Adoption of AI tools in Academic Work: Exploring the Intention of Fashion Students through Technology Acceptance Model

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Abstract

Artificial intelligence (AI) is bringing significant transformations to how organizations and businesses are delivering products or services and developing customer relationships. Numerous users are embracing AI tools across diverse fields. AI has been significantly influencing all aspects of the fashion industry, from the creative design process to product development to the ever-evolving consumer behavior. For more than a decade, the fashion industry has been using AI to forecast fashion trends and customer needs. AI is also making a significant impact in academia, and the scope for artificial intelligence in education is extensive. AI tools provide effective support to students in their learning and academic tasks, such as assignments and projects. Recently, there have been several debates about the impact of AI usage on academics and related activities, particularly in the context of students' academic work. The use of AI in fashion education appears promising for developing design explorations and other related activities. Using the Technology Acceptance Model (TAM), this study investigates the relationship between the students' belief in AI usage for fashion learning and their behavioral intention to adopt AI for their academic-related work. The primary data was collected using a structured questionnaire based on the Technology Acceptance Model (TAM). A total of 112 responses from fashion students were used to determine the correlation between their beliefs about AI and their behavioral intentions towards it. The SEM analysis discovered that beliefs on AI tools and perceived usefulness of AI tools have a significant positive impact on the behavioral intention of using AI tools for academic works, both directly and indirectly. Based on the findings, the researcher has attempted to offer managerial suggestions to stakeholders, including students, educational institutions, and AI tool developers. The study suggests clear rules and policies for integrating and using AI tools in students' academic work.

Keywords: Artificial intelligence tools, beliefs, behavioral intention, fashion students, perceived ease of use, technology acceptance model, perceived usefulness

Introduction

Fashion field is one of the leading industries which contribute significantly to the World economy with as estimated value of US$ 3000 billion (O'Connell, 2019; Fashion United, 2019). Artificial Intelligence (AI) an academic discipline that was established in the field of computer science in 1956, which enabled computers and machines to operate intelligently. AI gives an extensive impact towards all the dimensions of fashion field and more than a decade, AI has been adopted in the fashion industry for forecasting fashion trends and customer needs (Csanák, 2020). AI is also having a considerable impact in the academic field, and the scope for its integration in education is extensive (Anderson, Boyle and Reiser, 1985; Baker, 2016; Roll, Russell and Gašević, 2018; Seo et al., 2020b; VanLehn, 2011), varying from custom-made learning for students and automation of teachers' repetitive tasks to AI-powered evaluations and appraisals (Popenici and Kerr, 2017). To say, AI teaching systems can deliver personalized assistance, support, or feedback through customized learning content based on student-specific learning capabilities or knowledge levels (Hwang et al., 2020). AI teaching assistants help teachers save time to answer learners' simple, repetitive questions in online discussion platforms (Goel and Polepeddi, 2016). AI data analytics enables educators to understand students' performance, progress, and potential (Roll and Winne, 2015; Fong et al., 2019; Seo et al., 2021; Holstein et al., 2018). Similarly, students have started using the AI for their academic learning and works to complete their assignments, exercises etc., more effectively. Scholars those who are pursuing creative or design education have developed several beliefs and attitudes towards the adoption of AI for their academic learning and they have started adopting the AI in their academic work. In fashion education the students have to develop creative designs, illustrations, trend forecasts etc., where the scope of application of AI by the students is very broad. TAM postulates that perceptions about innovation are instrumental in developing attitudes that ultimately lead to behavior in the use of the system. The Technology Acceptance Model (Davis, 1989) was considered to be the most useful to predict consumer acceptance of IT. This study adopts the TAM to understand and observe the AI diffusion in the academic learning and works by fashion students. This study is aimed at to understand the fashion students' beliefs towards the AI usage in fashion learning, evaluate the perceived ease of use of the AI tools for their academic work, analyze the perceived usefulness of AI tools in their learning and work and finally examine the impact of these variables on behavioral intention towards implementation of AI tools in the near future.

Review of Literature and Hypothesis Development

Artificial intelligence

AI encapsulates machine learning, natural language processing, or different kinds of algorithms (Zawacki-Richter et al., 2019). According to Wartman and Combs (2018), people generally think of artificial intelligence as the capability of machines or computers to think and perform as humans, representing efforts towards computerized systems to replicate the human mind and actions. Mohammed and Watson (2019) define artificial intelligence as the skillful imitation of human behavior or mind by tools or programs. Ng (2017) believes that artificial intelligence is a new type of electricity for this age. Artificial intelligence would be the fundamental building block of the Fifth Industrial Revolution by proving itself to be a powerful factor in ensuring economic development (Golić, 2019). The comprehensive development of artificial intelligence will have an impact on macroenvironments, from the restructuring of the social order in the broadest sense to the education and administration processes in classes and schools. The growth of AI could significantly impact academic institutions, particularly those that adapt to the digital era and combine 21st century skills into their primary programs (Gocen and Aydemir, 2020). Karsenti (2019) suggests that new forms of technology will fill our lives and captivate our youth, and this case may leave educational institutions with no choice but to make space for them.

Artificial intelligence in education

AI systems replicate human intelligence processes like learning and reasoning to perform tasks (Gillath et al., 2021; Glikson and Woolley, 2020; Watson, 2019). AI-powered educational systems provide new potentials such as automatization of organizational or administrative tasks, generation of course content, or learner's evaluation and feedback (Chassignol et al., 2018; Bryant et al., 2020). Educational systems and technologies powered by AI have the potential to actively develop learners, and their acceptance appears to be widespread (Williams, 2015). Recent development of AI and its applications in education have the potential to transform educational tools, tasks, and roles (Akgun and Greenhow, 2022; Ninaus and Sailer, 2022). Educational technologies seem accepted by educators in their teaching, and studies show that attitudes of US educators towards educational technologies are generally positive (Williams, 2015). Similarly, about 80% of educators in France and German academicians use educational technologies in their teaching (Sailer, Murböck, and Fischer, 2021). Manyika et al. (2017) emphasize that excellent academicians will continue to exist in the future, teaching classes designed to boost learners' intelligence, creativity, and communication skills. According to Haseski (2019), the adoption of AI in the academic field will make learning more personal, provide effective learning experiences, enable students to discover their talents, improve their creativity, and reduce educators' workload. With increased adoption of artificial intelligence in education, significant transformations are expected in the educational systems and their processes. Sekeroglu, Dimililer, and Tuncal (2019) state that artificial intelligence could support educators to improve customized teaching for their students. Artificial intelligence can give access to appropriate and enhanced learning possibilities for excluded people and communities, people with disabilities, etc. (Pedró et al., 2019). Several studies demonstrate that AI techniques can deliver productive and customized approaches (Mohammed and Watson, 2019). Though teachers' involvement is inevitable for quality education, artificial intelligence facilitates more education and quality at all levels, particularly by providing personalization (Grosz and Stone, 2018).

AI in fashion

Artificial intelligence develops a combination of techniques that are very appropriate in the fashion industry. AI has the ability to handle big data with the attributes of uncertainty, complexity, and volatility in the fashion field and its related areas (Ren, Hui and Choi, 2018). AI techniques enable the effective analysis of various types of data, including point-of-sale (POS) data, social media data, textile physical data, virtual 3D data, and sensory data. In the fashion industry, AI technologies provide manufacturers with automated solutions. Several fashion brands and retailers have already begun utilizing AI techniques to accurately predict fashion trends that customers are likely to purchase. Some AI methods and AI-based mixed methods have shown effectiveness in forecasting fashion sales performance (Schmelzer, 2019).

Technology Acceptance Model

The Technology Acceptance Model (TAM) has emerged as a powerful model among models investigating IT adoption, including innovation diffusion and reasoned action theory (Lee, Kozar and Larsen, 2003). TAM examines that beliefs about innovation play a crucial role in shaping attitudes, which in turn influence the behavior of adopting the system. TAM demonstrates that perceived usefulness and perceived ease of use stimulate the users' intention to utilize a technology (Davis, 1985; Davis, 1989; Davis, Bagozzi, and Warshaw, 1992). Numerous technology acceptance studies have cited TAM as a crucial model for defining and predicting system use (Lee, Kozar and Larsen, 2003). Also, few researchers have effectively utilized TAM to study Internet-related technology acceptance (Davis, 1993; Segars and Grover, 1993; Tornatzky and Klein, 1982). Researchers have also utilized TAM to examine the adoption of technology in the academic field. Drennan, Kennedy, and Pisarksi (2005) find that positive perceptions of ease of usage and benefits of online flexible learning tools influence student satisfaction. In the digital educational environment setup, personality attributes like personal innovative behavior in the domain of information technology and computer apprehension are the two variables studied in the virtual learning environment (VLE) framework. Van Raaij and Schepersa (2008) reveal that perceived usefulness significantly affects VLE adoption. Many scholars have adopted TAM in e-learning acceptance (Weerasinghe and Hindagolla, 2017; Shen and Eder, 2009) and utilization of mobile learning technologies (Mugo et al., 2017; Kim et al., 2013).

Beliefs in AI tools

Fishbein and Ajzen (1975) describe beliefs as constructs that ''represent the information'' about an object at the cognitive level, and explain that attitudes are the emotional responses that correlate regularly with cognitive beliefs. Researchers have identified a significant association between trust beliefs and trust intentions within consumers (McKnight, Cummings and Chervany, 1998). Just as attitudes and beliefs influence individuals' decision-making processes in their daily routine, they also have a significant influence on the integration of technology. This explains the direct effect attitudes and beliefs play in the technology integration process (Chen, 2008). Salleh et al. (2010) express that intentions and perceptions are major influencers on beliefs and attitudes. Eagly and Chaiken (1993) assert that beliefs serve as the fundamental building blocks of attitudes, explaining them as the subjective likelihood that a particular object possesses a particular attribute. Bhattacherjee and Premkumar (2004) explain that user beliefs and attitudes play an important role in influencing the use of information technology. They suggest that these beliefs can evolve over time as users gain initial experience with IT usage, leading to subsequent changes in their IT usage behavior. Several scholars have identified a significant positive association between beliefs and technology integration (Kagan, 1992; Pajares, 1992; Chan and Elliott, 2004; Kim, et al., 2013; Ottenbreit-Leftwich, et al., 2010), as well as adoption among teachers (Ertmer, 2005; Niederhauser and Stoddart, 2001). Judson (2006) suggests that analyzing the connection between beliefs and technology integration may help to explain the association. Based on this, the following hypotheses are formulated:

H1: Beliefs in AI tools have a significant positive effect on perceived ease of use (PEOU) of AI tools.

H2: Beliefs in AI tools have a significant positive effect on perceived usefulness (PU) of AI tools.

H3: Beliefs in AI tools have a positive influence on fashion students' behavioral intention (BI) to use AI tools for academic work.

Perceived ease of use

According to Davis (1985), perceived ease of use is defined as the extent to which an individual trusts effort-free technology usage. Therefore, in the late 20th century, Loiacono (2000) used the concept of perceived ease of use to measure the ease of reading and understanding of information displays. Belanche, Casolo, and Guinalu (2012) reveal that in the retail business context, the ease-of-use website predicted customers' satisfaction with the purchase experience and purchase intention. When it pertains to accepting AI tools in academic work, students' perception of ease of use shapes their perception of how effortless it is to use these tools for academic tasks without significant effort. Hence, the following hypotheses are formulated:

H4: Perceived ease of using AI tools positively influences perceived usefulness to use AI tools for academic work.

H5: Perceived ease of using AI tools positively influences fashion students' behavioral intention to use AI tools for academic work.

Perceived usefulness

Perceived usefulness refers to a user's belief that a particular technology or system would enhance their career performance, and it has a positive impact on their behavioral intention (Davis, 1989). Several scholars support this association between perceived usefulness and behavioral intention (Bhatiasevi and Yoopetch, 2015). Within the framework of adopting AI tools in academic work, perceived usefulness pertains to how fashion students perceive its effectiveness and efficiency in their academic work. Users perceive the degree to which they can access information through a particular technology (Gefen and Straub, 2000). Previous studies have shown that perceived effectiveness aids in the use of social networks for collaborative learning (Davis, 1989). Hence, the following hypothesis is proposed:

H6: Perceived ease of using AI tools positively influences fashion students' behavioral intention to use AI tools for academic work.

Theoretical framework

The theoretical framework was based on the technology acceptance model developed by Davis (1989). Figure 1 illustrates the research model for this study.

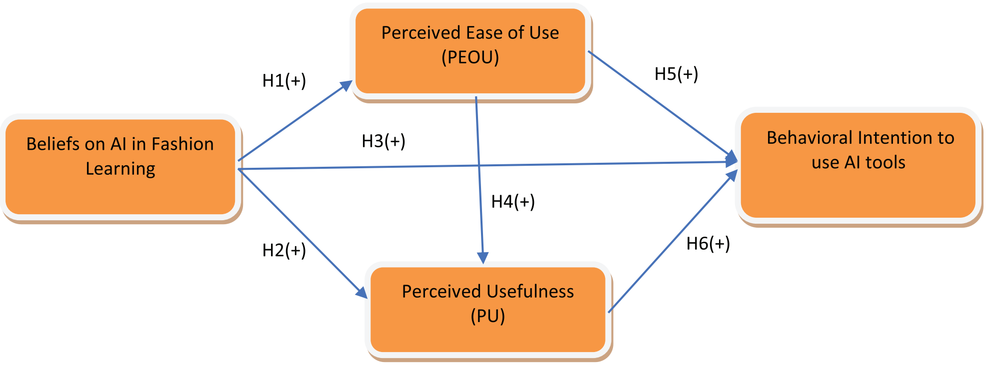

Figure 1: Theoretical framework for the study

Methodology

This research design is exploratory in nature. The convenience sampling technique was selected for this research to include fashion students currently enrolled in an offline fashion course. To maintain respondents' anonymity and overcome time and place constraints, the study conducted a web-based survey, which made it easier to contact respondents than other survey methods such as personal and telephone interviews and other self-administered survey techniques. A total of 112 usable responses were received. To provide the respondents' profile, descriptive statistics were applied. Data analysis has been done using SPSS 16.0 and SmartPLS.

Measurement development

A structured questionnaire was developed to measure the beliefs of the respondents, the perceived ease of use of the AI tools, the perceived usefulness of the AI tools in their academic learning and work, and their behavioral intention to further utilize AI tools for their academic learning. The beliefs on using AI tools for fashion learning were measured by six items; the perceived ease of use was measured by five items; the perceived usefulness was measured by five items; and the behavioral intention was measured by two items. A 5-point Likert scale was used to score all these items, ranging from strongly disagree (1) to strongly agree (5). The demographic section of the questionnaire included variables such as age, gender, type of course (UG, PG, Others), year of study, location, and frequency of AI usage.

Data Analysis

Descriptive statistics

The demographic descriptive analysis in Table 1 shows that out of 112 responses, the majority of the respondents were female (86.6 percent), and 62.5 percent belonged to the 21-23 year age group. Majority of the respondents were pursuing a PG degree (69.6 percent), and half of them were in their first year. 72.3 percent of the respondents were from Tier 2 cities, and in terms of AI usage, 46.4 percent had frequently used it, followed by 44.6 percent who had sometimes used AI.

Table 1: Demographic description of the respondents

		Frequency	**Percent**
Gender	Male	15	13.4
	Female	97	86.6
	Total	112	100
Age	18 - 20	19	17
	21 - 23	70	62.5
	24 - 26	17	15.2
	Above 26	6	5.4
	Total	112	100
Course	UG	34	30.4
	PG	78	69.6
	Total	112	100
Year	1st Year	56	50
	2nd year	24	21.4
	3rd year	28	25
	4th year	4	3.6
	Total	112	100
Location	Tier 1	1	0.9
	Tier 2	81	72.3
	Tier 3	30	26.8
	Total	112	100
Usage Frequency	Frequently	52	46.4
	Sometimes	50	44.6
	Rarely	10	8.9
	Total	112	100

Source: Primary data

Reliability statistics

The study uses Cronbach's alpha to check the internal reliability of the questionnaire. Composite reliability, also known as construct reliability, evaluates a measure's internal consistency by assessing its response to its items. It only applies to measuring instruments that contain multiple items. A construct captures the Average Variance Extracted (AVE) metric, which is proportional to the amount of variance due to measurement error.

From Table 2, it is inferred that the Cronbach's alpha for all the variables is greater than 0.7, which indicates a relatively high internal reliability for the questionnaire. It suggests that the questionnaire's reliability is acceptable. Cronbach's alpha results are greater than 0.7, composite reliability is greater than 0.7, and AVE values are above 0.5, indicating that the data is reliable and valid.

Table 2: Reliability statistics

Variables	No. of items	Cronbach's alpha	Composite reliability	Average Variance Extracted (AVE)
Beliefs on AI for Fashion Learning	6	0.85	0.891	0.581
Perceived Ease of Use	5	0.847	0.890	0.619
Perceived Usefulness	5	0.844	0.890	0.621
Behavioral Intention to Use	2	0.937	0.969	0.941

Source: Primary data

KMO and Bartlett's test

KMO and Bartlett's test of sphericity were done to assess the sampling adequacy and fit of the data for analysis. From Table 3, it is inferred that the value of KMO statistics for all the variables is above 0.5. The Bartlett's tests approximate chi-square values for belief in AI (χ^2=303.255, df-15, p<.05), perceived ease of use (PEOU) (χ^2=244.373, df-10, p<.05), perceived usefulness (PU) (χ^2=235.131, df-10, p<.05), and behavioral intention (BI) (χ^2=164.615, df-1, p<.05). For all the variables, the value of KMO statistics was above the acceptable limit of 0.5, and Bartlett's tests were significant, indicating the suitability of data for data analysis.

Table 3: KMO and Bartlett's test

S.No.	Constructs	KMO Measure of Sampling Adequacy	Bartlett's Test of Sphericity		
			Approx. Chi-Square	df	Sig.
1	Beliefs on AI for Fashion Learning	0.813	303.255	15	.000
2	Perceived Ease of Use	0.812	244.373	10	.000
3	Perceived Usefulness	0.754	235.131	10	.000
4	Behavioral Intention to Use	0.510	164.615	1	.000

Source: Primary Data; KMO - Kaiser-Meyer-Olkin measure of sampling adequacy

Simple regression analysis

Simple regression analysis was conducted to test the individual effect of independent variables on the dependent variables.

According to Table 4, the independent variable belief in AI ($\beta = 0.573$, $t = 6.512$; $p < .05$) has a significant positive effect on perceived ease of use (PEOU) as a dependent variable. This reinforces Hypothesis H1.

Perceived usefulness (PU) as a dependent variable, the independent variables Belief on AI ($\beta = 0.724$, $t = 11.021$; $p < .05$), and Perceived Ease of Use ($\beta = 0.666$, $t = 9.358$; $p < .05$) have a significant positive effect on the perceived usefulness (PU). This supports hypotheses H2 and H4.

Behavioral Intention (BI) as a dependent variable, the variables Belief on AI ($\beta = 0.662$, $t = 9.26$; $p < .05$), Perceived Ease of Use ($\beta = 0.496$, $t = 5.991$, $p < .05$), and Perceived Usefulness ($\beta = 0.754$, $t = 12.038$, $p < .05$) have a significant positive effect on Behavioral Intention (BI). This supports hypotheses H3, H5, and H6.

Table 4: Simple regression analysis

Independent Variables	PEOU			PU			BI		
	Beta β	t	Sig	Beta β	t	Sig	Beta β	t	Sig
Beliefs	0.573	6.512	0.000	0.724	11.021	0.000	0.662	9.26	0.000
PEOU	-	-	-	0.666	9.358	0.000	0.496	5.991	0.000
PU	-	-	-	-	-	-	0.754	12.038	0.000

Source: Primary data

Structural equation analysis

The SEM analysis was conducted using SmartPLS v.4.1.0.0 software. The present study selected a single-stage analysis with simultaneous estimation of both structural and measurement models, as the model is theoretically based on latent variables and high-reliability measures.

Measurement model

Table 5 shows the results of the measurement model. For all the items, the loadings were above 0.5. For the measurement model, the factor loadings above 0.4 are considered satisfactory (Williams, Onsman and Brown, 2010; Fabrigar et al., 1999; Yong and Pearce, 2013). The factor loadings of all the items in this model were above 0.5. This indicates that all the items under all the factors are confirmed.

Table 5: Measurement model

Variables	Items	Loadings
Beliefs on AI for Fashion Learning	1.1	0.759
	1.2	0.739
	1.3	0.851
	1.4	0.799
	1.5	0.854
	1.6	0.521
Perceived Ease of Use (PEOU)	2.1	0.765
	2.2	0.853
	2.3	0.803
	2.4	0.671
	2.5	0.829
Perceived Usefulness (PU)	3.1	0.721
	3.2	0.875
	3.3	0.840
	3.4	0.811
	3.5	0.675
Behavioral Intention to Use (BI)	4.1	0.970
	4.2	0.970

Source: Primary data

Structural equation model

The structural equation model was carried out to study the hypothesized relationship among latent variables. Figure 2 illustrates the structural equation model showing significant and insignificant paths using standardized coefficients.

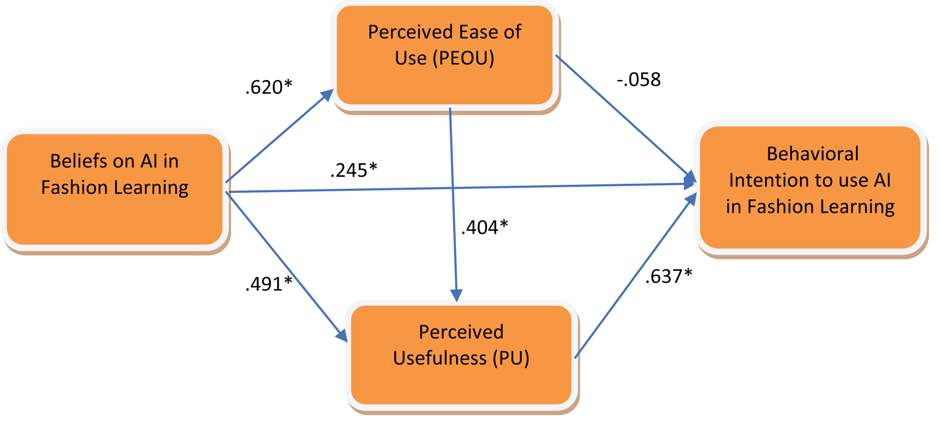

Figure 2: Structural equation model

SEM model fit

Table 6 contains the model fit indices for the SEM. The model is judged to be a good match when the standardized root mean squared residual (SRMR) is smaller than or equal to 0.08 (Jöreskog and Dag, 1996) and less than 0.10 (Henseler et al., 2014). This research model's standardized root mean squared residual (SRMR) is 0.081, indicating that the fit is reasonably good. The higher the fit, the nearer the NFI is to 1 (Kumar and Upadhaya 2017). The calculated and saturated model in this research has an NFI value of 0.812, which is in close proximity to 1. It denotes that the SEM model is a good fit. Similarly, the study model meets all of the general fit indices. These statistics and indices can be utilized to assess the model fit (Jöreskog and Dag, 1996).

Table 6: SEM model fit indices

	Saturated model	**Estimated model**
SRMR	0.081	0.081
d_ULS	1.221	1.221
d_G	0.619	0.619
Chi-square	383.437	383.437
NFI	0.812	0.812

Source: Primary data

SEM direct effect

Table 7 shows the direct effect of the research variables on the research model, including their standard deviation (SD), t-statistics, and p-value.

The path coefficients for the variables Belief in AI (B) and Perceived Ease of Use (PEOU) (γ =.618, t = 9.961, p<.05) and Belief in AI (B) and Perceived Usefulness (PU) (γ =.489, t = 5.914, p<.05) were both positive and significant. This result supports hypotheses H1 and H2. However, the path coefficients between belief in AI and behavioral intention (BI) (γ =.245, t = 1.939, p >.05) were positive but not significant. This result partially supports Hypothesis H3. This shows that belief in AI (B) has a partial direct effect on behavioral intention (BI).

The path values for perceived ease of use (PEOU) and perceived usefulness (PU) (γ = .404, t = 4.936, p<.05) were positive and significant. This finding supports Hypothesis H4. However, the results for perceived ease of use (PEOU) and behavioral intention (BI) were negative and not significant. This result does not support Hypothesis H5. Thus, H5 is not supported. This shows that perceived ease of use (PEOU) does not have a direct effect on behavioral intention (BI). The path coefficients for perceived usefulness and behavioral intention (BI) (γ = .637, t = 4.726, p<.05) were positive and significant. This finding supports Hypothesis H6. The R2 values for the factors perceived ease of use are 0.376, perceived usefulness is 0.640, and behavioral intention is 0.617.

Table 7: Structural equation model – direct effect

Path	St. Beta	SD	T-stat	P-value	Decision
B > BI	0.245	0.126	1.939	0.052	Partially Supported
B > PEOU	0.620	0.062	9.961	0.000	Supported
B > PU	0.491	0.083	5.914	0.000	Supported
PEOU > BI	-0.058	0.112	0.522	0.601	Not Supported
PEOU > PU	0.404	0.082	4.936	0.000	Supported
PU > BI	0.637	0.135	4.726	0.000	Supported
	R^2 value				
Perceived Ease of Use (PEOU)	0.376				
Perceived usefulness (PU)	0.640				
Behavioral Intention (BI)	0.617				

Source: Primary data

SEM indirect effect

Table 8 depicts the indirect effect of the variables in the research model, including their standard deviation (SD), t-statistics, and p-value. The result reveals that the indirect paths i) B > PU > BI and ii) B > PEOU > PU > BI have significant effects, while path i) B > PEOU > BI is not significant.

Table 8: Structural equation model – indirect effect

Indirect Effect	Estimate Coefficient	SD	T-stat	P-value	Decision
B > PU > BI	0.311	0.087	3.587	0.000	Significant
B > PEOU > BI	-0.036	0.071	0.508	0.612	Not Significant
B > PEOU > PU > BI	0.159	0.049	3.227	0.001	Significant

Source: Primary data

Discussion

The study aimed to examine how beliefs on AI in fashion learning, the perceived ease of use of AI tools, and the perceived usefulness of AI tools influence the behavioral intention of fashion students to utilize AI tools for their academic activities. A simple regression analysis was conducted to examine the individual influence of variables on the dependent variable. The results revealed that beliefs about AI tools have a significant positive influence on perceived ease of use, perceived usefulness, and behavioral intention. Further, perceived ease of use has a significant positive effect on perceived usefulness and behavioral intention. Also, perceived usefulness has a significant positive effect on behavioral intention.

The findings demonstrate that belief in AI tools has a partial direct effect on behavioral intention but has an indirect positive effect on behavioral intention through perceived usefulness (PU). Perceived ease of use (PEOU) does not have a significant positive influence on behavioral intention (BI), both in direct and indirect ways. Perceived usefulness (PU), both directly and indirectly, has a significant positive impact on behavioral intention (BI). In this research framework, perceived usefulness (PU) plays a crucial role as a mediator in shaping the intention of fashion students to utilize AI tools for their academic tasks. The analysis mostly aligns with the hypotheses while also revealing some unique features in the cognitive processes. Contrary to the general statement, fashion students' behavioral intention to use AI tools for academic work does not directly correlate with their beliefs about these tools. Instead, the behavioral intention to use AI tools depends primarily on perceived usefulness, not perceived ease of use. This finding shows that the fashion students are willing to use AI tools if they are convinced of the usefulness of the AI tools in their academic work. The findings reveal a close relationship between the behavioral intention to use AI tools in academic work among fashion students and their perceived usefulness and beliefs. Therefore, awareness of AI tools needs to be more effectively done through trust enhancers, such as involving trusted professional sources, so that the beliefs on AI tools among the fashion students would increase. For fashion students to adopt AI tools in their academic work in the future, they need to gain experiential knowledge from reliable and highly credible user experiences, which can lead to a higher acceptance of AI tools.

The study's findings validate the TAM model's theoretical component, indicating that users' beliefs, attitudes, and perceptions of the new technology's ease of use and usefulness shape their adoption of new technologies. It can be concluded that fashion students who hold positive beliefs about AI tools demonstrate a higher behavioral intention to utilize them. Fashion students, who excel in the field of creativity, can utilize AI tools to enhance their creativity, particularly in the area of design thinking, thereby providing effective design solutions. Educators can encourage fashion students to use AI tools for fashion learning and related academic activities. However, appropriate ethical guidelines may be developed for the use of AI tools in student learning activities. It is also recommended that students use AI tools in the final phase of academic activities, after they have independently completed their initial contributions. Once the student has made their initial contribution, they can utilize AI tools in the final phase to improve their final designs, or they can propose or recommend design solutions. Fashion students should be provided with adequate training on various AI tools, which are highly beneficial for the fashion industry, to ensure their effective and ethical use. When using AI tools for academic work, ethical considerations are the primary concern. As AI increasingly becomes a part of regular practice, it is expected that (a) fashion students should receive courses or training, and (b) the curriculum for fashion students should be updated with a significant focus on the applications of AI tools. Fashion students and educators should undergo proper training to understand and utilize the AI implementation in fashion education. The curriculum for specializations in fashion education, where AI integration becomes a regular practice, would also require an update to incorporate new pedagogical approaches. It's crucial for fashion students and educators to understand the various AI tools and software under development. High-level committees should develop proper regulations and guidelines for using AI tools in learning and academic activities.

Conclusion

This study aimed to contribute knowledge regarding how the antecedents, namely beliefs on AI tools, perceived ease of use, and perceived usefulness of AI tools, drive behavioral intention to use AI tools for academic activities by fashion students via the Technology Acceptance Model. The findings demonstrated that the proposed model effectively explained the influencers and processes behind fashion students' behavioral intention to use AI tools for their academic work. The suggested model provides a fundamental framework to understand how fashion students can accept or reject AI in fashion learning and related academic work. The research findings have implications for using AI tools for educational purposes and for general assimilation of AI tools into the fashion education field. Empirical evidence demonstrates that beliefs about AI tools and their perceived usefulness significantly influence the behavioral intention to use them. This article also adds to the existing literature on technology acceptance research in educational settings.

Considering that this study used researcher-controlled sampling, it is important to carefully generalize the study findings. Future researchers must validate the present study's findings using a more representative probability-based sample. The current research focuses on the behavioral intention behind the use of AI tools by fashion students. Thus, future studies may validate the findings in the context of other types of students. The model can incorporate several other variables such as peer influence, gadget usage skills, academic involvement, and academic performance.

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