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Consumer Reviews on the Voice-enabled AI Visual Assistants for Fashion Recommendation

- A Study of Amazon Echo Look -

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ABSTRACT

This study explores consumer usage and perceptions of Amazon's Echo Look, an AI-powered fashion assistant, to enhance understanding of consumer behavior and improve future AI fashion technologies. Using consumer review data collected from Amazon's website for the period 2017–2020, the research employed text mining techniques, including keyword analysis and co-occurrence network analysis, to identify key themes and factors influencing satisfaction and dissatisfaction. The results revealed that frequently mentioned keywords, such as styling, photos, and Alexa functionality, highlighted the product's appeal for managing personal style. Positive reviews praised photo quality, styling suggestions, and Alexa integration, while negative reviews focused on Wi-Fi connectivity issues, technical failures, and ineffective fashion advice. Applying Hassenzahl's psychological needs framework, the study found that the Echo Look met needs such as competence, autonomy, and relatedness but fell short in addressing privacy concerns and customization. The findings of this study provide insights into consumers' psychological and emotional responses to AI-powered fashion assistants, emphasizing the need for improved technical functionality, personalization, and user-centric design to enhance future developments in this domain.

Key words: AI fashion assistant with camera(카메라 기능이 있는 AI 패션 어시스턴트), AI personal assistant(AI 개인 어시스턴트), AI speaker(AI 스피커), Internet of Things(사물인터넷), psychological needs(심리적 욕구)

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I. Introduction

Imagine waking up to your AI (artificial intelligence) speaker suggesting the perfect outfit for today's meeting based on your calendar, individual preferences, style preferences, weather condition, and current social events. Through chatbots, style subscription services, and other solution tools, AI technology has reshaped fashion industries by creating new markets, generating value, and upgrading customer experiences (Son, 2020; Vietrov, 2024) For example, the fashion retailer, Zalando, offers an AI-based personalized fashion advisor which provides personalized recommendations and style guidance. Stitch Fix increased its investment in personal styling and experiment with Generative AI.

The consumer need for voice-enabled AI fashion assistants with camera is well expected to grow significantly considering the following trends. First, AI-powered fashion assistants, which analyze users' existing wardrobe and personal preferences, identify the appropriate image, predict upcoming fashion trends, and recommend the most appropriate clothing and accessories, are expected to revolutionize the way users shop, style, and curate our wardrobes(MoldStud, 2024). As technology evolves, there is a growing trend of consumers who seek AI-powered fashion assistants(Patel, 2024). According to a study conducted in 2023, nearly two-thirds of people surveyed expressed their positive attitudes toward AI recommendations for new products(Tighe, 2024). AI fashion assistants market size was worth around 69.82 million in 2022 and is expected to reach 1102.29 billion by the year 2031, growing at a 36% CAGR during the period of 2023-2031 (Insight Ace, 2023). Second, going further in AI solutions, the voice-enabled AI assistants are another important element that retailers, especially online retailers, are now looking forward to implementing(Jones, 2023). The fusion of voice-enabled AI and personal style assistants will play a significant role in consumer interaction with retailers. For example, Estée Lauder launched a voice-enabled makeup assistant in 2023, which helps customers choose beauty products using facial scanning and voice commands(Jones, 2023). Third, with the growing consumer demand for seamless and voice-activated shopping experiences, AI-powered smart speakers meet these expectations by offering seamless real-time fashion advice(Insight Ace, 2023). The need for voice commerce and the adoption of smart speakers is on the ascent(Fortune Business Insight, 2024; Statista Research Department, 2023). Smart speakers have become central controlling hubs for smart homes, making them integral in our daily lives and digital experiences. A combination of AI-powered smart speakers and personalized fashion advisors, AI-powered fashion assistants with camera can offer diverse services from style recommendations to information searches and online shopping through voice interaction.

With the rapid development of AI and voice technology, AI-powered smart speakers have transcended their roles as mere voice-controlled assistants; they are becoming fashion-savvy assistants, offering personalized style advice(Jones, 2023). Despite the expected growth in voice-enabled AI fashion assistants, little research has been conducted to understand consumer usage, needs, and expectations for voice-enabled AI fashion assistants with cameras, which leads to the following research questions: What factors are related to consumer opinions and satisfaction about AI fashion assistants? In order to enhance our understanding of consumer usage of AI-powered fashion assistants, we explored the consumer reviews on Amazon's Echo Look (hereafter Echo Look). Echo Look combines AI vision algorithms with fashion expertise to provide personalized style recommendations. It is an AI speaker that combines with a camera to take photos of the user and videos, serving as a digital fashion adviser, although Amazon no longer supports the Echo Look(Roston, 2022). There is no accessible data except the one from the Echo Look reviews. Accordingly, we explore customer reviews about Echo Look from Amazon.com. We specifically address the following research questions: (1) What are the most frequently mentioned keywords in consumer reviews about the Echo Look? (2) What factors are related to consumer satisfaction/dissatisfaction in positive (4-5 stars), negative (1-2 stars), and neutral (3 stars) reviews of the Echo Look? (3) How are the dimensions of consumers' psychological needs represented in user reviews of the Echo Look? Understanding consumer opinions about the use of Echo Look for fashion stylists is essential for enhancing user experiences and shaping the future of AI-powered fashion stylists. Besides, understanding how customers reviewed the device will help businesses and consumers that are currently developing and/or having interest in the speakers.

Through the analysis of Echo Look, this study aims to provide important insights into the development of AI-powered fashion stylists in the future. This study is expected to help improve user experience, promote technological development, raise consumer awareness of AI- based fashion advice and personalized recommendation systems, and understand their behavior and expectations in-depth by analyzing data from various angles using various text mining techniques.

II. Literature Review

1. Factors Influencing Consumer Experience with AI Fashion Assistants

As AI increasingly becomes an important player in marketing and customer-brand relationship management, a growing number of consumer research has been conducted in the context of AI personal assistants (AIPAs)(Ling, Chen, Ho, & Hsiao, 2021; Ling, Tussyadiah, Tuomi, Stienmetz, & Ioannou, 2021). A significant portion of the previous research has addressed questions exploring factors affecting user adoption of and resistance to AI-powered smart devices(Chouk & Mani, 2019; Hong & Cho, 2023; H. Ling et al., 2021; E. Ling et al., 2021), employing technology acceptance model(TAM)(Davis, 1989), the unified theory of acceptance and use of technology(UTAUT)(Venkatech & Davis, 2000; Vimalkumar, Sharma, Singh, & Dwivedi, 2021), the costs-benefits value model(Akdim & Casaló, 2023), and the innovation resistance model(Kleijnen, Lee, & Wetzels, 2009; H. Ling et al., 2021; E. Ling et al., 2021; Ram & Sheth, 1989; Szmigin & Foxall, 1998). For example, E. Ling et al.(2021) reviewed the literature, which summarizes the antecedent factors into usage-related (utilitarian benefits such as perceived ease-of-use, perceived usefulness, hedonic benefits such as perceived playfulness, enjoyment, social factors), agent-related (designed appearance, modality/portability, social ability, likability, empathy, anthropomorphism, gesturing), user-related (demographic factors, psychological factors including users' mental and emotional states (cognitive/utilitarian or emotional/hedonic), intrinsic motivation) ones, proposing that agent-related and user-related factors influence usage benefits, which in turn, influences consumer evaluation and adoption and use. While most frequently reported factors include utilitarian benefits of AI assistants benefits(H. Ling et al., 2021; Lu, Cai, & Gursoy, 2019; McLean & Osei-Frimpong, 2019), task-technology fit(H. Ling et al., 2021), engagement(Moriuchi, 2019), and trust(Balakrishnan & Dwivendi, 2021; Pitardi & Marriott, 2021) are also shown to affect consumer adoption of the devices.

As increasing attention has been paid to exploring factors that affect consumers' experiences with AI-powered consumer devices employing structured data with quantitative research methods such as surveys, little research has been conducted to uncover consumers' sentiments and hidden information from the actual usage of the devices, which can be better obtained from studies using unstructured customer data. Moreover, except for a few studies exploring factors for consumer attitudes and behavioral intentions to adopt AI devices for fashion(Kautish, Purohit, Filieri, & Dwivedi, 2023; Liang, Lee, & Workman, 2020), little research has explored consumer experiences with AI-powered assistants for fashion products or AI-powered fashion assistants with camera. Furthermore, most research has investigated factors for adoption of AI-powered personal assistants(Chouk & Mani, 2019; Hong & Cho, 2023; Kautish et al., 2023; Liang et al., 2020; H. Ling et al., 2021; E. Ling et al., 2021), although users' dissatisfaction with such devices has often reported(Sunnebo, 2019). For example, Echo Look, an AI-powered personal assistant for fashion with a camera, was a smart device designed for styling and outfit mana- gement. It integrated Alexa's voice assistant and allowed users to take voice-activated selfies and video clips, serving as a personal stylist. Key features included a Style Advisor for outfit recommendations through the Alexa app, 360-degree photo and video capabilities for viewing outfits from multiple angles, and voice control for hands-free operation. The device also synced with a mobile app for managing content and tracking style changes. Despite its innovative features and initial popularity after its 2017 launch, Amazon discontinued the Echo Look in May 2020 and ended its service in July 2020. According to Roston(2022), the Echo Look was a device that captured users' photos to provide fashion advice. Its feature requiring consumers to take daily photos of themselves raised privacy concerns, which became one of the key factors that discouraged many consumers from using the Echo Look. Moreover, since Amazon did not have a strong reputation as a destination for clothing and accessory purchases, users questioned the quality and reliability of Echo Look's fashion advice. The inability of Echo Look to deliver distinctive value also contributed to its lack of significant popularity in the market (Maxwell, 2020). Thus, studies addressing the service failures of AI-powered personal devices (Sun, Li, & Yu, 2022) are needed in order to enhance our understanding of how consumers experience and what consumers need and expect from the interactions with AI-powered personal assistants for fashion products. Therefore, exploring customers' positive and negative sentiments and needs from the experiences with AI personal assistants for fashion products from unstructured customer data, which was ignored in previous studies, is essential to gain customer insights into the process of how consumers feel and form attitudes or behavioral intentions toward such devices.

2. Psychological needs for user interaction with interactive devices

The literature emphasizing the role of users' psychological needs in creating pleasurable user experience (UX) in the Human-Computer Interaction suggests that the degree of need fulfillment is related to users' positive affect and pleasurable experience with interactive technology(Desmet & Fokkinga, 2020; Hassenzahl & Tractinsky, 2006; Hassenzahl, Diefenbach, & Göritz, 2010). In order for users to have pleasurable experiences, interactive devices can be purposefully developed in the design process (Fink, Langer, Burmester, Ritter, & Eibl, 2022). Especially for interactive technology, Hassenzahl et al.(2010) identify several universal psychological needs that are closely linked to positive affect and hedonic quality perceptions, which are derived from the experiences with interactive technology: competence, relatedness, popularity, stimulation, meaning, security, and autonomy. For instance, the sense of competence emerges when users master a device's functions, while relatedness reflects the sense of connection fostered through interactions with others via the device. Autonomy highlights users' ability to use a device freely and as desired, while security emphasizes the need for privacy and safety. Although these psychological needs have been extensively studied in general interactive technology contexts, their role in shaping consumer experiences with AI-powered personal assistants for fashion products remains underexplored. In particular, it is unclear whether such devices fulfill these needs or how unmet needs may contribute to dissatisfaction. By examining consumer reviews of the Echo Look, this study addresses this gap by analyzing how psychological needs are fulfilled—or left unmet—during interactions with an AI-powered fashion assistant. This focus on psychological needs also provides a novel lens to explore the broader implications of AI in fashion and consumer behavior. Unlike traditional studies of AI adoption, which emphasize utilitarian and hedonic benefits, this research integrates the psychological dimensions of user experience to gain a deeper understanding of consumer satisfaction and dissatisfaction.

III. Methods

1. Research questions

RQ 1: What are the most frequently mentioned keywords in consumer reviews of the Echo Look?

RQ 2: What factors are related to consumer satisfaction/dissatisfaction in positive (4-5 stars), negative (1-2 stars), and neutral (3 stars) reviews of the Echo Look?

RQ 3: How are the dimensions of consumers' psychological needs represented in user reviews of the Echo Look?

2. Data collection

This study aimed to analyze consumer opinions about the Echo Look's failure through text mining of consumer reviews. Text mining is a highly useful tool for analyzing customer feedback to improve systems and services. Numerous prior studies have utilized text mining to evaluate service quality and propose methods to enhance customer satisfaction(He et al., 2017; Wen, Chen, Liu, & Liang, 2024; Xu & Li, 2016).

The data for this study was collected from customer reviews on the Amazon website, spanning from the initial release of the Echo Look in 2017 to the discontinuation of service in 2020. A web crawler coded in Python by one of the authors was employed for data collection. The crawler gathered a total of 884 reviews, including reviewer information, product ASIN codes, review texts, overall product ratings, and review dates. Out of the 884 collected reviews, 418 reviews, which only included star ratings without text, images, or videos, and 16 reviews not written in English were excluded from the analysis. Consequently, a total of 450 reviews were used for the final analysis. The data collected for this study spans from 2017, the launch year of the Echo Look, to 2021, when the final reviews were submitted. Specifically, 192 reviews were posted in 2018, reflecting the product's initial adoption phase, and 224 reviews in 2019, marking a continued but steady interest. In 2020, as Amazon announced the discontinuation of the Echo Look, only 31 reviews were recorded, showing a significant decline in consumer feedback. By 2021, with the product fully discontinued, only three reviews were collected.

3. Analysis methods

This study employed a combination of text mining techniques and manual data curation to comprehensively analyze consumer reviews.

1) Text Mining Technique

Data preprocessing was first conducted to convert unstructured text data into structured data to analyze the text. Data preprocessing is the most critical step in text analysis. In this study, special characters, numbers, and punctuation were removed using regular expressions, and only English text was used for analysis. Next, a stopword dictionary was established in order to eliminate words devoid of semantic significance, such as conjunctions (e.g., for, and) and pronouns (e.g., the, a), thereby isolating only substantial content. In this study, all morphemes in the textual data were utilized for the keyword analysis, except for numbers and special characters, which were excluded during the preprocessing stage. This decision was made to ensure that the analysis captured the full range of linguistic information present in the consumer reviews without restricting the dataset to specific parts of speech, such as nouns, adjectives, or verbs. Subsequently, keyword analysis was performed to identify words or phrases that condense important issues within the review data. For this analysis, Python's Natural Language Toolkit (NLTK) was utilized to perform lemmatization, a process that groups different inflected forms of a word to analyze them as a common base form. Following this, a bi-gram analysis was conducted using the Gensim library. Bigrams are sequences of two consecutive words, and their analysis helps identify commonly co-occurring word pairs, which may encapsulate meaningful patterns or relationships in the text. For example, the words 'take' and 'photo' frequently co-occurred and were identified as the bi-gram 'take__photo,' highlighting a key feature of the Echo Look related to its photo-taking functionality. Gensim's bi-gram model was trained on the preprocessed data to detect frequent word combinations, which were then integrated into the analysis to better capture contextual significance. Finally, the Counter function was used to perform frequency analysis, which counted the occurrences of individual words and bi-grams within the dataset. This allowed for the identification of the most frequently mentioned terms, providing insights into recurring themes and consumer sentiments in the reviews.

A co-occurrence network analysis was conducted to identify factors influencing consumer satisfaction and dissatisfaction. Since text mining involves the analysis of unstructured data, it requires more complex processing compared to traditional structured data mining methods(Choi & Lee, 2021). Co-occurrence network analysis excels in visualizing the relationships and connections between keywords, making it an effective method for categorizing satisfaction and dissatisfaction factors and identifying related keyword clusters. Additionally, the use of Jaccard coefficient-based network visualization provides a deeper understanding of consumer sentiments by highlighting strong associations between keywords in the context of their reviews. In this study, KH-coder Version 3.0, a text mining software, was used to analyze co-occurrences and visualize the network connecting frequently used words. According to Higuchi(2017), a co-occurrence network prioritizes stronger relationships based on the Jaccard coefficient, calculated by dividing the number of sentences containing both words by the number of sentences containing at least one of the words. In the diagrams, the size of the circles represents the frequency of word occurrence across all sentences, while the thickness of the lines indicates the frequency of co-occurrence, expressed through the Jaccard coefficient. This analysis automatically detects several strongly connected word groups. The consumer reviews were categorized into positive (4-5 stars), neutral (3 stars), and negative (1-2 stars) based on star ratings, and co-occurrence network analysis was performed separately for each of the three types of review data.

2) Manual Data Curation for Psychological Needs Analysis

While keyword analysis and co-occurrence network analysis provided valuable insights into recurring themes and keyword relationships, these methods are limited in their ability to capture the context and sentiment behind the words.

To address the limitations of text mining techniques, this study incorporated manual data curation, aligning with the principles of qualitative content analysis. Customer experiences were analyzed based on Hassenzahl's seven dimensions of psychological needs, which provide a framework for understanding experiential value(Hassenzahl, 2013). Manual curation was chosen over automated topic modeling methods like LDA, as user-generated content often contains noise that can obscure meaningful themes(Bigne, Ruiz, Perez-Cabañero, & Cuenca, 2023). Unlike automated methods, manual curation allows for precise categorization and interpretation, particularly when exploring nuanced concepts such as psychological needs. This approach ensures that both the quantitative patterns identified through text mining and the qualitative nuances of consumer sentiment are adequately represented in the analysis.

IV. Results

1. Keyword Analysis of Echo Look

Keyword analysis was performed to identify words or phrases that encapsulate significant issues in the review data. As shown in 〈Table 1〉, frequently mentioned words in consumer reviews included 'photo,' 'camera,' 'take_picture,' and 'take_photo,' indicating that the photo-taking feature is perceived as one of the primary distinguishing functions of the Echo Look. Addi-

〈Table 1〉 Top 50 Keywords from Frequency Analysis of Consumer Reviews

Word	Frequency	Word	Frequency
photo	158	clothes	38
look	144	nice	37
use	139	fashion	36
outfit	118	set	35
love	103	ask	34
camera	101	return	33
device	86	style	33
app	80	best	31
time	80	selfie	30
work	80	closet	28
echo_look	75	bad	28
amazon	73	speaker	29
good	73	fun	28
feature	68	wardrobe	28
buy	67	bad	27
great	65	take_photo	26
alexa	59	price	26
phone	53	wish	25
want	50	new	24
need	48	easy	23
wear	45	mirror	22
echo	44	useful	21
help	44	suggestion	20
take_picture	44	play_music	20
video	42	issue	19

tionally, words such as 'look,' 'outfit,' 'clothes,' 'fashion,' 'style,' 'selfie,' 'closet,' and 'wardrobe' confirm that the Echo Look is recognized as a smart device specialized in fashion. Furthermore, words like 'love,' 'good,' 'great,' 'nice,' 'best,' 'fun,' and 'useful' were frequently mentioned, indicating positive user experiences with the Echo Look. Conversely, terms such as 'bad,' 'issue,' and 'return' highlight where consumers felt improvements were needed. This dual presence of positive feedback and areas for improvement demonstrates a balanced view of consumer satisfaction and dissatisfaction.

2. Factors related to consumer satisfaction and dissatisfaction

To identify the factors influencing consumer satisfaction and dissatisfaction, consumer reviews were categorized based on star ratings into positive (4-5 stars), neutral (3 stars), and negative (1-2 stars) reviews. The results revealed 123 negative reviews, 49 neutral reviews, and 278 positive reviews. Subsequently, a co-occurrence network analysis was performed on each of the three types of review data: positive, neutral, and negative. This categorization and subsequent analysis helped to identify key factors contributing to consumer satisfaction and dissatisfaction for each review type.

1) Co-occurrence analysis for positive reviews

The results of the co-occurrence analysis derived using KH-coder indicate that users frequently mention specific keywords together in positive reviews. According to 〈Fig. 1〉, users share their experiences of using the Echo Look to command Alexa to take photos and achieve better results compared to typical selfies (different-selfie-say-alexa). They enjoy using Echo Look to check their outfits and take stylish photos, particularly appreciating the quality of the pictures (look-use-love-outfit-well-picture-great). Positive reviews prominently feature experiences related to the video and camera functions of the Echo Look, noting its usefulness compared to other Amazon products (work-good-amazon-product-compare-video-camera-first-home-find). Additionally, consumers provide accounts of their positive experiences with Alexa in carrying out fundamental tasks such as playing music and providing weather updates through Echo Look (give-music-play-weather-ask).

Overall, positive reviews emphasize various features of the Echo Look, particularly highlighting its usefulness in taking photos and checking outfits. Users find that the Echo Look provides better results than typical selfies and appreciate the convenience of taking full-body photos easily. The ability to use Alexa's basic functions while utilizing the additional features of the Echo Look is also positively mentioned. Collectively, the Echo Look is evaluated as a useful device that provides fashion styling assistance along with everyday Echo functionalities.

2) Co-occurrence analysis for neutral reviews

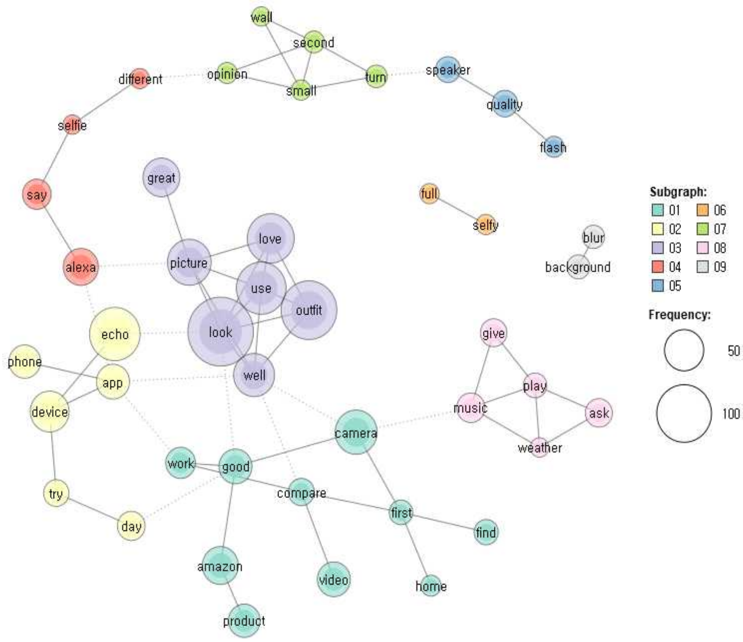
The co-occurrence analysis results for neutral reviews indicate that consumers share diverse experiences regarding specific features or aspects of the product without a clear positive or negative sentiment. For example, as can be seen in 〈Fig. 2〉, neutral reviews often mention scenarios where consumers purchased the product but did not use it frequently or found it fell short of their expectations, resulting in low usage (least-wear). Additionally, complaints about software update issues, design flaws, and difficulties during the setup process are common in these reviews (update-bad-designer-drop-set-know). Neutral reviews also express dissatisfaction with technical defects, particularly issues related to the camera and photo quality (technology-woman-dslr-fix-slider-replicant-blurry-phone). There are also mentions of difficulties in interacting with customer service and resolving problems (call-service-customer). Meanwhile, evaluations of the product's usefulness appear to be mixed (useful-day-year).

Overall, neutral reviews share various experiences regarding specific features or aspects of the product without clear positive or negative emotions. Users commonly mention the frequency of use, design issues, technical defects, and dissatisfaction with customer service. These reviews highlight situations where the product falls short of expectations or causes inconvenience in specific circumstances. Some users acknowledge the product's usefulness but still feel that significant improvements are needed. Overall, neutral reviews indicate that while the product receives good evaluations for certain features, multiple issues limit overall user satisfaction.

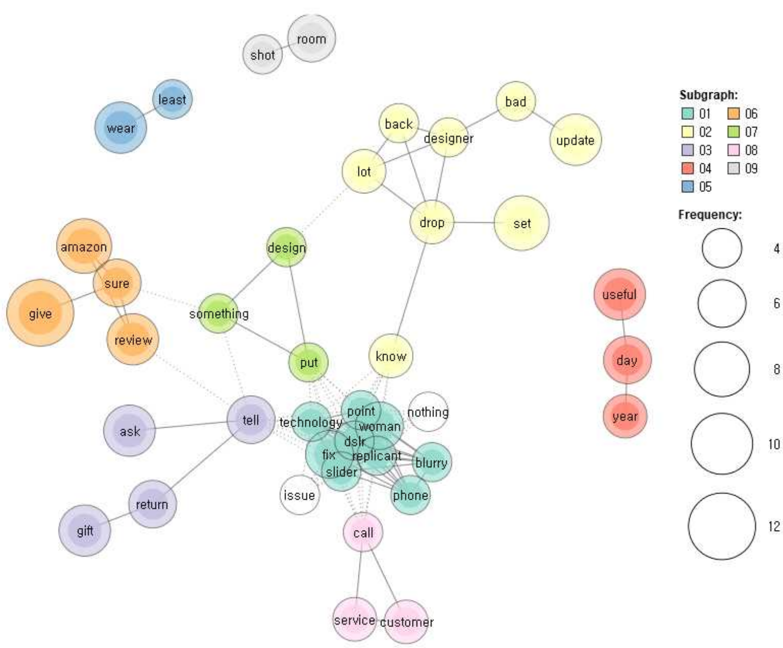
3) Co-occurrence analysis for negative reviews

The co-occurrence analysis results for negative reviews highlight the keywords and contexts where users mainly express dissatisfaction (see 〈Fig. 3〉). According to the findings, consumers frequently experience technical issues such as Wi-Fi connectivity problems, the need for updates, and connection failures (try-customer-wifi-check-phone-update-option-clothes-wear-style). Consumers also point out functional problems like difficulties with setup (problem-set-slider-useful-point-fix-woman-talk-outfit-feature-put-keep-question-ask-flash-music-play). Additionally, they criticize the lack of responsiveness from customer service, the difficulty in resolving technical issues, and inadequate responses to customer requests (technology-connect-call). The product quality is perceived as below expectations, with particular disappointment in durability and performance (poor-quality). Issues related to photo quality, the inconvenience of the app, and the overall difficulty of using the product are also mentioned (picture-product-amazon-use-app). Problems with initial setup and ongoing use are frequent in negative reviews (nothing-need-mirror-consumer-help). This consumer dissatisfaction is often expressed as a financial loss (waste-money). Complaints about the distinctive styling advice feature of Echo Look are also notable (give-fashion).

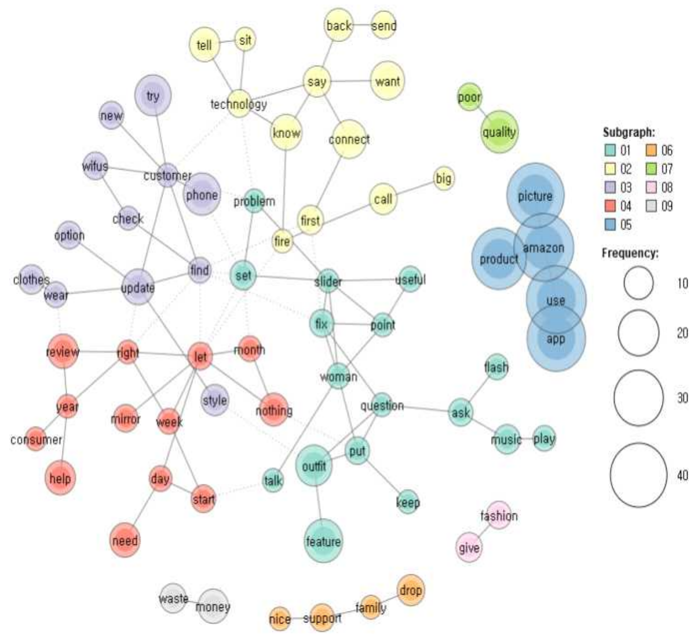
Overall, in the reviews, consumers evaluate the fashion advice feature as falling short of expectations and not providing practical assistance. Negative reviews primarily mention technical issues, functional problems, lack of responsiveness from customer service, declining product quality, usability issues, general dissatisfaction, financial waste, and issues with fashion-related features. This feedback indicates that the Echo Look product fails to meet customer expectations in various aspects, particularly receiving significant complaints about technical and quality issues.



〈Fig. 1〉 Co-occurrence Analysis for Positive Reviews



〈Fig. 2〉 Co-occurrence Analysis for Neutral Reviews



〈Fig. 3〉 Co-occurrence Analysis for Negative Reviews

3. Consumer psychological needs dimensions in Echo Look user reviews

To analyze customer experiences related to the Echo Look across various dimen- sions and to understand how the product meets psychological and emotional needs, Hassenzahl's psychological needs framework was employed. The analysis revealed that the Echo Look addresses a range of consumer psychological needs.

1) Relatedness

The need for relatedness, which encompasses the desire to interact with others, feel connected, and experience care, can be described through words like 'community,' 'style-check,' 'recommendation,' 'Facebook,' 'Instagram,' and 'social media.' Specifically, reviews mentioning the ability to upload photos to the Amazon community for style advice and the convenience of sharing photos taken with the Echo Look on social media platforms like Facebook and Instagram indicate that the Echo Look fulfills consumers' relatedness needs. Additionally, Alexa is frequently mentioned as a companion for seeking advice and engaging in conversation, suggesting that AI can also serve as an object of relatedness, not just humans. Notably, users often refer to Alexa as 'she' highlighting the personal connection they feel with the AI assistant. Overall, these aspects illustrate how the Echo Look satisfies the consumers' relatedness needs by enabling social interactions and providing a platform for community engagement and personal connections, even with AI.

2) Meaning

The desire to deeply understand oneself and develop one's potential to make life meaningful can be described using words like 'narcissist' and 'discover.' Specifically, reviews mentioning the discovery of personal style and satisfaction with one's appearance through daily photos taken with the Echo Look illustrate this concept. For instance, some users noted how taking daily photos helped them discover their style preferences and gain confidence in their appearance. This self-reflection and exploration of personal identity contribute to a sense of meaning in their lives, as they better understand themselves and develop their potential through the use of the Echo Look. Overall, these insights show that the Echo Look helps fulfill the consumers' need for meaning by enabling self-discovery and satisfaction with their personal style.

3) Competence

The need to feel capable and experience mastery or problem-solving can be described using words like 'accomplish,' 'difficult,' 'experiment,' 'setup,' 'Google,' 'YouTube,' and 'try.' Specifically, reviewers mention that users are seeking out YouTube or Google for setup assistance and successfully setting up the Echo Look, or experimenting to find the optimal camera angle, indicating that the product fulfills buyers' needs for competence. Additionally, words like 'compliment' and 'confident' highlight that when users share their styles using the Echo Look and receive positive feedback from others, it boosts their confidence. This positive reinforcement and the ability to navigate and master the features of the Echo Look contribute to users feeling more competent. Overall, the Echo Look helps meet the competence needs of consumers by enabling them to overcome challenges, experiment with features, and gain confidence through positive social feedback on their style.

4) Security

The need to control uncertain and risky elements to feel safe can be described using words like 'categorize,' 'accurate,' 'align,' 'safety,' 'concern,' 'privacy,' and 'Wi-Fi.' Specifically, reviews often mention concerns about privacy and security. Consumers who believe that these privacy concerns are unfounded tend to write positive reviews, expressing confidence in the product's safety measures. On the other hand, those who perceive these concerns as real often leave negative reviews, reflecting their anxiety and dissatisfaction. Overall, the Echo Look addresses security needs by influencing user perceptions of privacy and safety. Positive reviews highlight the sense of security and trust in the product, while negative reviews underscore the need for better reassurance and transparency regarding privacy and security features.

5) Pleasure

The desire to have enjoyable and positive experiences can be described using words like 'fashionable,' 'fashionista,' and 'stylish.' Particularly in the context of fashion, pleasure is derived from being perceived as fashionable or stylish. Consumer reviews often reflect this by noting that users find joy and positivity in receiving compliments and recognition for their fashion sense. The Echo Look contributes to this by helping users curate and showcase their style, which enhances their enjoyment and satisfaction. Overall, the Echo Look meets the pleasure needs of consumers by enabling them to feel fashionable and stylish, thus providing enjoyable and positive experiences related to their personal appearance and fashion choices.

6) Stimulation

The need for novelty and excitement, and the desire to avoid boredom, can be described using words like 'new,' 'revolution,' 'unique,' and 'various.' Specifically, reviews often express satisfaction with using a new product and its features, as well as the ability to explore new, diverse, and unique styles through the Echo Look's fashion advice feature. Consumers appreciate the Echo Look for introducing new elements into their fashion routines and providing the opportunity to experiment with various styles. This novelty and the ability to continually discover and try different looks keep the experience exciting and stimulating. Overall, the Echo Look fulfills the stimulation needs of consumers by offering new and unique features that encourage the exploration of diverse and innovative fashion styles, thus preventing boredom and adding excitement to their daily routines.

7) Autonomy

The need for autonomy, which involves having control and making independent choices, is demonstrated through reviews where users mention organizing and documenting their wardrobes. This allows them to quickly and accurately select or purchase desired items. Users appreciate that the Echo Look helps them manage their fashion choices independently, providing a sense of control over their shopping and styling decisions. The ability to efficiently catalog and access their wardrobe empowers users to make informed and autonomous decisions about their fashion. Overall, the Echo Look fulfills the autonomy needs of consumers by enabling them to take control of their wardrobe organization and shopping processes, leading to more independent and self-directed fashion choices.

V. Conclusion

In the fashion industry, there is a significant consumer demand for AI-based fashion advice and personalized recommendation systems. In addition, the voice commerce and AI smart speaker markets still have substantial growth potential. In response, Amazon launched the Echo Look in 2017, a device designed for AI-based fashion advice and voice commerce, but discontinued its production and support in 2020. This study aims to analyze the reasons for the failure of the Echo Look through text mining of consumer reviews, providing crucial insights for the development of future AI- based fashion recommendation services. To achieve this, customer review data were collected from the Amazon website, spanning from the product's launch in 2017 to the end of its service support in 2020, which led us to the following conclusions. First, a keyword analysis was performed to identify words or phrases that encapsulate key issues related to the Echo Look. The results showed that users frequently used fashion and style-related terms in their reviews, indicating that they valued the Echo Look for managing and improving their style. Next, consumer reviews of the Echo Look were categorized into positive, neutral, and negative, followed by a co-occurrence network analysis to identify factors related to consumer satisfaction and dissatisfaction. Positive reviews highlighted satisfaction with photo quality, styling features, and Alexa's basic functions. Neutral reviews shared various experiences regarding usage frequency, design flaws, technical issues, and customer service. Negative reviews predominantly mentioned Wi-Fi connectivity problems, functional issues, lack of customer service responsiveness, and declining product quality, with significant dissatisfaction regarding the effectiveness of the fashion advice feature. Lastly, an analysis of the customer experience using Hassenzahl's psychological needs framework revealed that the Echo Look meets various consumer psychological needs. These include relatedness through interaction and connection with others, meaning by discovering and being satisfied with their style, competence through mastering the product's use, security through privacy concerns, pleasure through the enjoyment of use, stimulation from new experiences, and autonomy by using the product in their desired manner.

The analysis, integrating results from the factors related to consumer satisfaction and dissatisfaction and consumer psychological needs dimensions in Echo Look user reviews, indicates that while the product meets various psychological needs of consumers, indicates that while the product meets various psychological needs of consumers, there are areas needing improvement. For example, enhancing security to address privacy concerns, improving customer service, providing customization options for users, adding new features and updates to maintain interest, enhancing the visual and functional appeal of the product design and camera performance, and incorporating sophisticated recommendation systems and personalized style suggestions could lead to the development of products and services that more effectively meet consumers' psychological needs in the future.

This study contributes to fashion business literature by offering new insights into consumers' psychological and emotional responses toward AI voice-enabled visual stylists, using Amazon's Echo Look as a case. We analyzed online reviews about Echo Look posted by consumers on Amazon, utilizing text mining techniques, including keyword analysis and co-occurrence network analysis. First, this study identified key words representing consumers' responses to the Echo Look and highlighted key issues such as photo quality, styling features, and technical problems. Interestingly, the number and breadth of key words conveying positive sentiments were greater than those reflecting negative sentiments, despite the service's failure in reality. This result may imply that consumers are likely to be favorable toward and reconsider using AI assistants for fashion advice in the future if operated effectively. Furthermore, the identified factors might explain why the Echo Look was unsuccessful. Technical issues such as Wi-Fi connectivity problems and functional issues appeared to be significant factors that led consumers to avoid or stop using the Echo Look's fashion advice. These findings advance current knowledge of consumers' responses to AI-based digital assistant services within the context of fashion recommendation services. Next, we further explored the relationships between consumers' psychological needs and the identified issues. To our knowledge, this is the first study that classified keywords and issues based on Hassenzahl's model of basic psychological needs for interactive experiences. The results showed that key sentiments aligned differently with underlying basic needs, underscoring the importance of considering users' psychological needs to gain an in-depth understanding of consumer behavior in response to AI voice-enabled visual stylist services.

The results of this study provide valuable insights for retailers and AI service providers exploring multi-modal AI technologies to enhance customer experiences. Key features of AI assistants inducing positive emotions, such as visual and conversational support through photos, outfits, and interactions with Alexa, should be emphasized in developing new AI-based services. Conversely, negative aspects like poor synchronicity and difficult usage should be addressed with advanced technological solutions to transform these weaknesses into opportunities. Additionally, the results showed that consumer psychological needs respond to perceptions of AI-based recommendation services dynamically. Therefore, companies should integrate knowledge of their target market's characteristics, such as primary psychological needs, into the design and implementation of their AI virtual assistant platforms. Overall, our findings highlight the importance of consumer-oriented services for AI service providers and retailers keen on this previously failed service.

This study has several limitations that should be addressed in future research. First, the analysis relied exclusively on consumer reviews from Amazon's website, focusing on the Echo Look, a discontinued product. This reliance on a single platform limits the diversity and scope of the data, potentially introducing biases specific to Amazon's user base. Future studies should incorporate data from multiple sources, such as social media, forums, or other retail websites, to capture a broader range of consumer sentiments and behaviors.

Second, this study relied on user-generated content, which may be subject to self-selection bias. Consumers with strong opinions, whether positive or negative, are more likely to leave reviews, leading to an overrepresentation of extreme views. To mitigate this, future research could employ surveys or interviews to gain a more balanced understanding of consumer experiences and expectations.

Third, while this study used text mining methods for review analysis, it did not employ advanced natural language processing (NLP) techniques capable of capturing nuanced language elements, such as sarcasm, idioms, or context-specific meanings. Integrating advanced NLP models like sentiment analysis, sarcasm detection, or context-aware models (e.g., BERT, GPT) could enhance the ability to interpret sentiment and contextual subtleties in user-generated content.

Lastly, the dataset included basic reviewer information, such as user names, product ratings, and review dates, but lacked demographic details like age, gender, or location. This limitation restricts the ability to analyze how reviewer characteristics influence their experiences or satisfaction. Future studies could address this by using datasets with richer demographic attributes or by incorporating complementary survey data to provide deeper insights into consumer behavior.

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