customer data and artificial intelligence becomes more sophisticated, the convenience and availability of AI tools will increase. James Freeze, a former Forbes Council member, has pointed out that people don't care whether they are talking to a human; they just want a quick answer. According to his company's survey, two-thirds of consumers said they would be comfortable speaking with AI-powered customer service as long as they could speak normally and problems could be resolved quickly. The same survey found that 76% of people would be comfortable with hospitals using AI-powered disinfecting robots, and 66% would be comfortable with robots in grocery stores performing functions such as cleaning up spills or restocking shelves (Freeze, 2021). Another survey found that 81% of employees believe AI improves their overall performance, and 68% ask their employers to bring more AI-based technology into the workplace (SnapLogic, 2021). AI can also help employees strengthen customer relationships by providing personalized customer support (Burns et al., 2023). On the other hand, AI requires humans to evolve its processes. For example, humans must provide AI with data sets for learning and train it to provide meaningful results when queried. AI can only maintain its proper operation if humans support AI (Rowinski, 2022).

It should also be noted that the roles of AI and humans are different; AI is good at improving efficiency, and humans are good at making personal connections. The sweet spot between the roles of AI and humans can be found by augmenting the system without over-automating it. For example, a home purchase gives a good insight into this balance: AI tools such as recommendation engines help customers find a set of houses they like, and agents walk through them to decide which one to buy. AI offers the most value when we use AI to augment the system, not replace humans (Freeze, 2021).

To summarize the literature review, while the aforementioned studies emphasize the importance of recommendation engines, they lack the exploration of how recommendation engines impact different product categories and their interaction with consumers throughout the customer journey. This calls for a more in-depth investigation to understand their influence across different product types throughout the customer journey. Our research addresses a notable gap in the existing literature, where there has been limited discussion of the varying effectiveness of AI tools across product categories. By examining this gap, we aim to contribute to the understanding of how AI tools influence customer purchase behavior across different product categories, such as fashion, content (which represent hedonic aspects), and electronics (which represent utilitarian aspects).

SURVEY

Our goal is to gather information about the use of AI-powered tools and satisfaction levels across all stages of the customer journey. In this section, we describe the survey methodology and data collection procedures to achieve this goal.

Survey Design

A series of multiple-choice questions (with the exception of those inquiring about the frequency of usage) was created using Google Forms and made available to survey participants via a link. The survey was anonymous, and no rewards were offered for participation. The survey questions were divided into three sections. Part 1 asked participants to provide background information regarding gender and the frequency of their use of online platforms. Part 2 assessed the perceived usefulness and satisfaction with the recommendation engine for fashion, content, and electronics throughout all stages of the customer journey (i.e., awareness, consideration, purchase, and post-purchase). Finally, Part 3 asked participants to provide their views on the necessity of human support for fashion, content, and electronics.

Survey Questions

The survey questions used in this study are as follows. Parts 2 and 3 used a five-point Likert scale.

- Part 1
  - Q-a: Gender
  - Q-b: Frequency of using online platforms to buy products
  - Q-c: Time per access to buy products online
  - Q-d: Frequency of using online platforms to view video or music content
  - Q-e: Time per access to view video or music content
- Part 2
  - Q1: Frequency of using a recommendation engine
  - Q2: Usefulness of the recommendation engine
  - Q3: Satisfaction with the recommendation engine from the following seven perspectives.
    - Q3-1 (Consideration stage): The recommendation engine suggests products or content that match my personal preferences and needs
    - Q3-2 (Awareness stage): It helps me discover new products, content, or brands
    - Q3-3 (Consideration stage): It provides many alternatives to choose from
    - Q3-4 (Purchase stage): It helps me make decisions about buying products or choosing content
    - Q3-5 (Purchase stage): It makes buying products or choosing content easy
    - Q3-6 (Post-purchase stage): It suggests products or content based on my previous purchases
    - Q3-7 (Post-purchase stage): It helps customers make repeat purchases on the same online platform
- Part 3
  - Q4: Which support do you prefer when navigating online platforms?
  - Q5: How much human support is needed from the following seven perspectives?
    - Q5-1: Comparison and information about products or content
    - Q5-2: Procedures for return or exchange of products or content
    - Q5-3: Payment and shipping
    - Q5-4: Instructions and settings
    - Q5-5: Support for questions about products or content
    - Q5-6: Additional information and customer service about products or content
    - Q5-7: Support for orders and shipping

Data Collection

The survey was conducted online using Google Forms for students at Nagoya University of Commerce and Business in Japan. 258 students submitted responses from 7/11/2023 to 7/21/2023. We excluded nine responses that did not answer most of the questions; thus, the total number of valid responses was 249.

RESULTS

In this section, we summarize general findings that we believe are important for marketing applications. The full results for questions Q1 through Q5-7 of the survey are presented in the appendix.

Table 1. Results of Q-a – Q-e

Q-a	Female 18.1%, Male 81.9%
Q-b	Median 1.0 (mean 1.8) times/month
Q-c	Median 20.0 (mean 27.8) minutes/access
Q-d	Median 20.0 (mean 23.0) times/month
Q-e	Median 2.0 (mean 7.0) hours/access

Table 2. Customers Who Use Recommendation Engines (Results from Q1)

Response	Fashion	Content	Electronics
Do not use at all or do not often use	38.2%	24.5%	49.8%
Neither	12.9%	21.3%	21.7%
Sometimes or always use	49.0%	54.2%	28.5%

Table 3. Customers Considering Recommendation Engines Useful (Results from Q2)

Response	Fashion	Content	Electronics
Not useful at all or not so useful	12.9%	11.3%	16.2%
Neither	39.5%	39.5%	49.8%
Somewhat or very useful	47.6%	49.2%	34.0%

Frequency of Using Online Platforms: Results of Questions Q-b – Q-e

We asked participants about frequency (the number of visits and the duration of each visit). Since outliers strongly influence the mean values, the median values would be a good index to represent the frequency of visits to online platforms. Table 1 shows that the median customer visits online platforms (e.g., Amazon and Rakuten) for purchasing products once a month (Q-b) and spends 20 minutes per visit (Q-c), while they visit online platforms (e.g., Spotify and Netflix) for watching video or music content 20 times a month (Q-d) and spend two hours per visit (Q-e).

Use of Recommendation Engines

In the fashion and content categories, our survey respondents either sometimes or always use a recommendation engine (i.e., click on the recommended item) with a probability of 49.0% and 54.2%, respectively. The probability of using a recommendation engine is much lower in the electronics category: only 28.5% (see Table 2).

Levels of Usefulness and Satisfaction

We show the results of the levels of usefulness and satisfaction in Tables 3 and 4, respectively. These two tables exhibit a similar pattern: More people find recommendation engines useful and are satisfied with them in the fashion and content categories than in the electronics category.

The Customer Journey

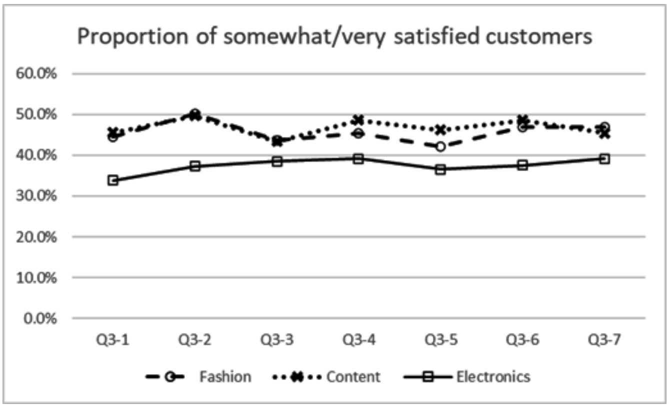
To understand how satisfaction levels change at different stages of the customer journey, we evaluate the proportion of satisfied participants (i.e., the sum of somewhat satisfied and very satisfied participants) at the awareness (Q3-2), consideration (Q3-1 and Q3-3), purchase (Q3-4 and Q3-5), and post-purchase (Q3-6 and Q3-7) stages. Our survey shows that satisfaction levels (especially at the awareness stage) are higher in the fashion and content categories than in the electronics category at all stages of the customer journey (see Figure 1). In contrast, dissatisfaction levels are higher in the

Table 4. Customers Satisfied with Recommendation Engines (Results from Q3-1 – Q3-7)

Response	Fashion	Content	Electronics
Not at all satisfied or not so satisfied	7.0%.	7.7%.	8.9%.
Neither	47.3%.	45.6%.	53.7%.
Somewhat or very satisfied	45.7%.	46.7%.	37.4%.

Note. Average proportions for questions Q-1 – Q3-7 are presented in the table.

Figure 1. Customers Satisfied Throughout All Stages of the Customer Journey



electronics category than in the fashion and content categories at all stages of the customer journey (see Figure 2).

Necessity for Human Support

In Q5-1 through Q5-7, we asked participants if they needed human assistance when using online platforms. Table 5 shows the average responses for the seven questions, Q5-1 to Q5-7. It shows that the majority (more than 50%) think human support is somewhat or absolutely necessary. In particular, about 31% think that human support is absolutely necessary for electronics products. Overall, our

Figure 2. Customers Dissatisfied Throughout All Stages of the Customer Journey

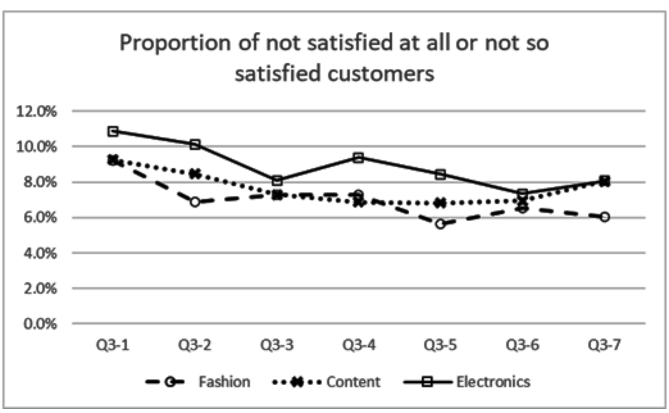
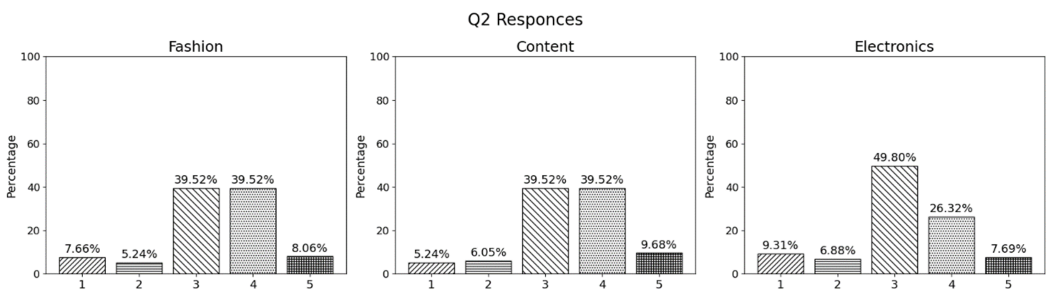


Table 5. Customers Who Consider Human Support Necessary When Using Online Platforms

Response	Fashion	Content	Electronics
Not at all necessary	3.1%.	3.1%.	2.5%.
Not so necessary	6.6%.	7.4%.	4.9%.
Neither	32.1%.	34.5%.	31.4%.
Somewhat necessary	33.0%.	31.8%.	30.3%.
Absolutely necessary	25.1%.	23.3%.	30.9%.

Figure 3. Distributions of Responses for Q2 in Fashion, Content, and Electronics



findings suggest that while customers are intrigued by AI recommendation engines, their expectations for AI support are not high. We will explore this issue further in the discussion session.

DATA ANALYSIS

We applied data analysis tools to conduct a descriptive analysis of the survey data collected in this study. Specifically, we first performed a similarity analysis for response patterns for fashion, content, and electronics products; then, we performed a correlation analysis to find relationships between participant responses for each question. For this analysis, we used Python and its libraries (NumPy, Pandas, Matplotlib, and Seaborn).

Similarity Analysis

According to the survey results, the response patterns in the fashion and content categories look similar to each other, while they look different from the patterns in the electronics category; for example, see Figures 3, 4, and 5, which show the distributions of responses for questions Q2, Q3-2, and Q3-6 in the fashion, content, and electronics categories (see full results in the appendix).

We quantitatively confirm that the response patterns of fashion and content are close and those of electronics are farther. For this purpose, we evaluate three indices: optimal transport (OT) cost, Euclidean distance (ED), and cosine similarity (CS). *OT cost* is the minimum transport cost of probabilistic mass from one probability distribution to another. OT cost is a popular index in machine learning for measuring the distance among distributions. When OT cost is smaller, distributions are closer; OT cost is zero when two distributions are identical.

ED is the Euclidean distance (L2 norm) between the two points in a five-dimensional space, each representing a distribution of responses. ED is smaller when two distributions are closer; ED is zero when two distributions are identical. Finally, *CS* is the cosine of the angle between two vectors in a five-dimensional space, where each vector corresponds to a distribution of responses. If CS is

Figure 4. Distributions of Responses for Q3-2 in Fashion, Content, and Electronics

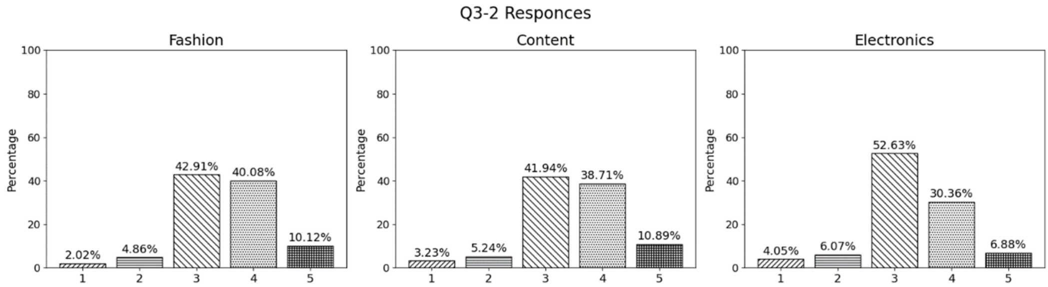
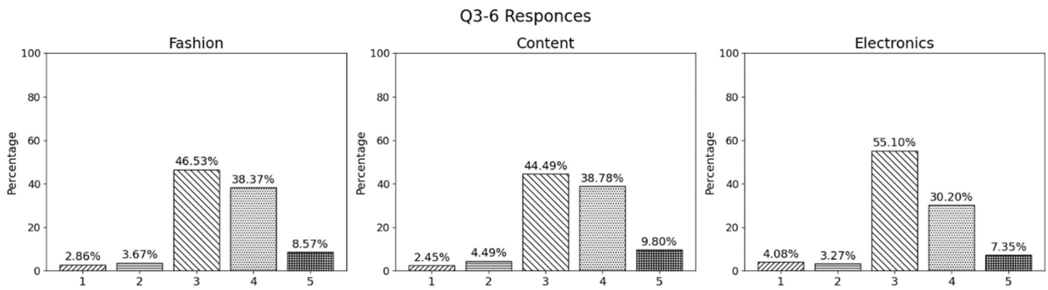


Figure 5. Distributions of Responses for Q3-6 in Fashion, Content, and Electronics



closer to one, two vectors are pointing in the same direction (and thus, two vectors are closer to each other since all vectors, or distributions, are normalized). CS is equal to one when two distributions are identical.

We examine the similarity among the three categories for the patterns for the levels of use (Q1), usefulness (Q2), and satisfaction (Q3-1 to Q3-7). Table 6 shows all three indices (OT, ED, and CS) that measure the distances (similarities) among the distributions. Table 6 shows that, for all questions from Q1 to Q3-7, the patterns of responses in the fashion and content categories are close to each other, while the patterns for electronics are relatively different from those in the fashion and content categories. This result implies that customers' perceptions (frequency, usefulness, and satisfaction levels) of recommendation engines are similar for fashion products and media content even though they are different; one is tangible and the other is intangible. For the responses from Q4 and Q5-1 to Q5-7 questions, we do not observe the same result. We explore more about this finding in the discussion section.

Correlation Analysis

We examined how participant responses to one question are related to their responses to other questions. Specifically, we conducted a correlation analysis using the responses of 249 participants in each of the three categories (i.e., fashion, content, and electronics). We calculate the Pearson correlation coefficient (PCC) between the responses to the questions. The PCC is closer to one when responses to one question are positively correlated with another and closer to zero when uncorrelated. Figures 6, 7, and 8 show correlation matrices in a heatmap format; a value in each cell represents the PCC; a darker red color indicates that the PCC is closer to one.

Figure 6 presents many new findings. First, the responses to questions Q-b (frequency of visiting online platforms for products) and Q-e (frequency of visiting online platforms for media content)

Table 6. Similarity Among Distributions of Responses in Fashion, Content, and Electronics

Question.	Distance between Categories.	OT.	ED.	CS.
Q1	Fashion–Content	0.349*.	15.123*.	0.957*.
	Fashion–Electronics	0.369.	23.521.	0.893.
	Content–Electronics	0.719.	26.567.	0.855.
Q2	Fashion–Content	0.073*.	0.957*.	0.999*.
	Fashion–Electronics	0.189.	0.893.	0.957.
	Content–Electronics	0.261.	0.855.	0.955.
Q3-1	Fashion–Content	0.035*.	3.038*.	0.999*.
	Fashion–Electronics	0.156.	13.059.	0.978.
	Content–Electronics	0.190.	13.386.	0.978.
Q3-2	Fashion–Content	0.042*.	2.240*.	1.000*.
	Fashion–Electronics	0.215.	14.314.	0.973.
	Content–Electronics	0.188.	14.193.	0.973.
Q3-3	Fashion–Content	0.020*.	2.624*.	0.999*.
	Fashion–Electronics	0.085.	6.272.	0.995.
	Content–Electronics	0.097.	5.492.	0.997.
Q3-4	Fashion–Content	0.049*.	3.925*.	0.998*.
	Fashion–Electronics	0.115.	6.866.	0.994.
	Content–Electronics	0.155.	10.496.	0.985.
Q3-5	Fashion–Content	0.076*.	6.011*.	0.996*.
	Fashion–Electronics	0.104.	6.273.	0.995.
	Content–Electronics	0.149.	11.144.	0.985.
Q3-6	Fashion–Content	0.037*.	2.581*.	0.999*.
	Fashion–Electronics	0.127.	11.97.	0.982.
	Content–Electronics	0.155.	14.009.	0.976.
Q3-7	Fashion–Content	0.060*.	5.112*.	0.997*.
	Fashion–Electronics	0.135.	8.689.	0.990.
	Content–Electronics	0.123.	8.177.	0.993.

Note. * indicates the smallest distances

are uncorrelated with each other and are uncorrelated with their responses to other questions about use, usefulness, satisfaction, and human support. Since participants are already familiar with online platforms, their familiarity with online platforms seems not to impact their perception of online platforms. Second, we observe that there exist relatively strong correlations among the levels of use (Q1), usefulness (Q2), and satisfaction (Q3-1 to Q3-7) regarding the recommendation engine; see the diagonal sub-matrix of Figure 6. We also observe strong correlations among the needs for human support (Q5-1 to Q5-7); see the lower right diagonal sub-matrix of Figure 6. The off-diagonal sub-matrices of the correlation matrix in Figure 4 indicate a (weak) positive correlation between the levels of use, usefulness, and satisfaction (Q1, Q2, Q3-1 to Q3-7) and the needs for human support (Q5-1 to Q5-7). This result implies that those who find the recommendation engine useful or are

Figure 6. Correlation Matrix for Responses in the Fashion Category in a Heatmap Format

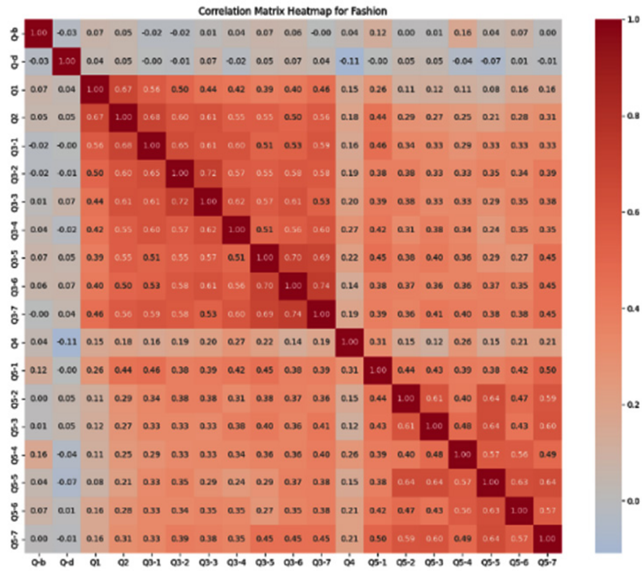
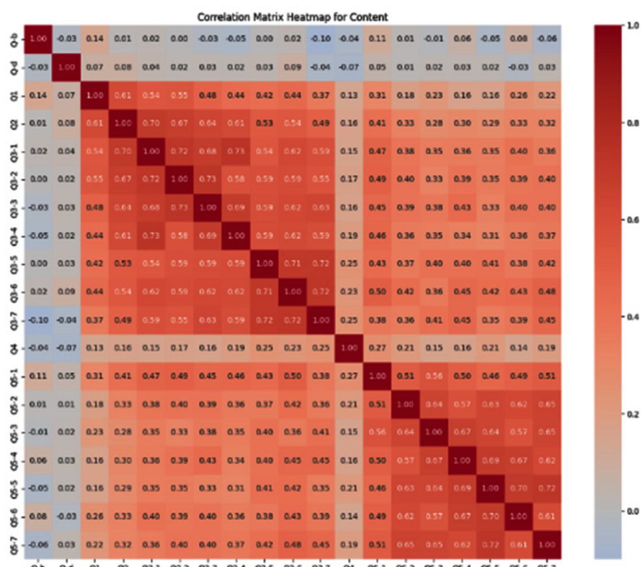


Figure 7. Correlation Matrix for Responses in the Content Category in a Heatmap Format

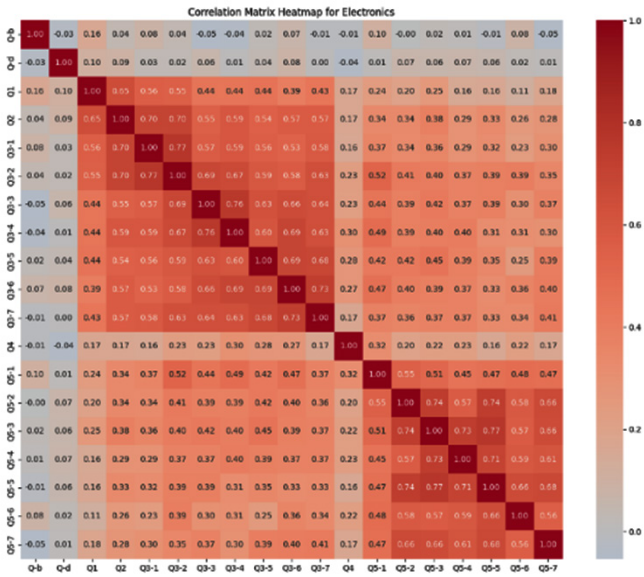


satisfied with it think human support is necessary. The correlation matrices for the other two categories (content and electronics) show a similar pattern, see Figures 7 and 8.

DISCUSSION

AI tools are currently used in online marketing, and their effectiveness has already been recognized both practically and academically, as noted in the literature review. However, little is known about

Figure 8. Correlation Matrix for Responses in the Electronics Category in a Heatmap Format



how the impact of AI tools on customers differs across product categories. This study aims to address this research gap and provide practitioners with insights to improve the effectiveness of AI tools.

Recommendation Tool Effectiveness by Product Category

This study examines the impact of AI tools across three product categories: fashion, electronics, and content. The survey results and the similarity analysis of the distribution indicate that the effectiveness of the recommendation tool for fashion and content is comparable, while the effectiveness of the tool for electronics showed different patterns. The survey results indicate that the recommendation tool is used less for electronics than for fashion or content. In addition, those who consider the tool useful and satisfactory are fewer for electronics than for fashion or content. Furthermore, a correlation analysis of the survey suggests that the tool is less utilized in online sales of electronics because the tool is perceived to be less convenient and satisfying for electronics purchases than for fashion products and media content. The following section examines the possible reasons why the tool is perceived as less convenient and less satisfying for electronics products.

Promoting Recommendation Tools for Electronics Products

Why are recommendation tools less convenient and less satisfactory for purchasing electronics products? There are three possible reasons: product lifecycle, trend, and the need for support. The first is product lifecycle: fashion and content are constantly updated with new products. Consumers lack sufficient knowledge about newer products, and thus, the need for a recommendation tool is high. On the other hand, people may purchase electronics products based on their past positive or negative experiences with electronics and thus do not utilize the tool. The second factor is a trend. Individuals may desire to purchase and wear a fashionable item that others are wearing or watch a popular movie that others are watching. In such cases, individuals may simply follow the recommendation tool since the tool provides the most up-to-date information based on big data. Conversely, individuals may not necessarily follow a trend when purchasing electronics products. The reliability of items or an experience with a manufacturer may be more important than a trend. The final factor is the need for support. It is possible that individuals may be less satisfied with the recommendation tool if they consider AI's customer support for electronics products to be inadequate.

The Customer Journey

The level of satisfaction with the recommendation tool varies significantly by product category but remains almost constant across all stages of the customer journey within each product category. Specifically, the satisfaction level for the fashion and content categories is higher than that for the electronics category at all stages of the customer journey. The overall satisfaction level is slightly higher at the awareness stage of the customer journey, but there was no significant difference among the stages. Notably, the results of the correlation analysis show a high positive correlation between satisfaction levels at different stages of the journey. Thus, individuals who are satisfied (or dissatisfied) at one stage are likely to be satisfied (or dissatisfied) at another stage, suggesting that satisfaction with the tool is more a function of the product category than a function of the stages of the customer journey.

CONCLUSION AND FUTURE RESEARCH

This paper investigates the effectiveness of recommendation engines, the most commonly used AI tool in online sales, for three product categories: fashion, media content, and electronics. The results show that recommendation engines are effective for purchasing fashion items and media content but not for electronics products. The higher satisfaction levels for fashion and content, as opposed to electronics, may be due to the shorter product lifecycles of the former; since many new products are introduced in the fashion and content categories, customers may find recommendation engines a good source of information to catch a trend. In contrast, recommendation engines may not be considered a useful tool in the electronics category due to its longer product lifecycle; customers may find other sources of information, such as word of mouth, previous customer experience, brand image, and customer support, more important than the information provided by recommendation engines. Electronics products also require more customer support, with the survey showing that people prefer human support to AI support for electronics. In summary, even though recommendation engines are considered effective tools in online businesses, there is still room for improvement. To further promote the use of such tools, the weakness of the tool needs to be improved. Our survey results suggest that a hybrid AI–human approach may be effective; for example, AI tools answer simple questions promptly, while human agents focus on hard-to-answer questions.

One limitation of this study is that it only looks at recommendation engines among various AI-driven marketing tools at one point in time. To understand the impact of AI marketing tools, we need more studies that cover a wide range of tools over a longer period. When using AI-powered technologies to improve the customer experience, it's critical to consider integration with new digital touchpoints both inside and outside the e-commerce platform. The way customers move through their journey is constantly changing, so we should aim to create a holistic AI-powered experience engine that considers the ongoing evolution of the customer journey.

This study provides a foundation for future research endeavors and paves the way for higher levels of customer satisfaction and engagement. To advance our understanding of the impact of emerging technologies on the customer journey, it is imperative to elucidate their role within the customer experience landscape. To this end, Table 7 provides a useful conceptual framework for practitioners seeking to capture the skillful use of appropriate AI-powered tools in online marketing and optimize customer satisfaction throughout the journey.

We currently observe a growing number of AI-powered tools, not just recommendation engines, that are also important in online marketing and e-commerce. These tools each serve unique functions at different stages of the customer journey. Building on the conceptual foundation outlined in Table 7, it is important for businesses to identify the specific roles of these new tools at each stage of the

Table 7. Impact of AI-Powered Marketing Tools Framework in the Customer Journey

Tool	Awareness	Consideration	Purchase	Retention	Advocacy
Social media advertisements	high	medium			
Recommendation engines	low	high	medium		
Chatbots		medium	high	low	
Virtual try-on tools		high	medium		
Size and fit assistants		high	high	medium	
Email offers			medium	high	
Virtual styling tools			high	low	
Promotions and discounts			high	medium	
Referral programs				high	medium

customer journey, while assessing their overall impact and exploring strategies for integrating these tools.

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CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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Figure 9. Distribution of Q1 Responses

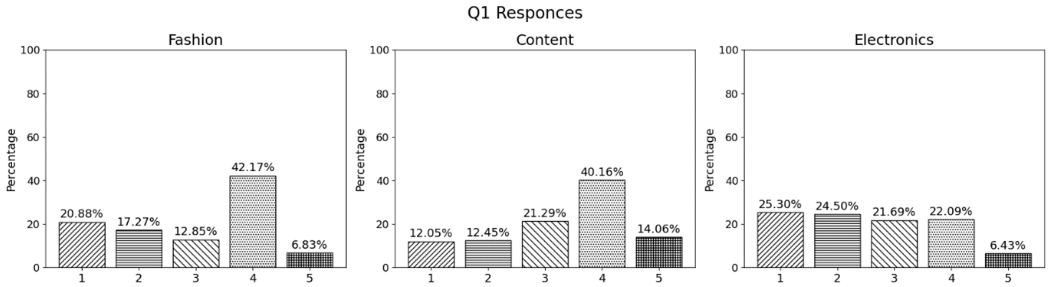
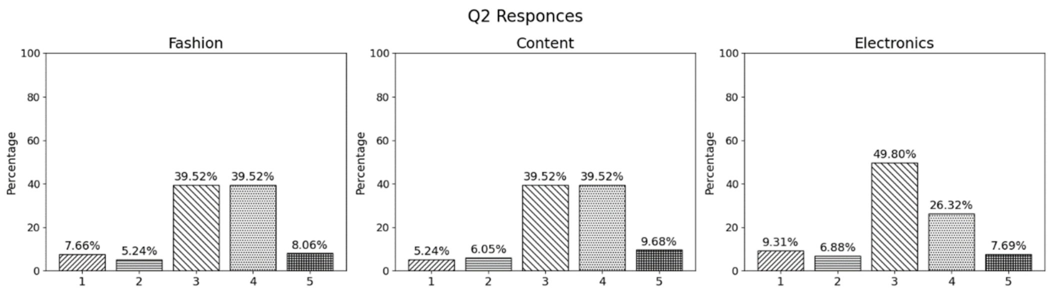


Figure 10. Distribution of Q2 Responses



APPENDIX

Figures 9–25 show the distributions of responses to questions in the fashion, content, and electronics categories, showing similarities in the distributions of responses in the fashion and content categories in most questions.

Figure 11. Distribution of Q3-1 Responses

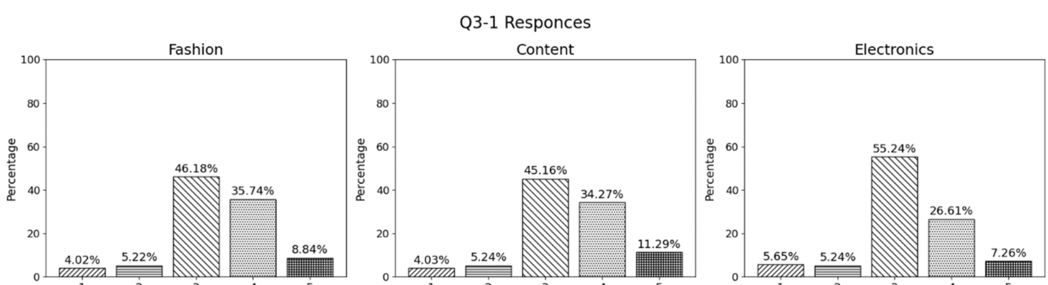


Figure 12. Distribution of Q3-2 Responses

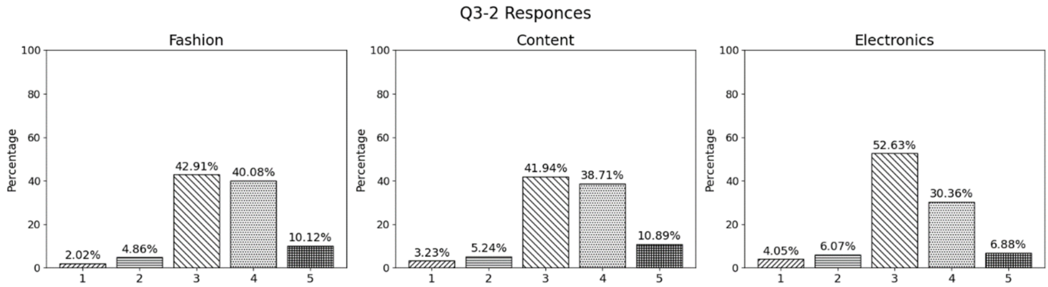


Figure 13. Distribution of Q3-3 Responses

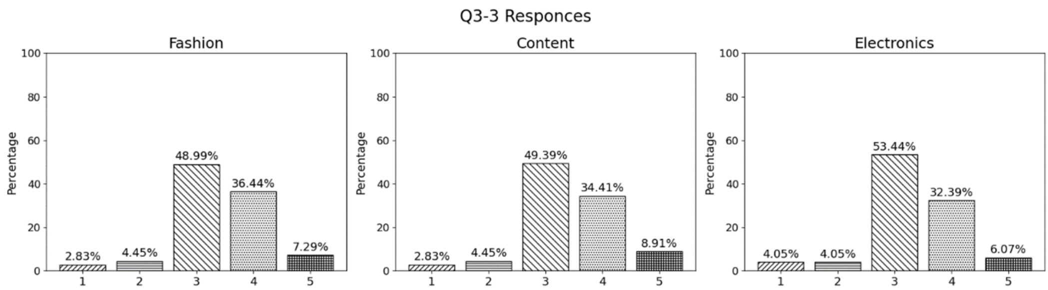


Figure 14. Distribution of Q3-4 Responses

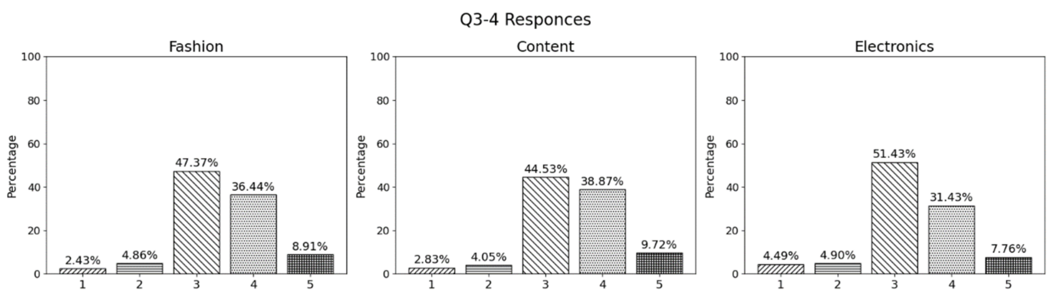


Figure 15. Distribution of Q3-5 Responses

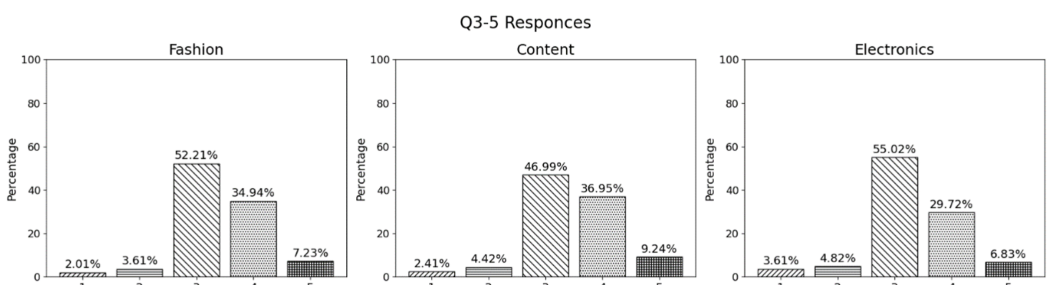


Figure 16. Distribution of Q3-6 Responses

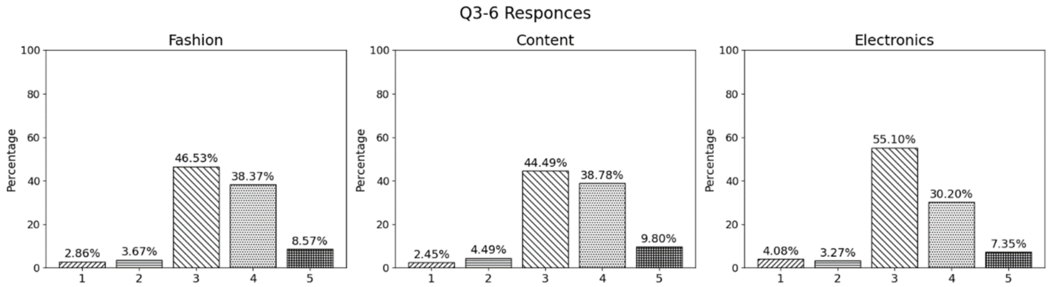


Figure 17. Distribution of Q3-7 Responses

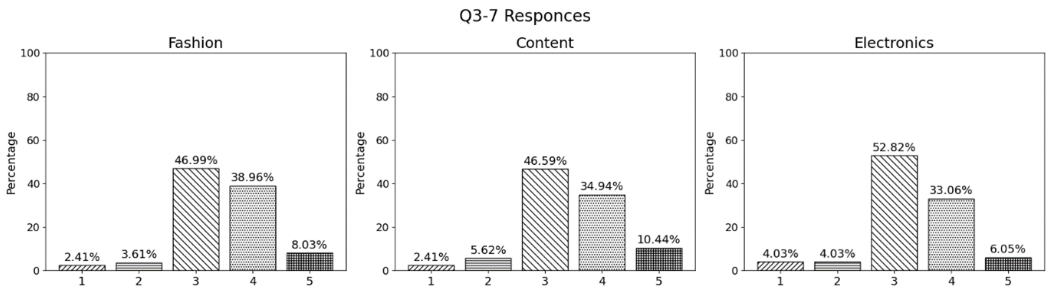


Figure 18. Distribution of Q4 Responses

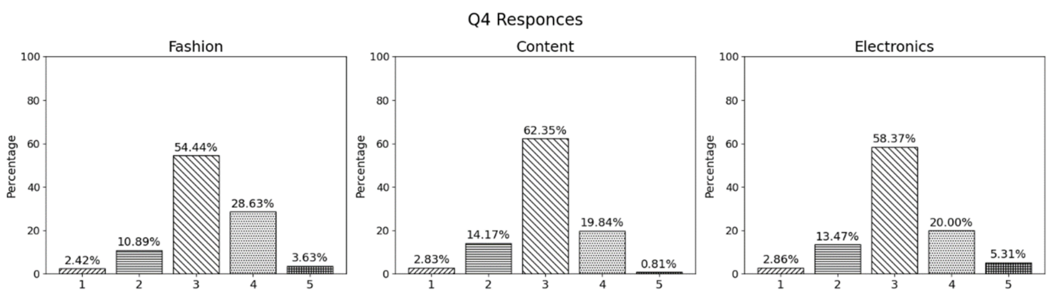


Figure 19. Distribution of Q5-1 Responses

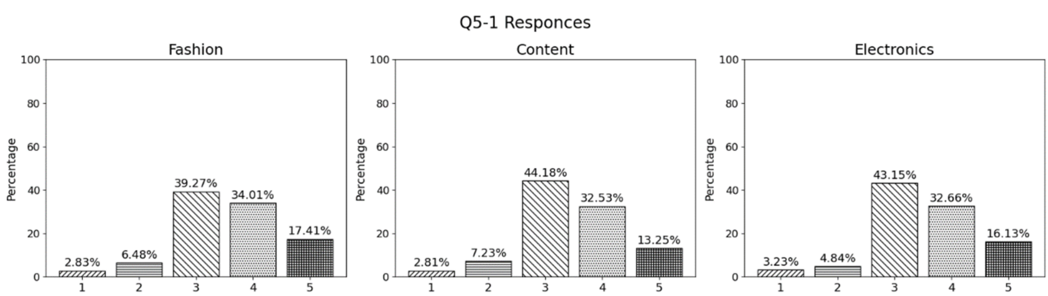


Figure 20. Distribution of Q5-2 Responses

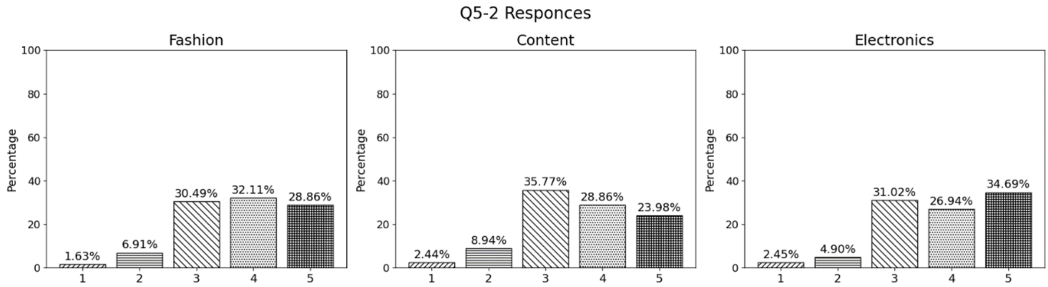


Figure 21. Distribution of Q5-3 Responses

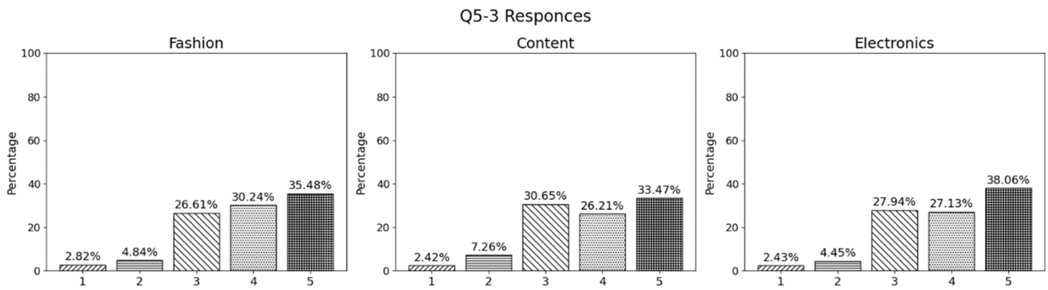


Figure 22. Distributions of Q5-4 Responses

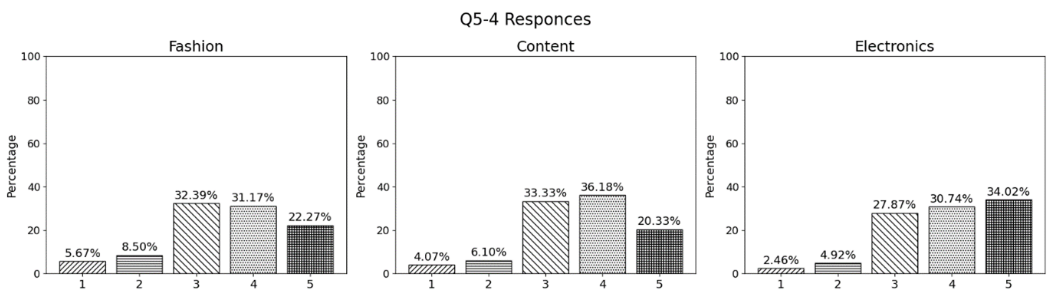


Figure 23. Distribution of Q5-5 Responses

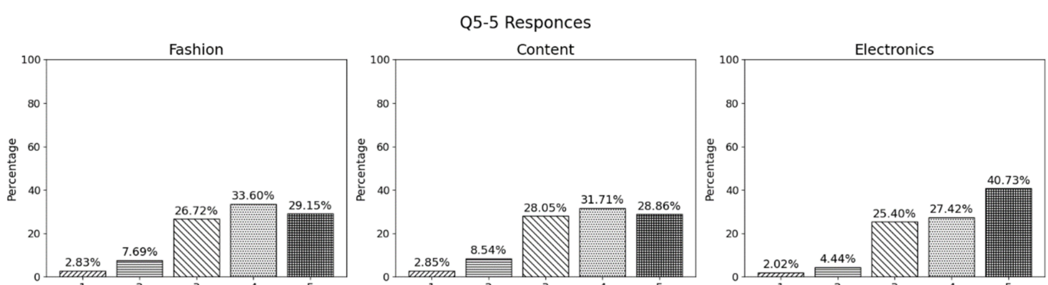


Figure 24. Distribution of Q5-6 Responses

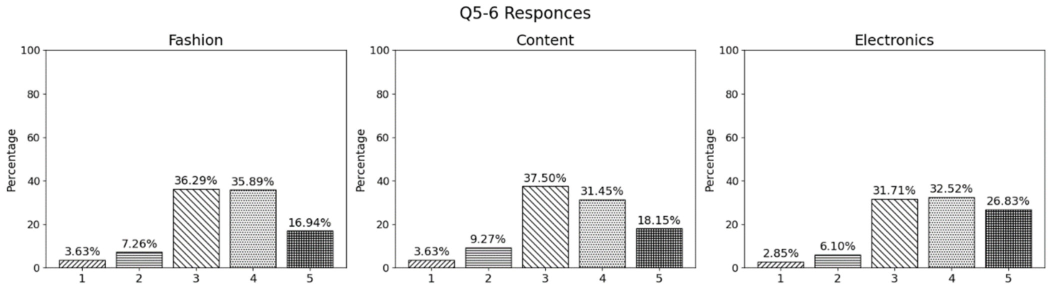
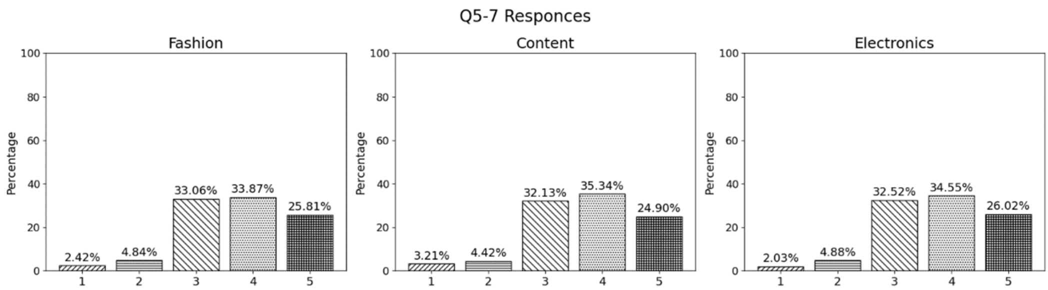


Figure 25. Distribution of Q5-7 Responses



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