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The Impact of Artificial Intelligence on Marketing in The Fashion Industry: A Study in Hai Phong City

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ABSTRACT

Artificial intelligence (AI), especially generative AI, is reshaping marketing by accelerating content creation, improving personalization, and augmenting customer-facing interactions. Yet in fashion where purchase decisions are highly visual, experiential, and sensitive to trust AI can simultaneously enhance customer experience and intensify concerns around privacy, bias, and misleading outputs. This study develops and tests a Stimulus Organism Response (S-O-R) framework to examine how AI-enabled marketing touchpoints (AI chatbots, AI-driven personalization/recommendations, and AI-powered try-on experiences) influence consumer trust and perceived value, which in turn drive purchase intention, eWOM, and loyalty in Hai Phong City. The context is timely: Hai Phong city's e-commerce market reached US$32 billion in 2024 (, and Hai Phong reports e-commerce revenue at ~16–18% of total retail and consumer service revenue, indicating a mature local digital commerce environment for studying AI marketing effects. The study proposes a cross-sectional survey design and PLS-SEM analysis to estimate direct, mediated, and moderated effects while controlling for AI literacy and prior online shopping frequency. The paper contributes by contextualizing AI marketing effectiveness in a second-tier but fast-digitizing Hai Phong cityese city and by operationalizing "AI marketing" through concrete touchpoints rather than vague "AI adoption" claims

Keywords: Artificial Intelligence (AI), Fashion; Marketing Fashion; Marketing in the fashion industry; Hai Phong city..

1. INTRODUCTION

Marketing is currently being re-engineered by AI systems that can generate content, automate customer interactions, and optimize targeting at scale. The fashion industry is a high-impact setting for AI marketing because it is visually intensive, trend-driven, and heavily reliant on customer experience yet also vulnerable to distrust (quality uncertainty, counterfeit concerns, return risk, and privacy anxiety).

The real question is not "AI có hay không" (it obviously exists), but AI creates value for whom, under what conditions, and at what cost. Generative AI can increase speed and personalization, but it also brings new failure modes hallucinations, biased recommendations, and intellectual property/ethics problems making "AI marketing" a double-edged sword.

Hai Phong city provides a strong emerging-market laboratory for this question. VECOM reports Hai Phong city e-commerce scale of 32 billion USD in 2024, with rapid growth and deep consumer penetration.

Hai Phong, a major port city and regional growth hub, reports e-commerce revenue at 16–18% of total retail and consumer service revenue above the national average figure cited in the same communication suggesting a digitally active consumer base suitable for studying AI-enabled touchpoints in fashion marketing.

Research and apply theory to build a regression model to measure the impact of artificial intelligence on Marketing in the fashion industry in Hai Phong city. The second method is a quantitative research conducted after data collection to evaluate the reliability of the scale, using multiple regression with the support of SPSS 26.0 software to re-evaluate the scale. Factor analysis, correlation analysis, and model testing and hypotheses were given earlier.

2. Literature review

2.1. Theoretical overview of artificial intelligence

Up to now, there have also been many domestic and foreign scientific researches on artificial intelligence (AI). However, to date, there is no consensus among the studies This is about AI . In department learn machine count, WHO Okay determined name to be wisdom pine bright core create, is intelligence demonstrated by machines, as opposed to natural intelligence demonstrated by humans performer. Usually, the term "artificial intelligence" is often used to describe machines (or computers) that mimic the "cognitive" functions humans associate with the mind human mind, such as "learning" and "problem solving".

Another study argues that artificial intelligence is a machine program control system count core create complex miscellaneous (bag including electricity death virtual, muscle electricity death, electricity death born learn - muscle learn or hybrid mixed) with its own or related cognitive and functional architecture (attached) required capacity and speed, possessing: (1) High level of cognitive ability; (2) The ability to improve advance, perfect; (3) The ability to self-adapt, accumulate and reproduce, emulate experience (where human experience). Larousse Dictionary defines artificial intelligence as "a collection of theories and techniques used to create machines capable of simulating intelligence of humans" (Cahier Vacances, 2018) .

From a legal perspective, many studies also aim to study the effects/impacts of AI on various fields of socio-economic life, the challenges posed and propose legal policies to regulate the issue. this topic. The publication *"WIPO Technology Trends 2019 - Artificial Intelligence"* released by the World Intellectual Property Organization (WIPO) has provided explanations and analysis based on specific data along with the assessment of experts from different angles. view of intellectual property . In it, the article *"Key issues arising from AI and policy responses"* analyzes some of the impacts brought by AI and how countries address those challenges such as: the impact of AI on employment (unemployment, reduced wages, increased inequality in society, stiff competition among countries providing cheap labor); network security issues (cyber attacks, use of AI for military purposes, increase in harmful acts on the network); data security; super intelligence (when technological intelligence surpasses human); control over AI technology (Government or private) (WIPO, 2019). Faced with such challenges that AI technology creates, governments of all countries face the problem: both to create a driving force for science and technology development, but at the same time to deal with the impacts of AI by mechanisms. , Legal policy. Some of the authors' studies refer to the legal nature of AI, the legal framework governing AI-related legal relationships .

Legal related works on AI such as author O. Yastrebov in the article with the topic "Legal Status of Artificial Intelligence Across Countries: Legislation on the Move", *European Research Studies Journal* , XXI(4) , pp.773-782 (O. Yastrebov, 2018); author Nguyen Van Quan with the article "Some impacts of artificial intelligence on the legal profession"; Faculty of Law, National University (Army, 2019); Author Nguyen Thi Que Anh and colleagues with the work "*Artificial intelligence with law and human rights*", Judicial Publishing House (Anh et al, 2019). However, at present, research works and articles under the perspective of the law on AI are not many and multidimensional.

AI is contributing to profoundly changing many aspects of life, gradually becoming one feebleness element mandarin important are not can short of the much receive area branch profession like love commercial, y economic, deliver transportation, labor in many countries... Particularly in the field of economics, the Company's research World Auditing firm PwC assesses AI as the biggest commercial opportunity for the economy The world is changing rapidly with the contribution of artificial intelligence amounting to 15,700 billion USD in 2020-2030 (Valentina Barcucci, 2020; Son et al, 2025; Toan et al, 2025) . Because of that, AI has become the focus of the race of many developed countries today now, dictionary Figure to be America and Central Country with the next plan, war comb play develop WHO with rules large tissue and pick technology WHO at the core of the acceleration of the economy. LIVE Hai Phong cityese Male, WHO are Go enter the living one way strong strong, replace position much labour job prime minister labour, history use strength labor dynamic child People. WHO Okay remind arrive day ass much and Okay see like one dynamic important force for the direction of socio-economic development of the country. The government considers AI will be disruptive technology in the next 10 years; At the same time, it is determined that this will be the "spike" needed Research has been conducted to take advantage of the opportunities brought by the industrial revolution 4.0. Upper hand department there, Main government also already build build war comb country family about industrial revolution 4.0 with job pros fairy play develop AI through many policy groups, in which, human resources are prioritized, such as AI training step grand learn, support support area area business Karma application use WHO, pros fairy head private give WHO pine via the fund, central bright innovation mind create.

2.2. The concept of Marketing Fashion

Fashion essentially involves change, defi ned as a succession of shortterm trends or fades. From this standpoint there can be fashions in almost any human activity from medical treatments to popular music. For the purpose of this book though, the concept of fashion will be taken to deal with the garments and related products and services (Mike Easey, 2009).

The competitive ethos of the fashion industry revolves around seasonality. The industry has a vested interest in developing new products for the customer at the expense of existing items: this process is known as planned obsolescence. Planned obsolescence is not confined to the fashion industry, it occurs in several other manufacturing sectors such as the electronics or automobile industries. While the concept of planned obsolescence can be appreciated from several perspectives, many customers constantly change in fashion products and services. Unfortunately, the rate and direction of change are usually slower and less predictable than the fashion industry would like.

In order for the change which is intrinsic to fashion to take place, the industry must continually create new products. Used in another sense, the term fashion means to construct, mold or make. Fashion, therefore, also involves a strong creative and design component. Design skill is essential and can be seen in all products from the made-tomeasure suit to the elaborate embroidery on a cardigan. The level of design can vary considerably from a basic item such as a T-shirt to the artistic creations of Coco Chanel, Christian Dior, Yves St Laurent or, in more recent times, Stella McCartney. To some the design of fashion garments can be viewed as an art in its own right, though this is a notion supported more in countries such as France and Italy than in Britain. The majority of garments sold do not come into this category, but the inspiration for the design of many of those garments may have come from works of art (Tony, 2007).

Fashion marketing is the application of a range of techniques and a business philosophy that centers upon the customer and potential customer of clothing and related products and services in order to meet the longterm goals of the organization. It is a major argument of this book that fashion marketing is different from many other areas of marketing. The very nature of fashion, where change is intrinsic, gives different emphasis to marketing activities. Furthermore, the role of design in both leading and reflecting consumer demand.

2.3. Personalization in Marketing Fashion

One of the key aspects in fashion is personalization. So personalization is basically something that is intended for a certain individual based on their likes and dislikes and what they cater as good for them. And we know that fashion industry included e-commerce worldwide is supposed to hit the 35 billion dollars Mark by 2020 this year and there's a need for applications which can help the user in making Intelligent Decisions on their day-to-day purchases or a system that can recommend them a model or something that is personalized to their liking.

So for this purpose the use of deep neural networks for this challenge is needed and we are going to discuss one of a system that is dubbed as FashionNet (Tong He, 2018) that consists of basically two components: a feature Network for the feature extraction function and a matching Network for the compatibility computation. The former one is achieved through a deep convolutional Network and the second one for that they adopt a multi-layered fully connected Network structure and design, and compare the three alternative architectures for FashionNet and to achieve personalized recommendations, what they do is that they develop a two stage training strategy, which uses the fine-tuning technique to sort of transfer a general compatibility model to the model that embeds personal preference.

This specific paper explores the deep use of neural networks for outfit recommendation and specifically for the personalized outfit recommendation. Now for this they encounter two key problems. The first one was modeling of the compatibility among multiple fashion items and obviously the second one was capturing users personal interest (Ken, 2014).

So for that the former one was solved by first mapping the item images to a latent semantic space with convolutional neural network and for the second one they adopt a multi-layer fully-connected network structure. And they also studied alternative architectures that combine feature learning and compatibility modeling (Alex Krizhevsky, et al. 2012). Different ways for the other problem. What they do is that they encode user-specific information in terms of parameters of the network. Although we know that each user may have his own unique personal taste and they follow some general rules for making outfits. But besides that the usual small number of training samples for individual users makes it very much important to borrow training data from other users that share similar tastes. Compare with these observations in mind, what they do is that they adopt a two-stage strategy for the training of their model network; the first stage basically learns a general compatibility model from outfits of users. And in the later stage, what they do is that they fine-tune the general model with the specific data that they get from the user in fine-tuning. It is an important technique for training deep neural networks for applications that have limited number of training samples.

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So in their approach they basically assume that heterogeneous fashion items can be grouped into n categories. Let's take an example where the three most social categories for fashion are usually shoes, tops and bottoms and outfit is a collection of fashion items which are usually coming from different categories. So an outfit can consist of a bottom, top and a pair of shoes. So given some historical data what they did that for any user outfit pair they pretty much assigned a rating score as the score kind of reflected the level of affection the user has for the outfit. So the higher the score then obviously the more appealing the outfit is for the users and those outfits that had the highest score were recommended to the users. So basically the rating system was used and the rating for a user outfit pair is determined by how well the items in the outfit go with each other (Christian Szegedy, 2015). So if you know a pair of red shirts and you know, let's say black slacks or tight jeans and maybe they go well instead of, you know, something with a yellow skirt and red shirt. So we generally see the author's design appropriate deep neural network structure to model the interactions among these items and they achieve Personalization by developing a two-stage training strategy and embed the user specific preferences in the parameter of the network.

2.4. Technology-based fashion marketing

In the fashion industry, the increasing use of TBS models has played an important role. The relationship between service innovation and intention to adopt through co-creation has been reported several times (Cappetta, Cillo & Ponti, 2006).

The TBS model has five basic constructs: customer willingness to co-create (WCC), customer intention to accept (AI), individual differentiation, and consumer innovation (INNO).) and control variables (Bagdoniene & Valkauskiene, 2016; Heidenreich & Handrich, 2015). The extensive literature review reports that there are five main psychographics commonly considered under the TBS model: customer trust (CI), customer engagement (INV), customer needs for interaction (INTER), customer willingness to co-create (WCC), and customer adoption intent (AI).

3. Research model

To understand the intention to adopt hyper-personalization through digital customers in the fashion industry, the present study proposed a conceptual framework based on the hypothetical factors proposed below. In the recommendation model, the extended TBRA represents the customer's intention to accept in a personalized way.

The researchers used three main structures from the TBS model (Heidenreich & Handrich, 2015) namely INNO, WCC and AI; perceptions, attitudes, subjective norms, and intentions to apply. In addition to the structures from the TBS model, the structures of TRA and the structures representing the preformal char, i.e. INVO, are also included in the assimilation process. Despite this, various published studies have shown the benefits of co-creation from different futures (Chen & Wang, 2016; Kamboj & Gupta, 2020; Sahi, Sehgal, & Sharma, 2017; Zaborek & Mazur, 2019), this type of profiling study is crucial to understand the importance of the concept of co-creation with hyper-personalization using customer digitalization using customer data in the fashion industry.

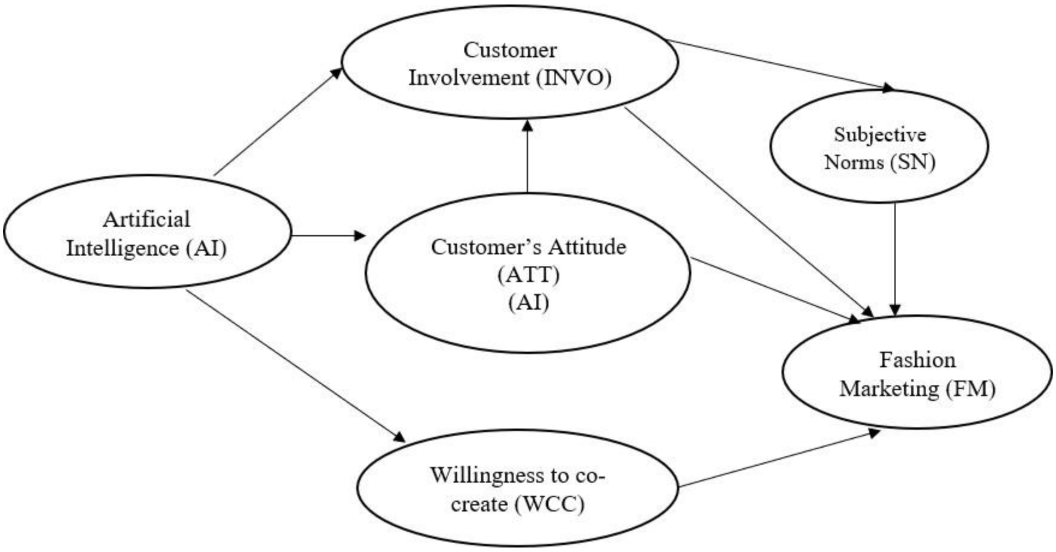

Fig 1: Research model of the impact of AI on fashion marketing

(Source: compiled by Author)

4. Research hypotheses

Artificial Intelligence (AI) with Customer Engagement (INVO)

Artificial intelligence will promote customer participation in improving product quality; artificial intelligence will make customer engagement faster, earlier than traditional information collection channels (Geetika Jain, 2024), It is the trend that an individual adopts technology products new in the past more often than in others and more often (Rogers, 2003; Sahin, 2006). Fashion innovation is an important factor that plays an important role in adoption intention and it leads to adoption of new fashion products (Jordaan & Simpson, 2006; Rahman et al., 2014). . Previous studies demonstrate that in the fashion industry, an individual with innovative behavior is inevitably inclined to use new technologies that establish a link between engagement and innovation (Cardoso, Costa., & Novais, 2010; Rahman et al., 2014)

H1: Artificial intelligence has a positive impact on customer engagement.

Customer Engagement (INVO) with Fashion Marketing (FM)

Consumer involvement is the degree to which an individual is involved in various tasks such as creating, producing, and providing fashion services. Innovation is the degree to which an individual adopts innovation earlier than other partners in the system; the term "earlier than others" means that the time of adoption is relatively earlier than others in terms of an individual's perception of system adoption (Rogers & Shoemaker, 1971; Rogers, 2003). It is the tendency that an individual uses new technology products and services in the past more often than others and more frequently (Rogers, 2003). Fashion innovation is considered to be an important factor that plays an important role in adoption intentions and it leads to the adoption of new fashion products (Jordaan & Simpson, 2006; Rahman et al., 2014).

H2: Customer participation has a positive impact on fashion marketing results.

Artificial Intelligence (AI) with ready co-creation (WCC)

To jointly create innovative solutions, it is important that artificial intelligence has a fast and effective impact on personalized fashion design; A very high level of customer involvement is also required to design personalized services because of an individual's quality time, just as resources are required to develop such a service (Fernandes & Remelhe ., 2016; Rodie & Kleine, 2000).

H3: Artificial intelligence positively impacts co-creation willingness

Artificial Intelligence (AI) with Customer Attitude (ATT)

According to the theory of rational action (TRA) (Ajzen & Fishbein, 1980; Davis, 1993), an individual's attitude plays an important role in determining an individual's behavioral beliefs about the use of science and technology applications and their intention to apply. Attitudes have a great impact on consumer participation while evaluating different criteria and cumulatively lead to a change in intention to apply for personalized local apparel in case customers use Use trendy trends.

H4: *Artificial intelligence will have a positive impact on customer attitudes*

H5a: Attitude of fashion customers is positively related to the effectiveness of fashion marketing activities.

H5b: Fashion customer attitudes are positively related to customer engagement using customer digitalization for hyper-personalization.

Personalization, Subjective Standards (SN) Affect Fashion Marketing (MF)

According to Ajzen & Fishbein, 1989, subjective norms have been considered as an important factor while studying an individual's behavioral intentions. An individual has a high influence of social norms on his/her behavioral intentions, which influence one's behavior and change an individual's perception of his/her immediate people. him (e.g. friends, family, relatives, colleagues and reference groups) (Schofield, 1975). An individual's behavioral intentions change as a result of direct social feedback (Barki & Hartwick, 1994; Burnkrant & Cous ineau, 1975). Young customers tend to be highly attracted to personalized and unique fashion products as they are more likely to be involved in knowing the latest trends and being influenced by friends and colleagues leading them. to the intention to apply new technology; Their individualistic personality is also consistent with this behavior (Wolburg & Pokrywczynski, 2001).

H6: Personalization and subjective standards negatively affect fashion marketing

5. Research Methods

5.1. Data

In this study, respondents were selected mainly on the basis of their experience their previous online shopping experience for a period of four to five month and use the custom feature for fashion products when shopping online. Hai Phong city with a population of nearly 100 million people by the end of 2025, with a diverse population structure and consumers' experiences when shopping online and their understanding when asked about the influence of AI on fashion marketing difference.

Experimental research phase: the authors conducted a small sample size (n=50), consisting of young graduate students who had shopped online in the last month to order customized products or services. correction. Primarily, there was an age screening method that was applied because we were referring to the age limit of the respondents, i.e. 18-44 years old (this age group includes a very selective population according to ability to use technology for procurement purposes), the value of the reliability index is said to be satisfactory.

Formal research phase: the author team conducted a large sample of 580 people by means of an online survey during the period from March to April 2025. The number of respondents was 487 people, with information Details in the table below:

Table 1: Descriptive statistics of the survey sample

TT	Criteria	Frequency	Ratio (%)
I	**Gender**	**487**	**100**
1	Male	213	43.74
2	Female	274	56.26
II	**Age (year)**	**487**	**100**
1	18-24	178	36.55
2	25-34	203	41.68
3	35-44	85	17.45
4	Over 44	21	4.31
III	**Education**	**487**	**100**
1	Common	9	1.85
2	Intermediate degree	68	13.96
3	College degree	267	54.83
4	University degree or higher	143	29.36
IV	**Job**	**487**	**100**
1	Service	232	47.64
2	Businessmen	70	14.37
3	Self-employed	44	9.03
4	Student	118	24.23
5	Housewife	23	4.72
V	**Personal income 1 year (USD)**	**487**	**100**
1	Under 1,000	62	12.73
2	1,000 - 3,000	87	17.86
3	3,000-5,000	130	26.69

TT	Criteria	Frequency	Ratio (%)
4	Over 5,000	208	42.71
VI	**Frequency of online shopping 1 year**	**487**	**100**
1	Less than 3 times	46	9.45
2	4-5 times	76	15.61
3	6-8 times	60	12.32
4	9-10 times	93	19.10
5	More than 10 times	212	43.53
VII	**Personal perception of AI impacting fashion**	**487**	**100**
1	Yes	454	93.22
2	No	33	6.78
VIII	**Online personalized fashion products shopping frequency (Per year)**	**487**	**100**
1	Newer	81	16.63
2	Hardly once or twice	205	42.09
3	Sometimes	97	19.92
4	Often	60	12.32
5	regularly	44	9.03

(Source: Author's survey and calculation results in 2025)

5.2. The scale

Based on the theoretical conceptual framework defined in Figure 1, and showing the relationships among the six main structures shown such as AI, INNO, INVO, WCC, ATT, SN and MF. To analyze stated relationships for different progenitors, entries for stated factors were adjusted from different studies. All items for different endogenous and exogenous variables are measured on a 7-point Likert scale, where 1: strongly disagree; 2: strongly disagree; 3; Disagree; 4: puzzled; 5: partial consent; 6: quite agree and 7: completely agree.

The factors have been measured in the study using a self-reporting scale for different items from various fashion-related studies, but there is a chance of bias that will reflect in the results. To overcome such issues, different statistical methods have been used in the present study (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

After measuring the relationship between the dependent and independent variables, the measurement scale has been placed in the initial section for independent variables and later for dependent variables (Hair et al., 1998).

6. Research results

6.1. Response rate, variance, standard deviation

To test the response rate, the authors conducted independent tests on the original data sample. The test is divided into 2 phases where late responses are considered similar to zero responses. Finally, all the responses that were collected were divided into two groups: early responders and late respondents (Kamble, Gunasekaran, & Dhone, 2020) . In the present study, during the first 4 weeks, we collected 147 responses that were considered early responses and the remaining 340 responses were collected as late responses. Then, for all the last 20 items, Harman's single factor test (Podsakoff et al., 2003), was performed to test for common method variance in the data and, subsequently, analysis. exploratory factors were used (with PCA, CA and varimax rotation with respect to the major axis). Using this analysis, the level of variance was explained in detail and the results indicated that the eigenvalues for all factors were found to be more than 1.0 (Hair et al, 1998). All of the major factors studied in this paper were found to have more than 55% of the variance, although there was about 25% of the variance unanswered. Therefore, no elements are removed. Notably, a large number of studies still use this method and it can be an addition to this method, we also used the marker variable method in our study and it represents clearly a relatively insignificant relationship between the original research model and the applied variable model.

6.2. Measurement model and reliability analysis

From the analytical framework built in Figure 1, the authors use structural modeling (SEM) Analysis was performed on the main data and each item of the structure shows the minimum acceptable limit of the index reliability 0.70. Therefore, all questionnaire structures are satisfactory with an index above 0.75 and are given in table 2.

Table 2. Measurement model indices

Items/ Variables	Standardized itemloading	Variance extracted	Composite Construct reliability
AI1	0.72	0.682	0.823
AI2	0.84		
AI3	0.76		
AI4	0.77		
INVO1	0.81	0.614	0.786
INVO2	0.70		
INVO3	0.77		
INVO4	0.73		
WCC1	0.75	0.735	0.872
WCC2	0.86		
WCC3	0.73		

ATT1	0.69	0.721	0.773
ATT2	0.73		
ATT3	0.76		
SN1	0.79	0.696	0.835
SN2	0.82		
SN3	0.83		
MF1	0.86	0.784	0.847
MF2	0.84		
MF3	0.78		

(Source: Author's calculation results, in 2025)

6.3 . Convergence analysis of data

According to the results of exploratory factor analysis, the convergence value is tested based on factor loading and correlation matrix analysis given in Table 3, the discriminant and convergent values of the questionnaire are shown. and it meets the requirements. in nature. Reliability and validity were evaluated by estimating the values of Cronbach's alpha, composite reliability, and extracted mean variance (AVE). The extracted mean variance (AVE) was found to be within the acceptable range and all values were higher than 0.5 (Baron & Kenny, 1986). The value of the extracted mean variance was found to be higher for all constructs than the coorelation coefficient indicating instrument validity. There are items that have been removed due to low factor load values during the validity of the scale according to exploratory factor analysis.

Table 3. Correlation matrix - between constructs

Constructs	WHO	INVO	WCC	AT	SN	MF
WHO	0.812*					
INVO	0.412	0.832*				
WCC	0.385	0.523	0.849 *			
AT	0.366	0.309	0.281	0.762*		
SN	0.369	0.231	0.331	0.333	0.711 *	
MF	0.268	0.519	0.264	0.251	0.239	0.864*

(Source: Author's calculation results, in 2025)

6.4. Structural model analysis

SEM was performed on the data followed by the measurement model, and all seven measures of the evaluated model are given in Table 4 and considered below acceptable (Gefen, Straub, & Boudreau, 2000). The results show that the conceptual model, which is structured, has a good overall fit and the responses are consistent with the proposed model stated.

Table 4. Measurement model - Goodness of fit indices

Goodness of fit index	Model fit result
Chi square	**565.9 (p = 0.00 < 0.05)**
CMIN/df	**1,162 (< 3.0)**
RMSEA	**0.045 (< 0.05)**
CFI	**0.971 (> 0.9)**
GFI	**0.919 (> 0.9)**
AGFI	**0.889 (<0.9)**
NFI	**0.934 (> 0.9)**

(Source: Author's calculation results, in 2025)

SEM analysis was analyzed to find out the effects of different paths according to the theoretical framework built in Figure 1 above, and the values of the t-test coefficients for the respective relationships were described. described below. All theorized relationships according to the conceptual framework were found to be intrinsically significant with the exception of the relationship between subjective norms and intention to apply (H6) and the relationship between attitude and intention to apply (H5a).

Customer innovation (Rahman et al., 2014) and willingness to co-create (Heidenreich & Handrich, 2015) emerged as important factors influencing individual engagement (Rahman et al. , 2014), and in turn, has a positive effect on intention to adopt. Therefore, the results indicate a positive hypothetical relationship between the factors mentioned above. In addition, if an individual is offered a number of innovative solutions, they are more likely to demonstrate a willingness to co-create, leading to adoption intent.

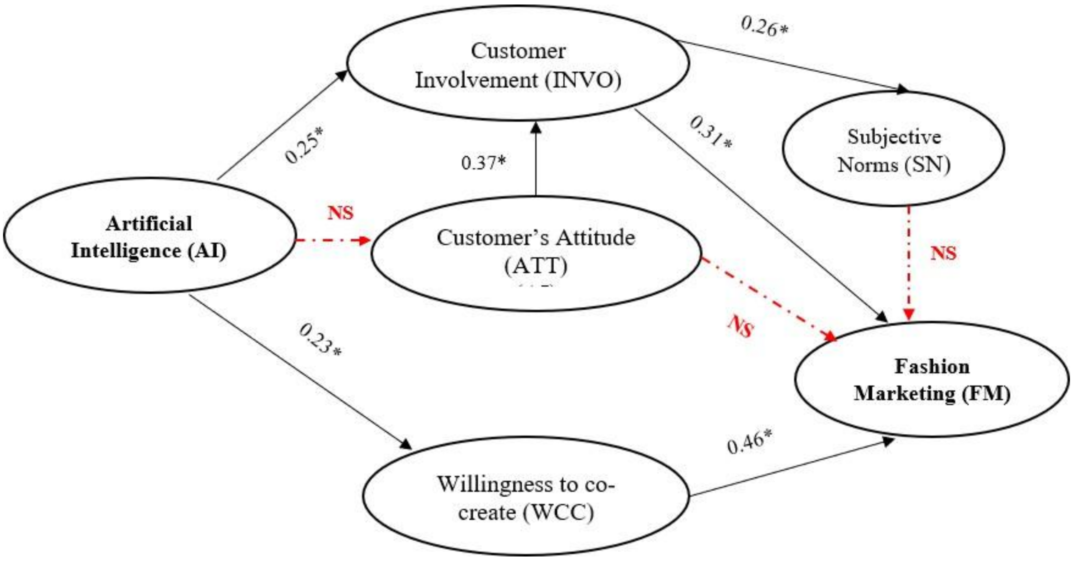

Fig 2: Research results on the model of the impact of AI on Marketing Fashion

(Source: compiled by Author)

6.5. Discussing research results

According to the results of data analysis, five factors were used to show the intention to accept influence on the results and effectiveness of fashion marketing, which are artificial intelligence, innovation, participation, and collaboration. creativity, attitudes, and subjective norms. Various reproduction relationships, hypothesized in the conceptual model, were tested and the results were as follows: if an individual innovates then they will engage in personalization (H1; β = 0.25, p = 0.00). The relationship between customers related to intention and intention to accept (H2; β = 0.31, p = 0.00) is also found to be significant and it implies that if an individual participates in involved in the personalization process, they will intend to apply to jointly create directions towards the personalization of fashion products. It implies that, based on the level of participation (high or low), an individual's intention to shop for fashion will be changed. Furthermore, the findings indicate that there is a positive correlation between innovation and willingness to co-create (H3; β = 0.23, p = 0.00), which implies that if an individual Individuals with innovative behavior are more likely to be a co-creator of personalized solutions leading to positive adoption intentions (H4; β = 0.46, p = 0.00) to individual fashion products. Another finding of the study was that attitude had a significant relationship with participation (H5b; β = 0.37, p = 0.00) but not intended to apply (H5a; β = 0.12 , p = 0.05). It implies that an individual's attitude can be related to personalization, but that attitude will not directly affect the intention to apply for personalization. Mainly because a person will have the intention to shop for a fashion product when they engage in the personalization process and develop the confidence to intend to shop. Similarly, subjective indicators also have a positive relationship with customer participation (H6; β = 0.26, p = 0.00). In the event that a person is not involved in the personalization process, he or she will not demonstrate an intention to apply for personalization through co-creation.

This study contributes to the understanding of the role of AI in engaging customers to develop innovative services based on their preferences and shop for fashion products. This has been largely overlooked in previous studies. This research will benefit companies that are trying to use AI to collect customer information in co-creating innovative services with customers and providing personalized services that are promising. better be accepted by customers and intend to use fashion products, thereby improving the effectiveness of fashion marketing products to customers in the fastest and most effective way. From the companies point of view, the customer emerges as an important aspect and plays an active role in the creation of innovative services. Therefore, this study also appreciates how customers can understand their expectations and requirements through customer engagement and co-creation of fashion services. The study contributes empirically to the discussion attesting to the role of customers and businesses in relation to customer engagement in fashion marketing and the creation of customer-centric innovation services.

7. Conclusion

The objective of this study is to provide a theoretical basis and a practical survey on the influence of AI on fashion marketing in Hai Phong city. The authors confirm that customer co-creation of innovative service solutions is influenced by customer digitalization and is driven by customer innovation, attitude, willingness to co-create and participation. Our research is the basis for forming the concept of co-creation of service innovation solutions in the fashion industry. The fashion industry can provide healthy, creative and superior services when the services/products are being co-created with customer engagement and innovation, thus achieving effective management. inventory management and balance supply and demand with sales and performance. This study explores how customers can co-create with companies and what companies should do in providing personalized services. This will add to our understanding of how companies can apply technology to increase the likelihood of customer adoption of innovative services. In this study, customers play an important role in creating innovative services as they are integrated as active partners through the application of AI to collect customer information. order for fashion businesses to offer the most satisfactory products and the best fashion services to customers in Hai Phong city

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