

Are Customers Ready for Artificial Intelligence to Be Used in Fashion?

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Abstract: Understanding how customers react to emerging technologies, particularly artificial intelligence (AI), is crucial for researchers and retailers alike, especially in light of the increased interest in fashion and digital advancements. Examining consumer perceptions and buying intentions about AI devices was the aim of the study. A conceptual model pertaining to consumers' attitudes and purchasing intentions toward an AI device—Echo Look—was developed and evaluated by modifying the technological acceptance model. In all, 626 participants (61% female) in the top 05 Indian cities between the ages of 20 and 60 took part in the study. The findings showed that customers' attitudes about AI were significantly influenced by perceived usefulness, perceived simplicity of use, and perceived performance risk. Purchase intention was positively impacted by good sentiments concerning technology. Implications for theory and practice are examined in light of these findings.

Keywords: Artificial intelligence, purchase intention, customer attitudes, fashion,

I. Literature Review and Hypotheses Development

The theory of reasoned action (TRA) was modified to create the technology acceptance model (TAM), which is especially designed to study information system acceptance. In addition to being economical and theoretically sound, TAM aims to explain the factors that influence computer acceptance across a wide range of end-user computing systems and user demographics (Davis, Bagozzi, & Warshaw, 1989). Therefore, one of the main goals of TAM is to give a foundation for tracking how external influences affect internal beliefs, attitudes, and intentions" (p. 985).

According to TAM, technology acceptance is primarily influenced by two specific beliefs: perceived utility and perceived ease of use (Davis et al., 1989). Perceived usefulness and ease of use were considered related constructs by the researchers even in the original TAM. Recent studies on technology in general have revealed no evidence of a link between the two notions (Leong, Ibrahim, Dalvi-Esfahani, Shahbazi, & Nilashi, 2018; Yang & Wang, 2019). Given that most responders were tech-savvy people between the ages of 25 and 44, it is possible that they thought the product was simple to use. As a result, consumers' perceptions of perceived usefulness may not always follow from perceived simplicity of use. This association was left out of our suggested model in order to be in line with current research and take participant characteristics into account. Like TRA, TAM assumes that behavioural intention (BI) to use—defined as a person's cognitive goal to utilise an information system—determines computer utilisation (Davis et al., 1989). BI is defined in marketing research as customers' propensity to buy, which is determined by a person's attitude toward the information system (S. Shim, Morris, & Morgan, 1989).

In the fashion industry, TAM has been routinely utilised to gauge customer acceptability of technology-related applications. Customers' attitudes and acceptance of wearable fitness technology (Lunney, Cunningham, & Eastin, 2016), online mass customisation technology (H.-H. Lee & Chang, 2011), and smart in-store technology applications in retailing (H.-Y. Kim et al., 2017) have all been tested using the model, which has confirmed positive relationships between perceived usefulness, perceived ease of use, and acceptance. In addition to discovering and adding new variables, researchers have expanded the basic TAM into several situations. To expand the original TAM, performance risks (H.-H. Lee & Moon, 2015) and technology attitudes (Rosen, Whaling, Carrier, Cheever, & Rokkum, 2013) were introduced in addition to the two main assumptions of perceived utility and perceived ease of use. To explore its moderating effects across groups with higher (vs. lower) fashion participation, fashion involvement was introduced to this study. Figure 1's conceptual framework displays the variables and hypotheses that are covered.

Perceived Usefulness

"The degree to which a person believes that employing a certain system would boost his or her job performance" is known as perceived usefulness (Davis, 1989, p. 320). It has been discovered that views on the usage of TAM are significantly influenced by perceived utility (J. Kim & Forsythe, 2007; Williams, Slade, & Dwivedi, 2014). With the Echo Look's built-in hands-free camera, users may snap pictures or videos of themselves (selfies). Customers can choose the trendiest outfit more effectively by using the product's style-check feature, which offers expert recommendations. Additionally, the depth-sensing camera and integrated lighting give users crisp, full-length images and movies that they can post right away to social media. These features and interactions can help customers choose what to wear more easily and will increase their efficiency in selecting the newest fashions. Customers will therefore probably see the new fashion AI product favourably. Thus, we suggest:

Hypothesis 1: Customers' attitudes toward AI will be positively impacted by perceived utility.

Perceived Ease of Use

One significant factor influencing the use of technology or systems is perceived ease of use (Davis, 1989, 1993; Davis, Bagozzi, & Warshaw, 1992; Mathieson, 1991). The significance of apparent ease of

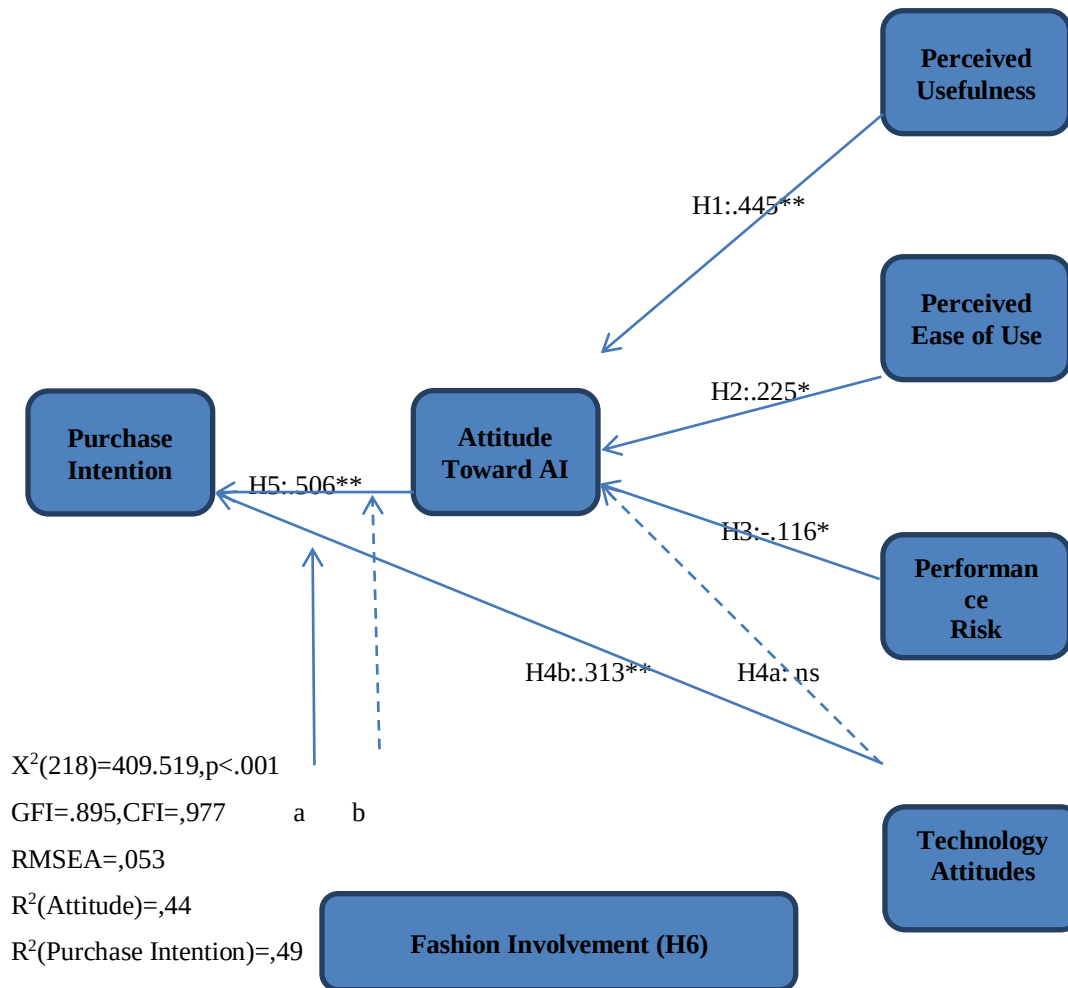


Figure 1 shows the conceptual framework and the outcomes of the tests.

Because a bad user interface might lead to people rejecting IT technology, usability has been emphasised in TAM (Venkatesh & Davis, 1996). According to Davis (1989, p. 320), perceived ease of use in TAM is "the degree to which a person perceives that utilising a certain system would be free of effort." Previous studies have confirmed that customers' attitudes toward technology and perceived ease of use are positively correlated. According to Lunney, Cunningham, and Eastin (2016), consumers' attitudes toward wearable fitness technology were positively impacted by perceived ease of use, while H.-Y. Kim, Lee, Mun, and Johnson (2017) discovered that perceived ease of use is a significant factor in determining the adoption of smart retail technologies. The AI product's ease of use indicates how simple it is to use and engage with the software. Customers can communicate with the device (the Echo Look) by using the Alexa voice control feature. According to Brill (2018), if digital assistants like Alexa are able to live up to customer expectations, then customer happiness would increase. Customers would therefore probably adopt a favourable view if this product was simple for them to use and interact with. Thus, we suggest:

Hypothesis 2: Customers' attitudes toward AI will be positively impacted by perceived simplicity of use.

Performance Risk

A person's subjective evaluation of a product's attributes, attribute levels, or results is known as perceived performance (Spreng & Olshavsky, 1992). According to Grewal, Gotlieb, and Marmorstein (1994, p. 145), there is "the potential that the product will not perform as planned and/or will not give the promised advantages." According to H.-H. Lee and Moon (2015), performance risk is the chance that a product may fall short of the buyer's expectations. Previous studies discovered that performance risk has a

negative impact on purchase intention (J. Park & Stoel, 2005) and attitude (Hwang, Chung, & Sanders, 2016). Therefore, customers' expectations will not be fulfilled, and a negative attitude is likely to arise if they are worried that the product will not work as they had hoped (for example, failing to fulfil the voice command and style-check capabilities). Thus, we suggest:

Hypothesis 3: Customers' perceptions of AI will be adversely affected by performance risk.

Attitude Toward Ai

According to Baron and Byrne (1987), attitudes are long-lasting, general assessments of individuals, things, or problems. Attitudes were defined as an "individual's favourable or negative judgment of executing the behaviour" by Ajzen and Fishbein (1980, p. 6). "Attitudes towards AI" in this study pertains to the particular product, Echo Look. It specifically refers to opinions about how well associated functions are performed by the product. The impact of customer attitudes on purchase intention has been validated by earlier studies (Belleau, Summers, Xu, & Pinel, 2007; Wu, Wu, & Chang, 2016). Therefore, we suggest:

Hypothesis 5: Customers' intentions in acquiring AI products will be positively impacted by their attitudes regarding the technology.

Fashion Involvement

According to E. J. Park, Kim, and Forney (2006), involvement is a metric that may be used to analyse consumer behaviour and divide up consumer markets. It establishes a person's propensity to actively participate in specific product acquisition activities or to pay special attention to products (H. Kim, 2008). "The extent to which consumers consider fashion-related activities as a major part of their life" is the definition of fashion involvement (O'Cass, 2004, p. 870). Product participation, purchasing behaviour, and consumer attributes are amongst the behavioural variables associated with clothing products that fashion involvement has been used to predict (Browne & Kaldenberg, 1997; Fairhurst, Good, & Gentry, 1989). When examining customers' purchasing habits, earlier researchers discovered that fashion engagement had moderating effects (J.-H. Lee & Im, 2008). According to J.-H. Lee and I (2008), the perceived justice of post-complaint behaviour varied depending on the degree of fashion participation. At a higher level of fashion participation, consumers place a higher value on fashion apparel, are less price-sensitive, and participate in more fashion-related activities, including testing out new fashion-related technology and looking for fashion news (Naderi, 2013; Yanshu & Guo, 2017). Celik and Kocaman (2017) came to the conclusion that technological preparedness is directly and significantly impacted by fashion engagement. Customers who are more interested in fashion are thought to be more likely to find the AI product enjoyable. Thus, we suggest:

Hypothesis 6: Customers with higher (as opposed to lower) levels of fashion participation are more likely to be impacted by (a) attitudes toward technology and (b) attitudes toward artificial intelligence on their intention to buy.

II. Research Method

Participants

The top ten Indian cities served as the sites for this study. Qualtrics was used to produce a self-administered online questionnaire, and Qualtrics Panel services were used to recruit a subject pool. Over the course of one week, 313 valid replies were received.

Procedure

After watching a 30-second ad for Amazon's Echo Look (Amazon Fashion, 2017), participants answered questions based on known research on perceived utility, perceived ease of use, performance risk, technology attitudes, attitude toward artificial intelligence, purchase intention, and fashion involvement. Five-point scales were used for fashion-related items, whereas seven-point scales were used for all other items. Completing the questionnaire took roughly fifteen minutes.

The stimulus employed was Echo Look. Amazon created it as a way to approach AI from the viewpoint of the end user, or consumer. In April 2017, the product was introduced by invitation, and in June 2018, it became available to the public (Eadicicco, 2017). Fashion AI, machine learning, Alexa voice control for Amazon Echo (a device that is put in the home and uses voice commands to manage linked tasks), and a camera are all combined in the Echo Look product (Applin, 2017). In addition, Echo Look functions as a virtual style adviser, allowing users to assess their current attire for style and aesthetic appeal (Applin, 2017). With the Echo Look's integrated illumination and depth-sensing camera, users can snap pictures and movies with voice commands and share them with friends right away (Amazon Fashion, 2017). Additionally, when customers are comparing two designs, the style-check feature—which blends machine learning and expert fashion advice—offers fashion recommendations (Amazon Fashion, 2017). Table 1.1 has the video URL.

Research Instruments

To find quality metrics for the research constructs in the suggested model, a thorough literature analysis was carried out (see Table 1). On the basis of validity and reliability, measures were taken from or modified from earlier studies.

Analysis

Descriptive statistics, reliability, structural equation modelling (SEM), and multi-group comparison were employed for data analysis using the statistical software packages SPSS 25 and Amos 25.

Table 1. Research Measurement and Its Source.

Construct	Variable Type	Source	Format After Adapted
Perceived usefulness	Exogenous variable	Cho and Fiorito (2009)	6-Item scale; 7-point Likert-type (very unlikely/very likely)
Perceived ease of use	Exogenous variable	Cho and Fiorito (2009)	6-Item scale; 7-point Likert-type (very unlikely/very likely)
Performance risks	Exogenous variable	H.-H. Lee and Moon (2015)	3-Item scale; 7-point Likert-type (strongly disagree/strongly agree)
Technology attitudes	Exogenous variable	Rosen, Whaling, Carrier, Cheever, and Rokkum (2013)	4-Item scale; 7-point Likert-type (strongly disagree/strongly agree)
Attitude toward AI	Endogenous variable	Batra and Ahtola (1991)	5-Item scale
Purchase intention	Endogenous variable	Dodds, Monroe, and Grewal (1991)	3-Item scale with the endpoints (very low to very high)
Fashion involvement	Moderating variable	O'Cass (2004)	11-Item scale; 5-point Likert-type (strongly disagree/strongly agree)

Note: The following is the URL to the Echo Look ad video: https://www.youtube.com/watch?v¼49X_fP4pPWPw. Artificial Intelligence (AI) 3.

Results Sample

Table 2 displays the demographic details of the sample. 50.8% of respondents were between the ages of 25 and 44 (range ¼ 20–60), with women making up the majority (61%). Based on median ratings, participants were divided into two groups: low (n = 276) and high (n = 250) for fashion participation.

Exploratory Factor Analysis (EFA)

27 scale items representing the exogenous and endogenous factors were subjected to an exploratory factor analysis (EFA) using the principal component analysis approach. One item of technology attitudes was removed because of excessive cross loading (>.40; Hair, Black, Babin, & Anderson, 2010). Six factors were measured by the 26 items that made up the final factor analysis solution, which explained about 85.06% of the variation. The scales' high reliability was demonstrated by the fact that all commonalities varied between.666 and.966, while Cronbach's al ranged between.785 and.982. Table 3 reports EFA loadings ranging from.748 to.932.

Confirmatory Factor Analysis (CFA)

The Echo Look's perceived utility, perceived simplicity of use, performance risk, technology attitudes, attitude toward artificial intelligence, and purchase intention were all the subject of a CFA. Three items were excluded from additional analysis due to their high modification indices. Two items were dropped based on perceived ease of use and one on perceived usefulness. Convergent validity was demonstrated by the excellent fit of the CFA on the 23 remaining items (χ^2 ¼ 339.827; df ¼ 215; χ^2 /df ¼ 1.581; $p < .001$; root-mean-square residual [RMSEA] ¼.043; comparative fit index [CFI] ¼.985; goodness-of-fit index [GFI] ¼.913). As suggested by the previous EFA, the construct validity of each individual construct in the model is supported by excellent fit indices.

With composite reliabilities above.80, as shown in Table 4, each item loaded heavily on its suggested constructs, demonstrating the measures' dependability (Hair et al., 2010).

Table 2. Demographic Characteristics of Research Sample.

Characteristic	Percent	Characteristic	Percent
Gender		Education	
Male	39.3	Less than high school	1
Female	60.7	High school graduate	12.7
Age		Some college	22.7

20–24	8.9	2-Year degree	9.3
25–34	28.2	4-Year degree	37.7
35–44	22.7	Professional degree	14.7
45–54	15.6	Doctorate	1.9
55–60	23.6	Total household income	
60 and above	1.0	Less than RS.50000	1.9
Ethnicity		RS.50000–90000	2.9
Hinduism	72.2	RS.100000–199999	5.1
Islam	11.2	RS.200000–299999	10.5
Christianity	9.9	RS.300000–399999	8.3
Sikhism	6.1	RS.400000–499999	9.3
Buddhism	0.3	RS.500000–599999	10.5
Other	0.3	RS.600000–699999	9.3
Employment		RS.700000–799999	7.0
Employed full time (40 or more hr per week)	47	RS.800000–899999	6.1
Employed part time (up to 39 hr per week)	9.9	RS.900000–999999	4.5
Unemployed and currently looking for work	6.1	RS.1000000–1499999	14.4
Unemployed and not currently looking for work	1.9	RS.1500000–1999999	6.4
Graduate student	1	RS.2000000–2499999	2.2
Undergraduate student	2.2	RS.2500000 or more	1.6
Retired	8	Marital status	
Homemaker	15.7	Married	54.0
Self-employed	3.7	Single	42.2
Unable to work	4.5	Other	3.8

Note. n ¼ 313.

The findings demonstrated that each construct's many indicators had strong internal consistency. With a range of .559 to .948, the average variance extracted (AVE) was higher than the suggested threshold of .50 (Fornell & Larcker, 1981). Strong convergent validity (items that are markers of a certain concept share a large proportion of variance in common) was demonstrated by all standardised CFA loadings, which were significant ($p < .001$) and exceeded .70 (range from .745 to .982). Additionally, discriminant validity (the degree to which a construct is actually different from other constructs; Fornell & Larcker, 1981; Hair et al., 2010) was confirmed by the fact that, as indicated in Table 5, the AVE for each construct was higher than the estimations of squared correlations between constructs.

Model Development and Hypotheses Testing

SEM (Hair et al., 2010; Kline, 2010) was used to test the research model. The model fit was very good (χ^2/df ¼ 409.591; df ¼ 218; χ^2/df ¼ 1.879; $p < .001$; RMSEA ¼ .053; CFI ¼ .977; GFI ¼ .895). A comparison of these values against recommended values suggests that the model estimation result is satisfactory (Kline, 2010; MacCallum, Browne, & Sugawara, 1996). Results of hypothesised relationships are summarised in Table 6. As shown in Table 6, perceived usefulness, perceived ease of use, performance risk, and technology attitudes positively influence consumers' attitudes toward AI. Attitudes toward AI have a direct positive effect on consumers' purchase intentions. Therefore, we

Discovered evidence in favour of Hypotheses 1, 2, 3, 4b, and 5. We found no evidence to support Hypothesis 4a, which proposed that consumers' attitudes toward AI are positively influenced by their attitudes toward technology.

Testing Moderating Effects

Two groups were created using the median score (33.00), which was the sum of the respondents' assessments on all 11 fashion-related questions. The items are from a study by O'Cass (2004) that assessed participants' interest in fashion apparel (e.g., "I am very interested in fashion clothing") and their perception of the significance of fashion apparel in their

Table 3. Exploratory Factor Analysis (EFA) Results.

Factor	Scale Item	EFA Loadings	Reliability
Perceived usefulness (PU)	Choose my outfit faster (PU 1)	.834	.980
	Improve my performance in choosing the most trendy outfit (PU 2)	.862	
	Increase my efficiency in choosing the most trendy outfit (PU 3)	.864	
	Enhance my effectiveness in choosing the most trendy outfit (PU 4)	.866	
Perceived ease of use (PEOU)	Make it easier for me to pick out what to wear (PU 5)	.841	.953
	Be useful for choosing the most trendy outfit (PU 6)	.860	
	Learning to operate this device would be easy (PEOU 1)	.810	
	I think I would find it would be easy to get this device to do what I want it to do (PEOU 2)	.801	
	My interaction with this device would be clear and understandable (PEOU 3)	.822	
	This device would be flexible to interact with (PEOU 4)	.803	
Performance risk (PR)	It would be easy to become skillful at using this device (PEOU 5)	.862	
	I think this device would be easy to use (PEOU 6)	.857	
	I am concerned that the product advertised in the video is different from the actual product (PR 1)	.891	.932
	I am afraid that the product advertised in the video would not perform the way I expect (PR 2)	.894	
Technology attitudes (TechAtt)	I am concerned about whether this product would really "perform" as well as it is supposed to (PR 3)	.863	
	Technology will provide solutions to many of our problems (TechAtt 2)	.779	.785
	With technology anything is possible (TechAtt 3)	.756	
Attitude toward AI	I feel that I get more accomplished because of technology (TechAtt 4)	.748	
	Worthless—Valuable (Attitude 1)	.761	.949
	Unfavorable—Favorable (Attitude 2)	.859	
	Disagreeable—Agreeable (Attitude 3)	.834	
	Harmful—Beneficial (Attitude 4)	.861	
Purchase intention (PI)	Dislike—Like (Attitude 5)	.801	
	The likelihood that I would purchase Echo Look (PI 1)	.808	.982

	The probability that I would consider buying Echo Look (PI 2)	.785	
	My willingness to buy Echo Look (PI 3)	.789	

Note. AVE $\frac{1}{4}$ average variance extracted; AI $\frac{1}{4}$ artificial intelligence.

Table 4. Confirmatory Factor Analysis (CFA) Results of Measurement Properties.

Scale Item	Composite Reliability	AVE	CFA Loadings
Perceived usefulness (PU)	.977	.896	
PU 1			.893
PU 2			.953
PU 3			.966
PU 4			.957
PU 6			.961
Perceived ease of use (PEOU)	.945	.811	
PEOU 2			.876
PEOU 3			.949
PEOU 4			.899
PEOU 5			.877
Performance risk (PR)	.899	.750	
PR 1			.818
PR 2			.978
PR 3			.790
Technology attitude (TechAtt)	.791	.559	
TechAtt 2			.822
TechAtt 3			.669
TechAtt 4			.745
Attitude toward AI	.952	.800	
Attitude 1			.766
Attitude 2			.946
Attitude 3			.929
Attitude 4			.900
Attitude 5			.919
Purchase intention (PI)	.982	.948	
PI 1			.962
PI 2			.982
PI 3			.977

Note. AI $\frac{1}{4}$ artificial intelligence.

Table 5. Squared Correlation Matrix with AVE on the Diagonal.

Variables	Attitude Toward AI	Perceived Usefulness	Technology Attitude	Performance Risk	Purchase Intention	Perceived Ease of Use
Attitude toward AI	.894					
Perceived usefulness	.610	.946				
Technology attitude	.439	.536	.748			
Performance risk	.256	.161	.125	.866		
Purchase intention	.636	.716	.492	.147	.947	
Perceived ease of use	.546	.608	.600	.282	.502	.901

Note. Values along the diagonal indicate the average variance extracted for each construct. Off-diagonal values indicate squared correlations between constructs. AVE $\frac{1}{4}$ average variance extracted; AI $\frac{1}{4}$ artificial intelligence.

life (for instance, "My life revolves around fashion apparel"). Although there was no difference in the groups' income, education, gender, or ethnicity, multivariate analysis of variance revealed that customers with greater fashion participation were younger and had more stable jobs than consumers with lower fashion involvement. A multi-group comparison was carried out to look at

Table 6. Summary of Hypotheses (1–5) and Testing Results.

Path to	Path From	Path Coefficient	p	Hypothesis Testing
Attitude toward AI	Perceived usefulness	.445	**	Hypothesis 1 supported
	Perceived ease of use	.225	*	Hypothesis 2 supported
	Performance risk	.116	*	Hypothesis 3 supported
	Technology attitudes	.032	ns	Hypothesis 4a not supported
Purchase intention	Technology attitudes	.313	**	Hypothesis 4b supported
	Attitude toward AI	.506	**	Hypothesis 5 supported

Note. AI $\frac{1}{4}$ artificial intelligence. * $p < .05$. ** $p < .001$.

These two groups differed in the extent to which attitudes towards AI, technology attitudes, perceived utility, perceived ease of use, performance risk, and the degree to which attitudes toward AI influenced purchase intention (Hair et al., 2010).

The estimation was done using a constrained multi-group model (Model 1/base model—no moderating effects). Every structural weight had to be the same for both groups. $W2 \frac{1}{4} 754.404$; $df \frac{1}{4} 447$; $w2/df \frac{1}{4} 1.688$; CFI $\frac{1}{4} .959$; RMSEA $\frac{1}{4} .047$) showed a satisfactory fit for this mode. The structural weights were then calculated separately for each group in an unconstrained multi-group model (Model 2—moderating effects). A good fit was shown by the unconstrained model ($w2 \frac{1}{4} 657.128$; $df \frac{1}{4} 436$; $w2/df \frac{1}{4} 1.507$; CFI $\frac{1}{4} .971$; RMSEA $\frac{1}{4} .04$). Consequently, the $w2$ difference ($Dw2 \frac{1}{4} 97.276$; $df \frac{1}{4} 11$; $p < .001$) between the two models was significant at the group level, suggesting that consumers with high and low fashion involvement differ in the extent to which perceived usefulness, perceived ease of use, performance risk, and technology attitudes on attitude toward AI influence purchase intention. Each path was limited independently, and the $w2$ difference was compared with the $w2$ threshold in order to further examine the impact of each exogenous variable. The findings show that, for customers with high versus low fashion participation, there is a considerable (99% confidence level) difference between the association between technological attitude and purchase intention. In particular, only customers with a greater level of fashion participation experience a significant impact of technological attitudes on purchase intention. As a result, Hypothesis 6a received support, while Hypothesis 6b did not. Figure 1 provides a summary of the test outcomes.

III. Discussion

A conceptual model was developed and tested in relation to consumers' attitudes and purchase intentions toward an AI product—Echo Look—by modifying the research measurement of TAM (Davis, 1989). First, in line with earlier research findings (H.-Y. Kim et al., 2017; Li & Huang, 2009), we found that consumers' attitudes toward AI were significantly predicted by perceived utility and perceived ease of use. One plausible explanation is that customers value the features that the AI product advertised. Customers' efficiency in choosing fashionable clothing was much increased by these features and the user-friendly system, which resulted in a more favourable opinion towards AI. Furthermore, we discovered from the results of the structural model that performance risk was a negatively significant predictor of customers' attitudes about AI. Customers would not be satisfied or appreciate the product if it did not perform voice command and style-check features, which would make them think negatively of artificial intelligence. It is interesting to note that this also implies that attitudes toward technology had a favourable impact on purchase intention, but not attitudes toward artificial intelligence. According to this line of reasoning, customers who are more Even if they might not have developed a firm opinion about a specific technical product, those who are enthusiastic about the technology are more willing to experiment with new ones. Like Belleau, Summers, Xu, and Pinel (2007), H.-H. Lee and Chang (2011), Li and Huang (2009), and others, we verified that attitudes regarding AI positively influenced purchase intention.

According to our findings, the relationship between technology attitudes and purchase intention was mediated by fashion participation, but not the relationship between AI attitudes and buy intention. According to Celik and Kocaman (2017), consumers who are more involved in fashion are more likely to be prepared to use new technology, but they are not yet ready to buy the fashion AI product. These findings are in line with earlier research. Maybe they are waiting for additional user feedback and an updated version of this unique product with better features or performance.

Implications

The study's findings have both theoretical and practical ramifications. By applying the methodology to the assessment of a new fashion technology by consumers, the study theoretically contributed to the TAM. Additionally, the TAM framework included attitudes toward technology, and our test findings showed that these attitudes had a beneficial impact on purchase intention. The inclusion of these characteristics offered information for upcoming studies on the use of AI in fashion. Furthermore, a national sample was used to apply the TAM, which might add to the body of current TAM work.

The design and findings of this study offered a methodical strategic improvement strategy from a managerial standpoint. In order to validate the findings from earlier researchers that functions and interactions with technology improved consumers' expectations and satisfaction, we first showed that consumers' assessment of perceived usefulness and perceived ease of use significantly influences their attitude towards AI (H.-Y. Kim et al., 2017; Wu et al., 2016). To maintain a user-friendly interface, retailers might continuously update the platforms of this new fashion technology product. The gadget currently allows users to take full-length photos, but it can only capture one image or video at a time. Users may be able to shoot "burst mode" shots and zoom in and crop the images for future development. Enhancing the interface with a front screen or mirror could potentially lead to a higher level of consumer acceptance. Second, consumers' perceptions of AI were adversely affected by performance risk. Echo Look, which was introduced in 2017 (Amazon Fashion, 2017), is still relatively new to the public and is only available for purchase via invitation. Furthermore, there are not any comparable fashion AI products available on the market to compare Echo Look to because the technology was initially introduced at the corporate level and has not yet reached the user level. Customers are therefore worried about this product's performance. Customers' fears about risk would be reduced if this product were more frequently featured and shown in periodicals, trade exhibitions, fashion shows, and social media. In order to better satisfy customer expectations, future upgrades may also have greater camera quality and a wider range of viewpoints.

Furthermore, this kind of fashion AI product can be created for in-store usage rather than just personal use at home, which would help customers learn more about fashion AI and reduce their risk concerns. An in-store environment may offer a chance to boost sales, ease customer confusion or worry regarding the best product, show off how simple it is to use, explain where the product's information comes from, and so on. Customers who have expressed interest in and involvement with such fashion events could be the target of a joint special event organised by a merchant and the firm that distributes Echo Look. For instance, by owning a store credit card, shopping more frequently, spending more money, and going to more fashion-related events than other customers, these clients have demonstrated that fashion apparel plays a big role in their lives. Customers who own a store credit card might be the target of an invitation-only event.

Finally, because customers with high fashion involvement are more inclined to try new fashion-related products and technology than customers with low fashion involvement, fashion participation would be an excellent approach for shops to find potential customers. Retailers should target high-fashion involvement clients first while marketing this unique offering. This consumer base can be contacted via public relations by reaching out to fashion innovators on social media and by using their current consumer profile (by asking them to complete a brief questionnaire) to identify individuals with greater fashion participation.

Limitations and Future Research

There are certain limitations to the current study that point to intriguing directions for further investigation. Participants in this study were drawn from India's top ten cities, which would have reduced the results' representativeness. Future studies could look

at the attitudes and intentions of both urban and rural consumers in making purchases. Furthermore, because the Echo Look was employed as a stimulus in this study and consumers had never used it before, research findings should be regarded with caution because of the rapid and constantly evolving nature of technological innovation. The study's applicability to other fashion AI products is limited by its concentration on a particular product, namely Amazon's Echo Look. Future studies can apply this present methodology to other fashion AI product categories (such as VPAs and in-store technologies) and contrast the opinions with customers' assessments after adoption.

Note

A verbatim transcript of the video that was shown to the participants is as follows:

"Alexa can help you look your best in addition to helping you with thousands of other things. "Alexa, snap this picture." Presenting the first-ever Echo with a hands-free camera, the Echo Look. Echo Look uses only your voice to capture pictures. You may take crisp, full-length pictures that are simple to share with friends thanks to its built-in lighting and depth-sensing camera, which blur the background to let your clothes stand out. Additionally, observe yourself in real time or record films to see one from all perspectives. "Alexa, record a video." Additionally, we have developed a simple method for obtaining a second opinion. Style-check is here. It blends guidance from fashion experts with the greatest machine intelligence. Simply select two looks and Style-Check will suggest outfits based on your personal preferences and current trends. You can even make your own lookbook with Alexa's assistance. It displays your attire and the time you wore it. You can therefore carry your closet with you wherever you go and keep track of your favourites.

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