

# Actual Usage Behavior Toward Generative AI-Based Fashion Shopping Platforms (GAIFSP) : Perspectives from DeLone and McLean's Information Systems Success Model

Debarun Chakraborty<sup>1</sup>

## Abstract

**Purpose :** This study focused on actual use behavior towards Generative AI-based Fashion Shopping Platforms (GAIFSP), intention to use, and factors influencing it by adopting the DeLone and McLean information systems success model as the theoretical foundation. The specific research objectives were to investigate the relationship of system quality, information quality, and service quality with users' intention to know and actual use of the systems.

**Methodology :** The research used a descriptive research design and a purposive sampling technique. A total of 440 respondents responded to the questionnaire.

**Findings :** People who were systematic and had high standards for the system design with effectiveness and accuracy in the information received were likely to have strong engagement with the platform. Unlike other types of innovative products, though, the habit of GAIFSP did not moderate the relation between intention and actual use; this could be attributed to the fact that GAIFSP was a new product.

**Implications :** Building on the theory, the study further included the introduction of the DeLone and McLean model to understand generative AI. It also has managerial implications for platform design, user assistance, and strategies aimed at user retention.

**Originality :** It provided a deeper understanding of the role of generative AI in achieving sustainable approaches.

**Keywords :** GAIFSP, DeLone and McLean IS success model, habit, actual use

**Paper Submission Date :** June 15, 2024 ; **Paper sent back for Revision :** October 15, 2024 ; **Paper Acceptance Date :** October 25, 2024 ; **Paper Published Online :** January 15, 2025

Online shopping has recently been taken to a completely different level with the help of large language models that rely on artificial intelligence (AI) technology (Chen et al., 2024). At the same time, various branding architectures have been brought forth, such as Amazon, Apple, and Google, which are AI-based shops that offer their users a distinctive shopping experience through enhanced personalization (Raut et al., 2025). An individual shopping journey experience is invented and perfected because of their past purchases and the potential to try or recommend different options when presented in a video format (Chakraborty & Dash, 2022; Huang et al., 2009). They can help create various products combined with AR/VR technologies, allowing the customer to see the outfit first-hand without trying it on (Alanadoly et al., 2024). In addition, they can predict and design novelty garments or patterns fitting the current market, allowing industries to introduce novel solutions and keep pace with the ever-changing marketplace (Babu et al., 2024).

The relevance of these platforms stems from the ability to integrate physical and virtual shopping (Sharma et al., 2022; Xi & Hamari, 2021). These enhance convenience and personalization, enhancing users'

---

<sup>1</sup> Associate Professor, Indian Institute Management Nagpur (IIM Nagpur), Plot No 1, Sector 20, MIHAN (Non-SEZ), Nagpur - 441 108, Maharashtra. (Email : [debarun84@gmail.com](mailto:debarun84@gmail.com)) ; ORCID iD : <https://orcid.org/0000-0002-0754-1120>

experiences and decreasing return rates, an area of concern in the fashion sector (McCormick et al., 2014; Murthy & Kumar, 2015). For the sponsors, these platforms improve supply chain management by anticipating demand and preventing overproduction through trend forecasts (Davies et al., 2024; Kumar & Singh, 2022). Oriented toward sustainable development, generative AI assists in producing digital samples, hence less environmental damage during the traditional sampling phase (Ma et al., 2024). Additionally, by offering unique sizes and styles, these platforms promote diversity, thus appealing to a larger group of customers and resulting in a more interesting and inclusive shopping experience (Naylor et al., 2012).

Even though generative AI-powered shopping platforms are getting widespread use, their success has not been evaluated using any theoretical framework such as the DeLone and McLean (D&M) information systems success model. As much as generative AI adds value to customer AI recommendations, virtual fitting, and predicting trends, previous research has largely revolved around technology or consumer adoption. Still, many success measures concerning this context, such as system quality, information quality, service quality, user use and satisfaction, and net benefits, have not been extensively studied. Also, the extent to which these platforms enhance user trust, influence user decisions, and overall long-term shopping experience has not been satisfactorily researched. This creates an essential deficiency in knowledge of how generative AI technologies respond to the success factors proposed in the D&M model. From here, two research questions are coming out:

✦ **RQ1 :** What are the effects of system, information, and service quality on intention to use and actual use in generative AI-based fashion shopping platforms (GAIFSP)?

✦ **RQ2 :** What are the moderating effects of habit intention to use and actual use in GAIFSP?

This study makes an academic and practical contribution by introducing the D&M IS success model and discussing the effectiveness of GAIFSP. The investigation takes a step further and uses the D&M IS success model to evaluate AI-driven applications, determining the role of system, information, and service quality on user satisfaction and the platform's overall success. From a practical standpoint, the research offers practical suggestions to fashion retailers, as well as designers of the platforms, to improve the experience of the users, enable confidence creation, and attain maximum net benefits for the consumers, the businesses, and the two actors. Third, it provides a deeper understanding of the role of generative AI in achieving sustainable approaches, enhancing the aspects of personalization, overcoming fundamental challenges of the sphere, including losses and decision-making of the consumers, and, thus, facilitating advances in innovation and competitiveness in the field of digital fashion.

## Background Literature

### *DeLone and McLean's Information Systems Success Model*

The D&M IS success model has gained wide application in understanding and assessing technology adoption in various contexts (Aldholay et al., 2018). This model integrates fundamental aspects such as system, information, and service quality to show the relationships between these dimensions and user satisfaction, system use, and net benefits from using the technology (Petter et al., 2008). For example, when emerging technologies such as generative AI-based platforms are being adopted, the model helps assess the level of users' acceptance by examining the system's attributes, information, and ease of use (Çelik & Ayaz, 2022). Moreover, the implementation focus means satisfaction from users and use engagement, which are critical aspects relating to the continued use of the technology (Kim et al., 2013). The net benefits dimension further helps link technology adoption to practical benefits, including improved efficiency, better decision-making, and organizational growth

(Petter et al., 2008). Therefore, the D&M IS success model has effectively evaluated diverse technologies (Petter et al., 2008). It suggests that it is both holistic and integrative since it does not only focus on individual aspects of technology utilization or penetration (Jasperson et al., 2005).

### ***Generative AI-based Fashion Shopping Platforms (GAIFSP)***

Recent advances in GAIFSP are changing the e-commerce paradigm as these AI-powered technologies are used to build more interactive and personalized online shopping experiences (Deng et al., 2024). These platforms use generative technologies to develop virtual fitting rooms, outfit recommendations, and personalized clothing designs for the user (Yan et al., 2022). Use cases include virtual fitting rooms, where users see how clothes would look and fit without putting them on in real life, and style recommendations, where AI recommends clothes to wear based on fashion trends and the person's personal information (Alanadoly et al., 2024). Retailers also use generative AI for demand forecasting, inventory management, and cutting down returns by informing buyers and helping to make wise spending decisions (Gupta & Mukherjee, 2024). Such platforms also play an important role in sustainability (Choi et al., 2023). In addition, these platforms help promote sustainability by facilitating digital profiling that reduces fabric waste as well as encouraging inclusive fashion through diversity and custom-made designs (Alanadoly et al., 2024). GAIFSP improves how people and businesses interact with the digital fashion industry by allowing higher levels of convenience, customization, and effectiveness (Gupta & Mukherjee, 2024).

## **Development of Hypothesis**

### ***Information Quality***

The high-quality information is accurate, relevant, complete, and up-to-date, instilling trust and confidence within the system and making it even more appealing for users to work with (Nicolaou et al., 2013). Platforms such as generative AI-based fashion shopping systems encompass providing accurate product descriptions, personalized recommendations, and eye-catching visuals to users to reduce the information gap and improve the decision-making process (Gorla et al., 2010). People tend to adopt new systems and continue to utilize them over time when the information they are provided is relevant and has credibility as it is an aligned behavior through systems like the technology acceptance model (Chau & Hu, 2002). Therefore, better information quality becomes one of the strongest arguments that further emphasizes organizational and technological use (Gorla et al., 2010).

➤ **H1** : Information quality has a positive impact on the intention to use.

### ***System Quality***

Past studies have shown the importance of system quality over the intention to use information systems, as system quality involves the system's technical characteristics, performance, functions, and ease of use (Gorla et al., 2010). The information provided by the work of systems has shown that system quality can be perceived as attributes such as reliability, ease of use, and security to positively influence user satisfaction and perception of usefulness, which again enhances intention to use (Gorla et al., 2010). The system quality, design, and seamless performance of the mobile applications significantly contributed to the user adoption of the mobile applications (Fang et al., 2017). Similarly, regarding e-commerce platforms, users are more willing to use systems that are well-integrated, responsive, and free of errors (Martínez-López et al., 2020). In advanced technologies such as generative AI-based platforms, the high system quality assists in providing adequate support of the complex system features such as virtual try-by-one or real-time recommendations, thus minimizing user irritation and

fostering further use (Andreoni et al., 2024). Nevertheless, such a gap requires further attention in studies investigating the relationship between the system quality and intention to use in the new generation of integrative domains of AI-based platforms and smart technologies (Pan et al., 2019).

➤ **H2** : System quality has a positive impact on the intention to use.

### ***Service Quality***

Service quality, which consists of customer service, availability of assistance resources, and the quality of the interaction itself, has been associated with increased satisfaction and the intention to use the technology systems (Gorla et al., 2010). High service quality builds user's trust in the system, thus encouraging more use and usage (Sharma & Sharma, 2019). In the case of online services, consumers are likely to accept the systems if they feel acknowledged and appreciated through attentive service (Gorry & Westbrook, 2011). For instance, for the GAIFSP, service quality is important for inquiring about technical support, helping customers with virtual try-ons, and solving issues related to customized recommendations (Gupta & Mukherjee, 2024). When customers get timely, accurate, and reassuring assistance, they are more likely to trust the system and aspire to use it in the future (Negash et al., 2003). The effect of service quality on the intention to use in new digital environments, particularly the ones powered by AI, is a phenomenon that requires more study (Gursoy et al., 2019).

➤ **H3** : Service quality has a positive impact on the intention to use.

### ***Intention to Use***

According to the technology acceptance model and the DeLone and McLean Information Systems Success Model, intention to use, which is affected by, among other things, perceived ease of use and perceived usefulness, tends to be a strong predictor of actual use (Aldholay et al., 2018). A user who intends to use technology has a positive probability of actual use, especially if the system and service are of good quality (Chakraborty & Altekar, 2021). In the same context, users with high intentions to use a system because of good interactions are likelier to use it in the future (Chakraborty, 2018; Chakraborty, 2021). In the case of Generative AI-assisted fashion shopping platforms, it is reported that users who declare an intention to use the platform because of its personalized features, such as virtual try-ons or AI recommendations, are more likely to purchase or interact with the platform frequently (Pappas et al., 2023). On the other hand, several studies also note that use intention has certain moderators, such as the system's reliability or the quality of user experience, which seem to determine its realization (Dash et al., 2022; Dash et al., 2023; Pahari et al., 2023). It is essential to undertake more in-depth studies in the future to explain the emerging pattern between intention and the eventual use of technology, particularly sophisticated technologies such as AI platforms (Yan et al., 2021).

➤ **H4** : Intention to use has a positive impact on actual use.

### ***Habit as a Moderator***

A habit, generally considered as recalling and executing the same routine actions on a system, may develop through repeated usage, shifting the consideration to its more automatic use (Chopdar et al., 2023). It suggests that habit operates as a mediator between intention and the use of the actual system; more habitual behavior, on the other hand, increases actual usage irrespective of strong intention to use (Venkatesh et al., 2023). Furthermore, the intention to use or perform some action with a system or a device is understood to be the primary enabler in the first interaction with a device (Cenfetelli, 2004). Still, a habit may override the user's intention to continue operating

the system over time. With regard to generative AI-based fashion shopping platforms, users who perform tasks such as virtual try-ons, personalization, and AI-based trend forecasts regularly will tend to use these platforms, which, in turn, will boost engagement levels (Gupta & Mukherjee, 2024). Therefore, although the intention to use to some extent affords adoption to some users at the early stages, the latter portion of usage would witness the central role played by the platform's usage in the discussions (Sinclair & Aho, 2018). These findings raise the question for further studies to undertake what interactions exist between these constructs, particularly those that concern emerging technologies such as AI platforms, and how these adopted habits can affect users' retention, usage frequency, and loyalty (Lee & Chen, 2022).

⇒ **H5**: Habit is moderating the association between intention to use and actual use.

## Methodology

The study's research hypothesis, as shown in Figure 1, is that the quality of information, systems, and services influences both the intention to use and the actualization of use behavior. The constructs used in the study were drawn from literature and were established scales, but their statements were modified to suit the present study. A 5-point Likert scale was used to evaluate the constructs. For each of the factors studied, indicators are listed in Table 2.

The participants are respondents from different regions of India who know (GAIFSP). A purposive sampling technique was adopted to select the participants. Observations of responses incorporated in questionnaires were with the use of a 5-point Likert scale. Analysis based on moderation of the variable habit has been undertaken, and the analysis is presented in Smart PLS version 4.0.

For data analysis, structural equation modeling using partial least squares was used to measure and evaluate the model and the hypotheses (PLS-SEM). Favoring structured questionnaires and purposive sampling, the online data were collected from different regions within India. This has led to sending prepared questionnaires to 43 managers and academicians for their responses regarding the appropriateness of the questions. After receiving this confirmation, the final questionnaire was forwarded to the intended respondent. The questionnaire was designed on Google Forms, and the link was sent to the respondents through WhatsApp, Email, Facebook, and LinkedIn pages. A total of 1,689 questionnaires have been distributed online. At the outset, the researchers asked the potential respondents certain questions.

⇒ **RQ1**: Have you heard of any GAIFSP?

⇒ **RQ2**: Are you making purchases on GAIFSP?

If yes is the answer to every query, the survey participants may proceed to answer the final questions of this survey. From January 2024 to April 2024, the researcher conducted this study with 440 respondents in India.

Every question statement in the survey was also examined for relevancy and accuracy, while the participants' responses were put on a scale ranging from *strongly disagree* to *agree strongly*. The authors indicated some demographic characteristics of the study, which are presented in Table 1 and may help better understand how some groups of respondents assess their perceptions and behaviors toward the GAIFSP. Table 1 illustrates the demographic profile of the participants.

**Table 1. Demographic Measures**

| Demographic Measures | Category           | Frequency (n = 440) | Percentage |
|----------------------|--------------------|---------------------|------------|
| Age                  | Age below 26 years | 128                 | 29.09%     |
|                      | 26 – 36 years      | 133                 | 30.23%     |

|                |                      |     |        |
|----------------|----------------------|-----|--------|
|                | 37 – 47 years        | 95  | 21.59% |
|                | 48 – 58 years        | 66  | 15.00% |
|                | Age above 58 years   | 18  | 4.09%  |
|                | Gender               |     |        |
|                | Male                 | 257 | 58.41% |
|                | Female               | 183 | 41.59% |
| Monthly Income | Less than INR 60,000 | 186 | 42.27% |
|                | USD 60,001 – 120,000 | 170 | 38.64% |
|                | USD 120,001 and more | 84  | 19.09% |

## Analysis and Results

The GAIFSP's actual usage as the dependent variable with several other manipulable constructs was tested using Smart PLS in PLS-SEM. The data preparation process precedes the model testing, in which several requirements are inspected, and data is transformed if needed. The normality was confirmed with the skewness and kurtosis standing at  $\pm 3$ . The common bias method (CMB) was calculated to confirm the data's effectiveness, and the factors statistically proved to explain less than 50% of the total variance, suggesting no major concerns about CMB. The degree of multicollinearity was assessed using the variance inflation factor (VIF), and it was determined that these

**Table 2. Factors with Sources and Loadings**

| Constructs                       | Item Nos. | Items                                                       | Sources                    | Factor Loadings |
|----------------------------------|-----------|-------------------------------------------------------------|----------------------------|-----------------|
| <b>Information Quality (INQ)</b> | INQ1      | GAIFSP provides me with information relevant to my needs.   | (Singu &                   | 0.949           |
|                                  | INQ2      | GAIFSP provides me with sufficient information.             | Chakraborty, 2022)         | 0.938           |
|                                  | INQ3      | GAIFSP provides me with accurate information.               |                            | 0.918           |
|                                  | INQ4      | GAIFSP provides me with up-to-date information.             |                            | 0.875           |
| <b>Service Quality (SEQ)</b>     | SEQ1      | GAIFSP provides on-time services.                           | (Singu &                   | 0.906           |
|                                  | SEQ2      | GAIFSP provides prompt responses.                           | Chakraborty, 2022)         | 0.9             |
|                                  | SEQ3      | GAIFSP provides professional services.                      |                            | 0.845           |
|                                  | SEQ4      | GAIFSP provides personalized services.                      |                            | 0.864           |
| <b>System Quality (SMQ)</b>      | SMQ1      | GAIFSP provides easy access to information.                 | (Singu &                   | 0.895           |
|                                  | SMQ2      | GAIFSP provides a fast response and transaction processing. | Chakraborty, 2022)         | 0.896           |
|                                  | SMQ3      | GAIFSP protects personal information privacy.               |                            | 0.912           |
|                                  | SMQ4      | I can use GAIFSP services whenever I want.                  |                            | 0.883           |
| <b>Intention to Use (ITU)</b>    | ITU1      | I intend to use GAIFSP in the next few months.              | (Chopdar et al., 2023)     | 0.928           |
|                                  | ITU2      | I predict I would use GAIFSP in the next months.            | (Singu & Chakraborty,      | 0.844           |
|                                  | ITU3      | I will try to use GAIFSP in my daily life.                  | 2022)                      | 0.866           |
| <b>Actual Use (ACE)</b>          | ACE1      | Most of my fashion shopping is done through GAIFSP.         | (Chakraborty et al., 2022) | 0.92            |
|                                  | ACE2      | I frequently use the GAIFSP to get exclusive items.         |                            | 0.907           |
|                                  | ACE3      | I regularly use GAIFSP to save time and effort.             |                            | 0.891           |
| <b>Habit (HAT)</b>               | HAT1      | Using GAIFSP is a habit for me.                             | (Chopdar et al., 2023)     | 0.951           |
|                                  | HAT2      | It is natural for me to use GAIFSP.                         |                            | 0.941           |
|                                  | HAT3      | I use GAIFSP without consciously thinking about it.         |                            | 0.908           |

indicators were not higher than five, thus the absence of multicollinearity. The indices, factor loadings, VIF, and references are all presented in Table 2 for further clarification.

The measurement model was tested to check the construct's reliability and validity. Measures such as factor loadings, composite reliability, and average variance extracted were looked into to establish convergent validity. It can be seen in Table 3 that the threshold of 0.7 was exceeded for all the factor loadings and CRs, and AVE values recorded above 0.5, which establishes construct validity.

The Heterotrait–Monotrait (HTMT) ratio was adopted to assess the discriminant validity. It is indicated in Table 4 that by a statistical margin, variances in HTMT preferred values in the conclusion on validation are lower than threshold values of 0.85.

The structural model sought to test the role of the proposed hypotheses. As presented in Table 5, out of the total

**Table 3. Convergent Validity**

|     | Cronbach's Alpha | Composite Reliability (rho_a) | Composite Reliability (rho_c) | Average Variance Extracted (AVE) |
|-----|------------------|-------------------------------|-------------------------------|----------------------------------|
| ACE | 0.892            | 0.901                         | 0.932                         | 0.821                            |
| HAT | 0.926            | 0.928                         | 0.953                         | 0.872                            |
| INQ | 0.939            | 0.943                         | 0.957                         | 0.847                            |
| ITU | 0.856            | 0.895                         | 0.912                         | 0.775                            |
| SEQ | 0.902            | 0.906                         | 0.931                         | 0.773                            |
| SMQ | 0.919            | 0.92                          | 0.942                         | 0.804                            |

**Table 4. Discriminant Validity**

|     | ACE   | HAT   | INQ   | ITU   | SEQ   | SMQ |
|-----|-------|-------|-------|-------|-------|-----|
| ACE |       |       |       |       |       |     |
| HAT | 0.584 |       |       |       |       |     |
| INQ | 0.567 | 0.62  |       |       |       |     |
| ITU | 0.467 | 0.512 | 0.517 |       |       |     |
| SEQ | 0.475 | 0.417 | 0.42  | 0.363 |       |     |
| SMQ | 0.354 | 0.538 | 0.497 | 0.445 | 0.235 |     |

**Table 5. Hypotheses Testing Results**

|                     | Original Sample (O)    | Sample Mean (M) | Standard Deviation (STDEV) | T-Statistics ( O/STDEV ) | P-values          | Hypothesis (Accepted/Rejected) | VIF             | f-square        |
|---------------------|------------------------|-----------------|----------------------------|--------------------------|-------------------|--------------------------------|-----------------|-----------------|
| H1: INQ → ITU       | 0.306                  | 0.307           | 0.055                      | 5.56                     | 0                 | Accepted                       | 1.432           | 0.092           |
| H4: ITU → ACE       | 0.225                  | 0.225           | 0.044                      | 5.064                    | 0                 | Accepted                       | 1.294           | 0.058           |
| H3: SEQ → ITU       | 0.156                  | 0.157           | 0.045                      | 3.458                    | 0.001             | Accepted                       | 1.179           | 0.029           |
| H2: SMQ → ITU       | 0.229                  | 0.23            | 0.046                      | 4.945                    | 0                 | Accepted                       | 1.276           | 0.058           |
| H5: HAT × ITU → ACE | 0.022                  | 0.021           | 0.049                      | 0.454                    | 0.65              | Rejected                       | 1.084           | 0.001           |
|                     | Q <sup>2</sup> Predict | RMSE            | MAE                        | R-Square                 | R-Square Adjusted |                                | Saturated Model | Estimated Model |
| ACE                 | 0.321                  | 0.827           | 0.662                      | 0.325                    | 0.32              | SRMR                           | 0.044           | 0.067           |
| ITU                 | 0.274                  | 0.855           | 0.675                      | 0.288                    | 0.283             | NFI                            | 0.9             | 0.897           |

hypotheses tested across the entire sample, only four were supported. The model's  $R$ -squared ( $R^2$ ) values were calculated to assess the explanatory power of the model, showing different levels of explanatory strength over the endogenous variables. The total explanatory power of the constructs was appraised using  $Q$ -squared ( $Q^2$ ) values, which presented a different level of predictive relevance of the constructs. The regression weights for effect size ( $f^2$ ) were also calculated to identify the magnitude of independent variables on the dependent variable. They were categorized as small ( $\geq 0.02$ ), medium ( $\geq 0.15$ ), and large ( $\geq 0.35$ ). Details of effect sizes against selected model fit indices were also presented in Table 5, and these confirmed a good overall model fit. The study can also appropriately verify the measurement and structural models, making it possible to analyze the relationships between the constructs in a reliable manner.

## Discussion

This research study proposes the following: information quality positively correlates to intention to use (H1) and is one of the factors that influence users' trust, satisfaction, and decision-making, suggesting a positive inclination toward technology-based services. The H1 has been accepted over here. Regarding fashion shopping platforms that utilize AI technologies to assist customers in the purchase process, it has been established that users can reduce their uncertainty and obtain better shopping experiences thanks to high-quality information, including detailed information about the products, adequate presentation, timeliness, and customization of the recommendations. When such information is given, users are willing to trust the system and become engaged with it as they feel the information is important, accurate, and relevant to them. For example, having good virtual fitting capabilities or personalized fashion advice enables users to appreciate the platform's usefulness and facilitates buying. The growth in the use of AI systems for fashion needs indicates that the quality of the information will greatly influence the intention to use such systems because both satisfaction and usefulness of the platform to be used are dependent on the provided quality. It is highly informative, and users will adopt and use the system.

System quality positively influences intention to use (H2) because it relates to ease of use, credibility, and general satisfaction with the platform. The H2 has been accepted over here. Apart from users' experiences, GAIFSP features can be maximized through a high system quality. Such features as virtual fitting, AI trend forecasting, and tailored recommendations will all work well when used at such a time. People are more satisfied with a system that is easy to use and does not experience downtimes. Most customers will prefer a site with minimal hitches and turnaround time as they will be keen on getting the best out of the platform when fully functional. Consistent shopping leads to favorable brand loyalty, and combined with a simple, easy-to-use platform, the customers remain engaged. In the highly competitive fashion market, where users have high expectations, customers' intentions to visit or use the system are high if the system quality is appropriate.

Service quality positively influences intention to use (H3) as it affects the combined amount of support, responsiveness, and overall satisfaction users obtain while interacting with the platform. The H3 has been accepted over here. Speaking particularly of the generative AI-enabled fashion AI shopping systems, the ability to respond quickly and appropriately to the users' troubles concerning product selection and virtual fitting or AI recommendations would be quite useful. Good quality customer support, through whatever channels, such as live chat, FAQ, or troubleshooting, boosts users' trust in the platform and improves their disposition toward the brand. Furthermore, besides positively impacting the overall brand image, high service quality can also create confidence, making the users feel appreciated and attended to during the shopping process. When users receive adequate and timely service, it helps them avoid frustration. It considers the likelihood of returning to use the system higher because it fits the quick and easy description. Hence, in addition to increasing user satisfaction, high service quality also positively impacts users' regular use of the platform. It promotes feelings of safety and trust needed for users to remain active.

H4 explains that the intention to use the system will result positively in the actual use of the system since it embodies the user's drive and readiness to operate the system, which often materializes in real activities as time progresses. The H4 has been accepted over here. With respect to Generative AI fashion shopping platforms, when users intend to use the platform even for AI-generated fashion trends or virtual try-ons, they are more likely to browse and purchase items. This want serves as a precursor for progressive or true usage as audiences try to satisfy their fashion needs through AI-integrated solutions that they find attractive or useful. Also, their basic intention to use is reinforced and increased as there is a value proposition in using the platform in the first place, such as a more efficient shopping process or an enhanced experience, which increases the chances of more use over time. It can be concluded, putting it simply, that a strong intention leads to commitment, whereby commitment purposefully leads to the use of the platform, further enhancing the user relationship with the system.

The impact of habit on the association between intention to use and actual use is insignificant (H5) in the case of GAIFSP. The H5 has been rejected over here. It is owing to the relative novelty of such platforms, as users may exhibit more deliberate intentions and situational influences rather than being driven by habitual behaviors. In the case of a more mature technology, where habitual usage emerges, AI fashion platforms are completely different in the sense that there are a lot of novel features like virtual try-ons and recommendation systems that necessitate users to search for products actively. Engagement is also driven by the intention to use, as users need to know how these novel features work to add value. Consequently, the level of habitual usage is not high enough to be the focal point in the intention–use relationship. Here, the reasons are the same: AI-driven platforms are relatively new for the users; therefore, they require active decision-making processes that will lead to the use of the platform. As the AI platform ages, user routines will gradually shape how they behave on the platform. Still, such interactions will not happen in the early days because the purpose of use is the dominating factor.

## **Implications**

### ***Theoretical Implications***

This study contributes theoretically to the extant literature by adapting the D&M IS success model to explain sustained usage behavior toward GAIFSP. This research integrates the model into the new context of generative AI. It expands the theoretical perspective of the impact of traditional IS success factors system, information, and service quality on actual usage behavior, operating within ever-changing technology. The findings emphasize that in the context of GAIFSP, high AI information quality, system quality, and service quality are essential for reducing the gap between the intention to use and the actual use of the system. This study also disputes the moderating effect of habit due to the argument that generative AI platforms' newness and evolving use characteristics may limit the degree of habit prevalent in older systems. Moreover, the applicability of these findings cannot be solely explained by user trust in AI, and other pertinent elements, such as perceived enjoyment, also need to be considered as this technology involves creativity and personalization. This study explores the relevance of the D&M model in emerging domains and how AI-specific variables can be incorporated into traditional IS success measures, which will enhance the theoretical development related to user behavior in the context of novel platforms incorporating AI technology.

### ***Practical Implications***

This research has important practical business implications for companies and developers of GAIFSP as it provides ways in which increasing actual usage behavior might be achieved. First, it is clear from the study results that system quality needs to be emphasized badly since platforms must be user-friendly, quick, and have no bugs,

as this affects user satisfaction on the platform and continues to keep them engaged. Retailers must consider information quality by adequately recommending accurate, relevant, and tailored fashion ideas to win confidence and ease decision-making to encourage repeat use. Service quality is another one of concern, as fast customer service and smooth resolution of problems can enhance user satisfaction and loyalty. Also, since habit may not impact the relationship between intention and actual use of such new platforms, businesses ought to have deliberate strategies to encourage consistent usage, such as gamified elements, loyalty programs, or changes aimed at showcasing new features. Educating users about using any AI aspects, including virtual try-ons or customizations for sustainable reasons, must be done to build confidence and erase any doubts that such features work. Addressing these issues will aid businesses in increasing user adoption and retention and allow them to become early movers in the expanding generative AI fashion retailing industry.

## **Conclusion**

To summarize, this research brings forth the factors that encourage actual usage of generative AI-based fashion shopping platforms or GAIFSP, particularly focusing on the system quality, information quality, and service quality attitude proportionally toward the usage of the interface. Thus, the results indicate that habit is not an important moderator of the relationship between intention and actual use. Still, this research emphasizes the need for developers of the platforms to target the delivery of a smooth experience with as many tailored, dependable services as possible to support continued usage. This study, which is based on the D&M IS success model, makes it possible to comprehend how users interact with AI systems and devise actionable solutions for successful user engagement and retention.

## **Limitations of the Study and Scope for Future Research**

This examination, while notably illuminating actual usage behaviors toward GAIFSP, has limitations that bear significance for future studies. First, this study limits itself to focusing on the perspectives that emerge from the D&M IS success model, forgetting that there may be other models, such as the unified theory of acceptance and use of technology (UTAUT) or expectation-confirmation theory (ECT), which could explain user behavior. Second, the analysis is delegated to the scope of this study, which is based on self-reported data that is subject to social desirability and non-accurate portrayal of actual usage patterns. This could be dealt with by future studies using behavioral tracking methods or experimental designs. Also, the status of habit as a non-significant moderator indicates that the features of GAIFSP require longitudinal studies to examine how the user's behavioral patterns change with repeated exposure to the platform. The study also fails to estimate enough individual differences in sources such as digital literacy, trust in AI, and even culture, which may also affect the usage pattern. In closing, given the rapid developments in generative AI, future studies may delve into features likely to emerge as AI-enabled sustainability and inclusivity in fashion design and how such trends would affect user interaction, expanding the understanding of this emerging field.

## **Author's Contribution**

Prof. Debarun Chakraborty formulated the research objectives and designed and executed extensive literature reviews to formulate the research hypotheses. He designed a survey questionnaire adapted from extant instruments, collected participants' responses, further analyzed those using standard statistical software, and interpreted the findings without bias. Finally, he documented this article.

## Conflict of Interest

The author certifies that he has no affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

## Funding Acknowledgment

The author did not receive funding from any institution, organization, or person to execute or publish this research.

## References

- Alanadoly, A. B., Sidhu, S. K., & Richards-Carpenter, N. (2024). AI landscape in fashion: Insights on transforming design, supply chains, marketing, and consumer experiences. In P. Raj, A. Rocha, P. K. Dutta, M. Fiorini, & C. Prakash (eds.), *Illustrating digital innovations towards intelligent fashion* (Vol. 18, pp. 417–439). Springer. [https://doi.org/10.1007/978-3-031-71052-0\\_16](https://doi.org/10.1007/978-3-031-71052-0_16)
- Aldholay, A. H., Isaac, O., Abdullah, Z., & Ramayah, T. (2018). The role of transformational leadership as a mediating variable in DeLone and McLean information system success model: The context of online learning usage in Yemen. *Telematics and Informatics*, 35(5), 1421–1437. <https://doi.org/10.1016/j.tele.2018.03.012>
- Andreoni, M., Lunardi, W. T., Lawton, G., & Thakkar, S. (2024). Enhancing autonomous system security and resilience with generative AI: A comprehensive survey. *IEEE Access*, 12, 109470–109493. <https://doi.org/10.1109/ACCESS.2024.3439363>
- Babu, M. M., Akter, S., Rahman, M., Billah, M. M., & Hack-Polay, D. (2024). The role of artificial intelligence in shaping the future of agile fashion industry. *Production Planning & Control*, 35(15), 2084–2098. <https://doi.org/10.1080/09537287.2022.2060858>
- Çelik, K., & Ayaz, A. (2022). Validation of the Delone and McLean information systems success model: A study on student information system. *Education and Information Technologies*, 27(4), 4709–4727. <https://doi.org/10.1007/s10639-021-10798-4>
- Cenfetelli, R. T. (2004). Inhibitors and enablers as dual factor concepts in technology usage. *Journal of the Association for Information Systems*, 5(11), 472–492. <https://doi.org/10.17705/1jais.00059>
- Chakraborty, D. (2018). Impact of celebrity endorsed advertisements on rural consumers' purchase intention towards mobile SIM cards: A study conducted in West Bengal. *Indian Journal of Marketing*, 48(10), 52–63. <https://doi.org/10.17010/ijom/2018/v48/i10/132335>
- Chakraborty, D. (2021). Factors influencing passengers' purchase intention towards app-cab services in metro cities of India: A study on smartphone users. *Indian Journal of Marketing*, 51(1), 41–54. <https://doi.org/10.17010/10.17010/ijom/2021/v51/i1/156933>
- Chakraborty, D., & Altekar, S. (2021). What drives people to use grocery apps? The moderating & mediating role of customer involvement and trust. *Indian Journal of Marketing*, 51(11), 23–37. <https://doi.org/10.17010/ijom/2021/v51/i11/166734>

- Chakraborty, D., Bhatnagar, S. B., Biswas, W., & Khatua, A. K. (2022). What drives people to adopt grocery apps? The moderating role of household size. *Business Perspectives and Research*. <https://doi.org/10.1177/22785337221091640>
- Chakraborty, D., & Dash, G. (2022). 'The new normal' and the strategies of marketers to attract consumers. *Indian Journal of Marketing*, 52(1), 58–62. <https://doi.org/10.17010/ijom/2022/v52/i1/167652>
- Chau, P. Y., & Hu, P. J. (2002). Examining a model of information technology acceptance by individual professionals: An exploratory study. *Journal of Management Information Systems*, 18(4), 191–229. <https://doi.org/10.1080/07421222.2002.11045699>
- Chen, J., Liu, Z., Huang, X., Wu, C., Liu, Q., Jiang, G., Pu, Y., Lei, Y., Chen, X., Wang, X., Zheng, K., Lian, D., & Chen, E. (2024). When large language models meet personalization: Perspectives of challenges and opportunities. *World Wide Web*, 27(4), Article no. 42. <https://doi.org/10.1007/s11280-024-01276-1>
- Choi, W., Jang, S., Kim, H. Y., Lee, Y., Lee, S.-G., Lee, H., & Park, S. (2023). Developing an AI-based automated fashion design system: Reflecting the work process of fashion designers. *Fashion and Textiles*, 10(1), Article ID 39. <https://doi.org/10.1186/s40691-023-00360-w>
- Chopdar, P. K., Lytras, M. D., & Visvizi, A. (2023). Exploring factors influencing bicycle-sharing adoption in India: A UTAUT 2 based mixed-method approach. *International Journal of Emerging Markets*, 18(11), 5109–5134. <https://doi.org/10.1108/IJOEM-06-2021-0862>
- Dash, G., Akmal, S., & Chakraborty, D. (2022). A study on adoption of e-health services: Developing an integrated framework in a multinational context. *Indian Journal of Marketing*, 52(5), 25–40. <https://doi.org/10.17010/ijom/2022/v52/i5/169415>
- Dash, G., Akmal, S., & Chakraborty, D. (2023). A study on adoption of mobile learning apps (MLA): Development of an integrated framework in a multinational context. *Indian Journal of Marketing*, 53(5), 8–24. <https://doi.org/10.17010/ijom/2023/v53/i5/172724>
- Davies, J., Sharifi, H., Lyons, A., Forster, R., & Elsayed, O. K. (2024). Non-fungible tokens: The missing ingredient for sustainable supply chains in the metaverse age? *Transportation Research Part E: Logistics and Transportation Review*, 182, Article ID 103412. <https://doi.org/10.1016/j.tre.2024.103412>
- Deng, H., Jiang, J., Yu, Z., Ouyang, J., & Wu, D. (2024). CrossGAI: A cross-device generative AI framework for collaborative fashion design. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 8(1), Article No. 35, 1–27. <https://doi.org/10.1145/3643542>
- Fang, J., Zhao, Z., Wen, C., & Wang, R. (2017). Design and performance attributes driving mobile travel application engagement. *International Journal of Information Management*, 37(4), 269–283. <https://doi.org/10.1016/j.ijinfomgt.2017.03.003>
- Gorla, N., Somers, T. M., & Wong, B. (2010). Organizational impact of system quality, information quality, and service quality. *The Journal of Strategic Information Systems*, 19(3), 207–228. <https://doi.org/10.1016/j.jsis.2010.05.001>
- Gorry, G. A., & Westbrook, R. A. (2011). Once more, with feeling: Empathy and technology in customer care. *Business Horizons*, 54(2), 125–134. <https://doi.org/10.1016/j.bushor.2010.10.003>
- Gupta, A. S., & Mukherjee, J. (2024). Framework for adoption of generative AI for information search of retail products and services. *International Journal of Retail & Distribution Management*, Vol. ahead-of-print No. ahead-of-print. <https://doi.org/10.1108/IJRDM-05-2024-0203>

- Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, 49, 157–169. <https://doi.org/10.1016/j.ijinfomgt.2019.03.008>
- Huang, P., Lurie, N. H., & Mitra, S. (2009). Searching for experience on the web: An empirical examination of consumer behavior for search and experience goods. *Journal of Marketing*, 73(2), 55–69. <https://doi.org/10.1509/jmkg.73.2.55>
- Jaspersen, J., Carter, P. E., & Zmud, R. W. (2005). A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quarterly*, 29(3), 525–557. <https://doi.org/10.2307/25148694>
- Kim, Y. H., Kim, D. J., & Wachter, K. (2013). A study of mobile user engagement (MoEN): Engagement motivations, perceived value, satisfaction, and continued engagement intention. *Decision Support Systems*, 56, 361–370. <https://doi.org/10.1016/j.dss.2013.07.002>
- Kumar, N., & Singh, V. (2022). Shopping with voice assistant: Understanding consumer intention and the mediating role of trust. *Indian Journal of Marketing*, 52(8), 51–65. <https://doi.org/10.17010/ijom/2022/v52/i8/171224>
- Lee, J.-C., & Chen, X. (2022). Exploring users' adoption intentions in the evolution of artificial intelligence mobile banking applications: The intelligent and anthropomorphic perspectives. *International Journal of Bank Marketing*, 40(4), 631–658. <https://doi.org/10.1108/IJBM-08-2021-0394>
- Ma, W., Li, R. Y., Manta, O., & Alzuman, A. (2024). Balancing wellbeing and responsibility: CSR's role in mitigating burnout in hospitality under UN-SDGs. *Sustainability*, 16(8), 3374. <https://doi.org/10.3390/su16083374>
- Martínez-López, F. J., Li, Y., Liu, H., & Feng, C. (2020). Do safe buy buttons and integrated path-to-purchase on social platforms improve users' shopping-related responses? *Electronic Commerce Research and Applications*, 39, Article ID 100913. <https://doi.org/10.1016/j.elerap.2019.100913>
- McCormick, H., Cartwright, J., Perry, P., Barnes, L., Lynch, S., & Ball, G. (2014). Fashion retailing – past, present and future. *Textile Progress*, 46(3), 227–321. <https://doi.org/10.1080/00405167.2014.973247>
- Murthy, D. N., & Kumar, B. V. (2015). Internet of things (IoT): Is IoT a disruptive technology or a disruptive business model? *Indian Journal of Marketing*, 45(8), 18–27. <https://doi.org/10.17010/ijom/2015/v45/i8/79915>
- Naylor, R. W., Lamberton, C. P., & West, P. M. (2012). Beyond the “like” button: The impact of mere virtual presence on brand evaluations and purchase intentions in social media settings. *Journal of Marketing*, 76(6), 105–120. <https://doi.org/10.1509/jm.11.0105>
- Negash, S., Ryan, T., & Igbaria, M. (2003). Quality and effectiveness in web-based customer support systems. *Information & Management*, 40(8), 757–768. [https://doi.org/10.1016/S0378-7206\(02\)00101-5](https://doi.org/10.1016/S0378-7206(02)00101-5)
- Nicolaou, A. I., Ibrahim, M., & van Heck, E. (2013). Information quality, trust, and risk perceptions in electronic data exchanges. *Decision Support Systems*, 54(2), 986–996. <https://doi.org/10.1016/j.dss.2012.10.024>
- Pahari, S., Polisetty, A., Sharma, S., Jha, R., & Chakraborty, D. (2023). Adoption of AI in the banking industry: A case study on Indian banks. *Indian Journal of Marketing*, 53(3), 26–41. <https://doi.org/10.17010/ijom/2023/v53/i3/172654>

- Pan, J., Ding, S., Wu, D., Yang, S., & Yang, J. (2019). Exploring behavioural intentions toward smart healthcare services among medical practitioners: A technology transfer perspective. *International Journal of Production Research*, 57(18), 5801–5820. <https://doi.org/10.1080/00207543.2018.1550272>
- Pappas, A., Fumagalli, E., Rouziou, M., & Bolander, W. (2023). More than machines: The role of the future retail salesperson in enhancing the customer experience. *Journal of Retailing*, 99(4), 518–531. <https://doi.org/10.1016/j.jretai.2023.10.004>
- Petter, S., DeLone, W., & McLean, E. (2008). Measuring information systems success: Models, dimensions, measures, and interrelationships. *European Journal of Information Systems*, 17(3), 236–263. <https://doi.org/10.1057/ejis.2008.15>
- Raut, S., Chandel, A., & Mittal, S. (2025). Enhancing marketing and brand communication with AI-driven content creation. In M. Tunio (ed.), *AI, corporate social responsibility, and marketing in modern organizations* (pp. 139–172). IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3373-0219-5.ch008>
- Sharma, S. K., & Sharma, M. (2019). Examining the role of trust and quality dimensions in the actual usage of mobile banking services: An empirical investigation. *International Journal of Information Management*, 44, 65–75. <https://doi.org/10.1016/j.ijinfomgt.2018.09.013>
- Sharma, S., Sharma, R., Kayal, G., & Kaur, J. (2022). Digital banking: A meta-analysis approach. *Indian Journal of Marketing*, 52(5), 41–68. <https://doi.org/10.17010/ijom/2022/v52/i5/169416>
- Sinclair, J., & Aho, A.-M. (2018). Experts on super innovators: Understanding staff adoption of learning management systems. *Higher Education Research & Development*, 37(1), 158–172. <https://doi.org/10.1080/07294360.2017.1342609>
- Singu, H. B., & Chakraborty, D. (2022). I have the bank in my pocket: Theoretical evidence and perspectives. *Journal of Public Affairs*, 22(3), Article No. e2568. <https://doi.org/10.1002/pa.2568>
- Venkatesh, V., Davis, F. D., & Zhu, Y. (2023). Competing roles of intention and habit in predicting behavior: A comprehensive literature review, synthesis, and longitudinal field study. *International Journal of Information Management*, 71, Article ID 102644. <https://doi.org/10.1016/j.ijinfomgt.2023.102644>
- Xi, N., & Hamari, J. (2021). Shopping in virtual reality: A literature review and future agenda. *Journal of Business Research*, 134, 37–58. <https://doi.org/10.1016/j.jbusres.2021.04.075>
- Yan, H., Zhang, H., Liu, L., Zhou, D., Xu, X., Zhang, Z., & Yan, S. (2022). Toward intelligent design: An AI-based fashion designer using generative adversarial networks aided by sketch and rendering generators. *IEEE Transactions on Multimedia*, 25, 2323–2338. <https://doi.org/10.1109/TMM.2022.3146010>
- Yan, M., Filieri, R., & Gorton, M. (2021). Continuance intention of online technologies: A systematic literature review. *International Journal of Information Management*, 58, Article ID 102315. <https://doi.org/10.1016/j.ijinfomgt.2021.102315>

### About the Author

Debarun Chakraborty (Ph.D.) is an Associate Professor (Marketing) at the Indian Institute of Management Nagpur, Maharashtra, Pune, India. He has published works on technology adoption, consumer behavior, and sustainability in high-impact factor journals. His research appears in top journals, namely, *Psychology & Marketing*, *Journal of Business Research*, *Technovation*, *Technological Forecasting & Social Changes*, *Journal of Retailing and Consumer Services*, *Journal of Hospitality Marketing & Management*, *International Journal of Consumer Studies*, *Journal of Computer Information Systems*, *Conflict Resolution Quarterly*, and *British Food Journal*, among others.