Information technology adoption in the fashion industry: Employee perspectives

Adopción de tecnologías de la información en la industria de la moda: Perspectivas de los empleados

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Abstract: Although information technology plays a critical role in driving innovation in the fashion industry, many firms continue to lag in adopting new technologies. This study examines users' acceptance of new technology in the fashion industry in a developing country. The main results of the proposed structural equation model reveal that internal project communication related to the system (PC) is the catalyst for new technology adoption. Thus, PC fosters computer playfulness and training, which shape beliefs about the system, such as perceived usefulness and perceived ease of use, and these beliefs ultimately drive the behavioral intention to utilize the system. This empirical study is among the first to explain technology adoption in the understudied context of the fashion industry in Latin America. The findings are particularly beneficial for managers in the fashion industry seeking to enhance innovation through the adoption of information technologies.

Keywords: Innovation · Technology acceptance · Information system · Information technology · Adoption · Fashion.

Resumen: Aunque la tecnología de la información desempeña un papel fundamental en impulsar la innovación en la industria de la moda, muchas empresas siguen rezagadas en la adopción de nuevas tecnologías. Este estudio examina la aceptación de las nuevas tecnologías por parte de los usuarios de la industria de la moda de un país en desarrollo. Los resultados del modelo de ecuaciones estructurales revelaron que la comunicación interna del proyecto, vinculada al sistema (PC), es el catalizador de la adopción de nuevas tecnologías. Por lo tanto, la PC fomenta el juego y el entrenamiento, dando forma a las creencias sobre el sistema, como la utilidad y la facilidad de uso percibidas, que, en última instancia, impulsan la intención de uso. Este estudio empírico es uno de los primeros en explicar la adopción de tecnología en el contexto poco estudiado de la industria de la moda en América Latina, utilizando una muestra específica de dicha industria. Los hallazgos resultan particularmente beneficiosos para los gerentes de la industria de la moda que buscan impulsar la innovación mediante tecnologías emergentes.

Palabras clave: Innovación · Aceptación de la tecnología · Sistema de información · Tecnología de la información · Adopción · Moda.

1. Introduction

Multiple studies confirm the influential role technology plays in innovation processes in the fashion industry (BoF-McKinsey, 2022; 2025; Casciani et al., 2022; Jin & Shin, 2021; Wang et al., 2022). Technology has already revolutionized how companies succeed in the global fashion industry, so fashion companies are expected to increase their tech investments to up to 3.5% of sales by 2030 (BoF-McKinsey, 2022). Improving innovation performance requires that companies first become skilled in adopting new technologies. Although most firm leaders recognize the critical role information technology plays in enhancing organizational-level innovation (Chen et al., 2015), technology cannot fulfill its role in creating and sustaining innovation or improving organizational innovation performance if positive decisions and practices for its use are not made (Taherdoost, 2018). Nevertheless, making informed decisions about information technology implementations is more challenging in rapidly changing and creative contexts, such as the fashion industry (Zahra et al., 2021). The global fashion industry will continue to face rapid transformations, complex issues, and numerous brands struggling to grow significantly (BoF-McKinsey, 2025). Furthermore, the Fourth Industrial Revolution (4IR) in fashion, or Fashion 4.0, is starting to generate new modes of production and consumption that will dramatically transform the industry (Jin & Shin, 2021). This shift requires ongoing digital transformations and the continuous adoption of emerging technologies in fashion (BoF-McKinsey, 2022; 2025; Wang et al., 2022; Zahra et al., 2021).

Much academic attention has been given to theoretical models explaining the adoption of new technology in business, such as the Theory of Reasoned Action (TRA) and the Technology Acceptance Model (TAM), among others (Taherdoost, 2018). TAM is the most widely used of these, "perhaps because of its parsimony and the wealth of recent empirical support" (Amoako-Gyampah & Salam, 2004, p.731). TAM generally views innovation as a product of adopting digital solutions designed to make business approaches more efficient. Prior studies have explored the adoption of traditional systems, such as e-learning systems (Lee et al., 2011), as well as modern systems, like perceived augmented reality (Oyman et al., 2022) and smart clothing (Hwang et al., 2016). However, studies on technology adoption are sometimes contradictory (Ursavaş, 2022).

There is a need for more studies to examine and extend TAM in complex IT settings, especially in specific business environments (Amoako-Gyampah & Salam, 2004), such as the fashion industry. Few academic investigations have been published on technology adoption in the apparel industry, and there is a lack of studies that apply technology-organization-environment theories to explain this adoption (Hoque et al., 2021). Besides, most of the literature on technology adoption in the fashion industry focuses on fashion consumer products, including digital technologies like virtual reality (VR), artificial intelligence (AI), and the Internet of Things (IoT) (Akram et al., 2022), and digital fashion items in the Metaverse (Milanesi et al., 2024). Therefore, testing TAM modifications in the fashion industry has mainly focused on the consumer perspective (Chan et al., 2024; Hwang et al., 2016). This means that further exploration is needed with fashion industry employees. TAM is highly popular among researchers and remains highly relevant today (Oyman et al., 2022; Wang et al., 2022), serving as the most helpful model for technology acceptance in workplace environments (Taherdoost, 2018). However, in response to geographical bias, academics have recently called for more research on technology adoption in regions such as Latin America (Bailey et al., 2022). Furthermore, additional research is needed to examine the variables influencing the use of different information systems across environments (Lee et al., 2005).

Based on these research gaps, this empirical study aims to explain user acceptance of information systems in the fashion industry and to examine the overlooked geographical context of Latin America. Among emerging countries in the region, Colombia's fashion industry was selected as the focus of this study due to its century-long tradition and global recognition. For instance, Colombiamoda, the industry's most prominent event (Ceballos et al., 2020), has established itself as a leading business platform within the region's fashion sector (Inexmoda, 2025). In this context, the current study aims to test an extended TAM by examining the factors of project communication, user training, and technology playfulness that influence the adoption of these systems. Here, project communication relates to all information provided to employees by those who implemented the system and to facilitate its adoption (Carter et al., 2001). Training refers to the process of educating users on how to use a system and its benefits (Amoako-Gyampah & Salam, 2004), while playfulness describes an ephemeral, unconstrained state of enjoyment and pleasure in human-machine interaction (Sun et al., 2023). The findings offer several contributions relevant to managers in the fashion industry and to academics interested in fashion studies, marketing, innovation management, and technology. Findings extend knowledge generation to promote human-technology-induced change in the fashion industry while highlighting the importance of communication in this process. As TAM studies have historically lacked generalizability due to the frequent use of student respondents, this study is among the few that utilize an industry sample.

2. Literature Review

TAM is an adaptation of the TRA to model user acceptance of information systems. Due to its popularity, TAM has become one of the most influential extensions of the TRA. However, it remains valid today in empirical research, particularly within fashion studies (Chan et al., 2024; Hwang et al., 2016; Wang et al., 2022). Despite the numerous empirical tests of the TAM models and multiple adaptations and extensions (e.g., Hwang et al., 2016), most empirical studies (e.g., Okpala et al., 2022) have statistically confirmed the basic TAM structure. Nevertheless, there appears to be sufficient evidence supporting the idea that the TAM model should be adapted to the context in which it will be tested (Taherdoost, 2018; Wang et al., 2022). For instance, Rondan-Cataluña et al. (2015) indicate that the attitude construct should be included when TAM models are applied to final consumers (e.g., Anwar, 2024; Hwang et al., 2016), as they are not obliged to use those technologies compared to other types of individuals, such as employees or students, who usually must comply with the use of specific technology systems. Therefore, the attitude construct is not required in the TAM when employees must use the system due to mandates from their superiors, regardless of their attitudes towards the system (Davis et al., 1989; Rondan-Cataluña et al., 2015). As the use of technology by employees is generally not voluntary, attitude should not explain Behavioral Intention to Use (BI) the system. As the present study focuses on employees, the utilized model does not include the attitude construct.

Accordingly, the original TAM model by Venkatesh and Davis (1996) has been modified to incorporate the BI construct and exclude the attitude construct. In this model, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are the central beliefs influencing computer acceptance behaviors (Davis et al., 1989). *Perceived Usefulness* is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p.320) because of the benefits users believe they will receive (Zeng et al., 2024). *Perceived Ease of Use* is "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p.320). In Anwar's (2024) terms, PEOU is the user´s perception of how simple it is to interact with technology. Beyond the basic TAM structure, Lee et al. (2011) confirmed the need to include external variables to better explain the acceptance of new technology in contexts outside the US. Thus, the following variables were chosen as determinants of the user's beliefs about the system (i.e., PU and PEOU): (1) Project Communication Related to the System, (2) Training, and (3) Computer Playfulness.

Project Communication Related to the System (PC) is the means by which information about the technology's benefits flows from individuals involved in implementation to employees, facilitating increased adoption (Carter et al., 2001). Mounting evidence indicates that making employees aware of technology facilitates understanding and deciding whether to adopt it (Bastan et al., 2022). Logically, employees start using a new information system after being aware of its existence. Even though many factors influence project performance, project communication is among the most relevant, as it is positively associated with project success in terms of completion and goal achievement (Majeed et al., 2021). Thus, PC is a variable affecting IT project success, and one aspect of success, probably the most relevant, is the effective adoption by employees of the IT implemented. Amoako-Gyampah and Salam (2004) found that PC and training are influential in ERP implementation projects.

There are multiple ways to inform potential users of a system, and the information they receive can vary considerably. Therefore, companies need to make targeted efforts to raise employee awareness in various ways and assess their effectiveness to ensure system adoption (Bastan et al., 2022). Nevertheless, communication alone cannot be successful because "education is one way of exploiting any technology," so training is also essential for individuals to properly use a system after they are made aware of its existence (i.e., have received information about a system) (Bastan et al., 2022, p.21). It is logical to conclude that when employees receive sufficient information about a system, they will start using it, playing with it, or planning to be trained to use it. In other words, as employees' perceived information flow regarding a system (PC) increases, so do their chances of receiving available training (T) and engaging in playful exploration of the system (Y). Based on these reasons, it is expected that,

H1$_a$: Project Communication Related to the System will have a positive effect on Training.

H1$_b$: Project Communication Related to the System will have a positive effect on Computer Playfulness.

According to Amoako-Gyampah and Salam (2004), the *Training* (T) variable captures perceived satisfaction with training mechanisms aimed at improving users' technology self-efficacy. When an employee goes through these mechanisms, T affects the PEOU and the PU (Amoako-Gyampah & Salam, 2004). Thus, training is an external factor influencing PEOU (Carter et al., 2001; Davis et al., 1989). Multiple lines of evidence further reveal that organizational factors, such as T, significantly affect both PEOU and PU, so T is a frequently introduced external variable influencing technology acceptance (Lee et al., 2005). More recent studies (e.g., Salloum et al., 2019) also confirm the need for training to encourage both PU and PEOU in system users. Therefore,

H2$_a$: Training will have a positive effect on Perceived Usefulness.

H2$_b$: Training will have a positive effect on Perceived Ease of Use.

Computer Playfulness (Y) is the internal variable for employees that refers to the individual's "degree of cognitive spontaneity in microcomputer interactions" (Webster & Martocchio, 1992, p.20) that anchors the idea that "plays a critical role in shaping perceived ease of use about a new system" (Venkatesh, 2000, p. 346). The essence of this subjective experience of playfulness is focus, enjoyment, and curiosity, which bring emotional pleasure to the user and enhance the valuable hedonic aspect of the interaction between humans and systems (Sun et al., 2023). For example, Davis et al. (1992) examined enjoyment as a factor influencing American MBA students' acceptance of word-processing software and business graphics programs. Their findings suggested that computer programs must be useful and enjoyable to facilitate playfulness and be accepted by users. That is why playful consumption influences behavioral intention to use new technology (Abbasi et al., 2022). Overall, some studies (e.g., Salloum et al., 2019) support the idea that playfulness with a system is a determinant of PEOU, while others (e.g., Lee et al., 2005) confirm the pivotal influence of playfulness on PU. For example, Zeng et al. (2024) demonstrated that interaction behaviors with AI-assisted customized fashion design software, which can be attributed to a playfulness attitude, positively impact both PEOU and PU. It is reasonable to propose that people who consider themselves playful, creative, inventive, etc., with computers, i.e., with high levels of computer playfulness, will be more prone to perceive a system's usefulness and ease of use than other individuals with low computer playfulness. Consequently,

H3$_a$: Computer Playfulness will have a positive effect on Perceived Usefulness.

H3$_b$: Computer Playfulness will have a positive effect on Perceived Ease of Use.

Multiple TAM studies further confirm that PEOU influences PU (Venkatesh & Davis, 1996; Salloum et al., 2019; Terzis & Economides, 2011; Zeng et al., 2024). Furthermore, PU and PEOU are essential variables in technology adoption, as they positively affect the attitude toward the *Behavioral Intention to Use the System* (BI) (Taherdoost, 2018), which is the intention to perform behaviors toward a system (Bastan et al., 2022; Davis et al., 1989). For instance, the greater the impact of PU on BI, the greater the likelihood of system adoption, both directly and indirectly (Ursavaş, 2022). Recent fashion studies (e.g., Milanesi et al., 2024) have also confirmed the positive and significant relation between PU and BI. That is why PU is a powerful trigger that stimulates the perceived values of systems (e.g., e-commerce platforms) and their adoption (Gupta et al., 2023). Also, the effect of PEOU can lead to the perception that such technology will benefit the individual, impacting BI (Terzis & Economides, 2011). Specifically, PEOU has a positive and significant impact on the intention to use fashion design software (Zeng et al., 2024). Hence, it is expected that,

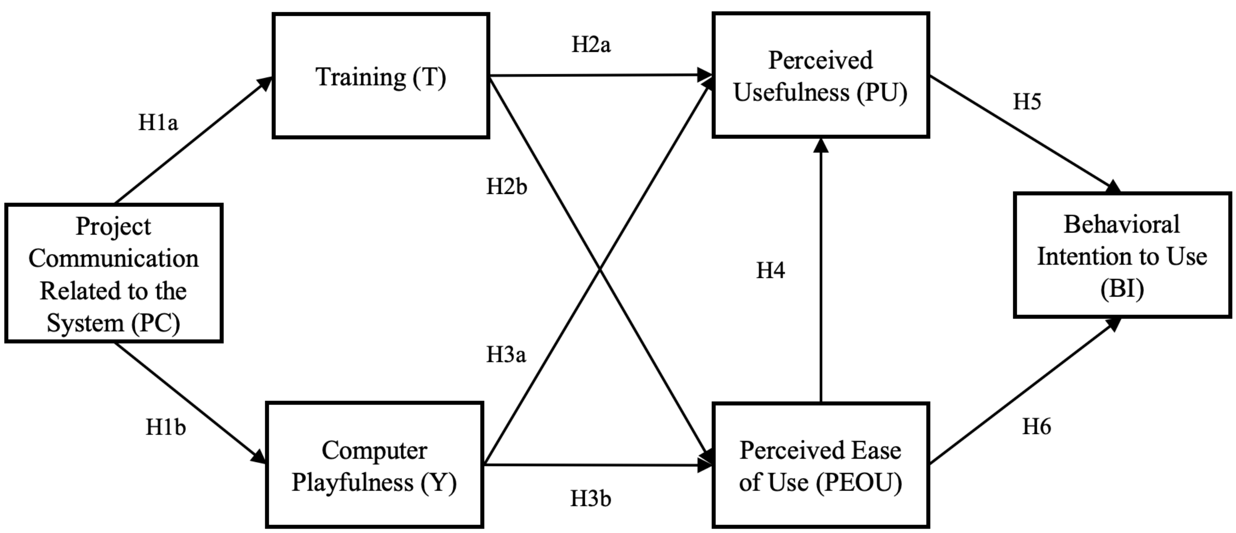
H4: Perceived Ease of Use will have a positive effect on Perceived Usefulness.

H5: Perceived Usefulness will have a positive effect on Behavioral Intention to Use.

H6: Perceived Ease of Use will have a positive effect on Behavioral Intention to Use.

The following Figure 1 introduces the proposed model for the present study.

Figure 1: The proposed theoretical model for new technology adoption in the fashion industry



3. Method

A Structural Equation Model (SEM) analysis was conducted to understand the proposed relationships.

3.1. Data Collection

The Qualtrics survey created by the researchers was distributed by Inexmoda (www.inexmoda.org.co/), a non-profit organization that runs the largest network of fashion stakeholders in Colombia (South America). Inexmoda sent a direct email invitation to participate in the study, including a link to the 10-minute survey, to more than 5,000 companies in its network. The email was sent 3 times over 1 month, and respondents were offered free attendance at a 4-hour workshop on innovation in the fashion industry. After the participant's consent, the survey began with two screening questions to determine whether they were currently working in the fashion industry and whether their organization had adopted information technology systems in the last 3 years. Then, respondents answered questions to understand their acceptance of and use of the new system(s) adopted by their organization, and the survey concluded with demographic questions.

In this study, a *system* is defined as the target technology, which relates to the specific information technology innovation adopted by the organization that serves as the primary focal point for employee beliefs and behavioral intentions (Venkatesh & Davis, 1996). This concept is limited to digital operational infrastructures as firms transition towards Industry 4.0, specifically those systems appropriate for knowledge- and technology-intensive industrial activities within the fashion value chain (Wang et al., 2022). The scope encompasses Enterprise Resource Planning (ERP), Warehouse Management Systems (WMS), AI-assisted design tools (Mortenson & Vidgen, 2016), and Product Lifecycle Management (PLM) (Zeng et al., 2024), among others, all of which are critical to fashion innovation. By focusing on these professionally implemented platforms rather than general-purpose software, the research examines how employees' perceptions are anchored in the specific tools reshaping the firm's operational landscape (Fromhold-Eisebith et al., 2021; Venkatesh & Davis, 1996).

Despite a 16% direct email response rate (> 900 collected surveys), only 288 people completed the Qualtrics online survey. Even though email surveys offer faster response times and cost efficiency, nonresponse is a predictable aspect of organizational behavior for various reasons (Fink, 2015), such as distrust of the external survey link or changes in email addresses. After checking the data quality, 209 responses were used in the final analysis. A total of 79 responses were excluded from the final dataset because respondents did not work in the fashion industry in Colombia, did not name the software, or provided only demographic information. Before the main data collection, a pretest with 108 responses ensured the survey was well-designed. Based on respondents' feedback, minor changes were made to the survey.

3.2. Power Analysis

To evaluate the adequacy of the final sample (N = 209) relative to the model complexity, a power analysis was conducted based on the CFA's RMSEA, following MacCallum et al. (1996) and implemented in SAS 9.4. The analysis tested close fit (H_0: RMSEA = .05) against poor fit (H_1: RMSEA = .08) with $\alpha = .05$ and $df = 341$. The post-hoc power to detect the specified misfit exceeded .99, indicating that the sample size was adequate for the complexity of the measurement and structural models.

3.3. Measures

Perceived usefulness (PU) and perceived ease of use (PEOU) were measured using a six-item scale adapted from Davis (1989). Project communication related to the system (PC) and behavioral intention to use the technology (BI) were measured using a two-item scale, and training (T) was measured using a five-item scale, all scales adapted from Amoako-Gyampah and Salam (2004). Lastly, computer playfulness (Y) was measured using a seven-item scale adapted from Venkatesh (2000). All constructs were evaluated using a 7-point Likert-type scale, ranging from 1 (strongly disagree) to 7 (strongly agree). Table 1 presents detailed information about the items used to measure each construct. Conceptual and back translations were applied to the scales (Fink, 2015).

The items used to measure the constructs were subjected to confirmatory factor analysis, followed by an evaluation of the proposed relationships among constructs (i.e., hypotheses H_1 to H_6) through structural path analysis. The analyses were conducted using Mplus version 8 using maximum-likelihood estimation.

Table 1: Measures and estimates

Items	λ	SE	95% CI	α
V1: (PC) Project Communication Related to the system (adapted from Amoako-Gyampah and Salam, 2004)				.84*
1. I was well-informed about the project through the company newsletters	.88	.042	[.799, .963]	
2. I was informed about the project through presentations, demonstrations, or roadshows	.83	.043	[.740, .909]	
V2: (T) Training (adapted from Amoako-Gyampah and Salam, 2004)				.93
1. The kind of training provided to me was complete.	.80	.031	[.736, .859]	
2. My level of understanding was substantially improved after going through the training program.	.89	.020	[.847, .926]	
3. The training gave me confidence in the NEW system.	.89	.019	[.853, .929]	
4. The training was of adequate length and detail.	.85	.025	[.802, .900]	
5. The trainers were knowledgeable and aided me in my understanding of the system.	.88	.021	[.838, .920]	
V3: (Y) Computer Playfulness (adapted from Venkatesh, 2000)				.95
The following questions ask you how you would characterize yourself when you use computers:				
1. Spontaneous	.83	.025	[.784, .881]	
2. Imaginative	.88	.019	[.838, .914]	
3. Flexible	.84	.024	[.791, .886]	
4. Creative	.90	.016	[.873, .935]	
5. Playful	.82	.027	[.768, .872]	
6. Original	.88	.019	[.847, .920]	
7. Inventive	.90	.016	[.869, .932]	
V4: (PU) Perceived Usefulness (adapted from Davis, 1989)				.96
1. Using the information system in my job enables me to accomplish tasks more quickly.	.92	.012	[.895, .944]	
2. Using the information system improves my job performance.	.90	.015	[.868, .927]	
3. Using the information system in my job would increase my productivity.	.91	.013	[.885, .938]	
4. Using the information system enhances my effectiveness on the job.	.86	.020	[.819, .897]	
5. Using the information system makes it easier to do my job.	.90	.014	[.875, .931]	
6. I find the information system useful in my job.	.91	.013	[.889, .940]	
V5: (PEOU) Perceived Ease of Use (adapted from Davis, 1989)				.93
1. Learning to operate the information system is easy for me	.83	.024	[.785, .880]	
2. I find it easy to get the information system to do what I want.	.79	.029	[.731, .845]	
3. My interaction with the information system is clear and understandable.	.86	.022	[.815, .900]	
4. I find the information system to be flexible to interact with.	.80	.028	[.742, .852]	
5. It is easy for me to become skillful at using the information system.	.86	.022	[.813, .898]	
6. I find the information system easy to use.	.85	.022	[.806, .893]	
V6: (BI) Behavioral Intention to Use (adapted from Amoako-Gyampah and Salam, 2004)				.78*
1. I expect to use the new information system.	.93	.015	[.899, .957]	
2. I expect the information from the new information system to be used.	.96	.013	[.939, .989]	

Note: **λ** = standardized factor loading; SE = standard error; 95% CI = 95% confidence interval; **α** = Cronbach's alpha. All loadings were significant ($p < .001$). *Since these are two-item measures, the Spearman-Brown coefficient was calculated to test for reliability as recommended by Eisinga et al. (2013).

4. Results

4.1. Sample Description

Most respondents held high-ranking positions in their organizations (64.59%), such as Manager or Director (34.93%), CEO (22.97%), Owner or Investor (4.78%), and Vice-Chairman (1.91%). Respondents' ages ranged from the early twenties to over 65 years old (*M*=38.47), with individuals aged 35 to 44 years old (35.41%) the most significant demographic group, followed by those aged 25 to 34 years old (33.49%). Most respondents were female (66.03%) and indicated that their highest academic degree was an undergraduate diploma (53.11%). When individuals reported on the software recently implemented in their companies, most referred to design software (30.62%), followed by Enterprise Resource Planning (ERP) software (13.88%) and social media, E-commerce, and Messaging software (12.92%). See Table 2 for sample details.

Table 2: Sample Characterization

Description	Frequency	Percent
Job Position		
Manager / Director	73	34.93%
CEO	48	22.97%
Designer	35	16.75%
Owner / Investor	10	4.78%
Consultant	8	3.83%
Instructor/Professor	7	3.35%
Analyst	5	2.39%
Executive	4	1.91%
Vice-Chairman	4	1.91%
Professional	3	1.44%
Missing	2	0.96%
Other	10	4.78%
Type of Software		
Design Software and Applications (Graphics, Prototyping, Embroidery, Trend Analysis)	64	30.62%
Enterprise Resource Planning (ERP) Software	29	13.88%
Social Media, E-commerce, and Messaging Application / Software	27	12.92%
Sales Software	14	6.70%
Productivity Application / Software	14	6.70%
Multiple Software	13	6.22%
Production Software	11	5.26%
Customer Relationship Management (CRM) and Database Management Software	7	3.35%
Inventory and Procurement Software	6	2.87%
Accounting Software	5	2.39%
Asset and Facility Management Software	4	1.91%
Project Management Software	2	0.96%
Human Resources Software	1	0.48%
Others	5	2.39%
Missing	7	3.35%

Description	Frequency	Percent
Education		
High School	7	3.35%
Technical Diploma	27	12.92%
Undergraduate Diploma	111	53.11%
Graduate Diploma	64	30.62%
Gender		
Female	142	66.03%
Male	72	33.97%
Age		
20-24	9	4.31%
25-34	70	33.49%
35-44	74	35.41%
45-54	40	19.14%
55 and over	16	7.66%

4.2. Measurement Model

A confirmatory factor analysis was conducted to evaluate the relationship between the observed and latent variables. A set of fit indexes with their recommended cutoff values was employed to assess the model fit; namely, a root mean square error of approximation (RMSEA)≤.08 (Browne & Cudeck, 1992), a standardized root mean square residual (SRMR)≤.08 (Hu & Bentler, 1999), and a comparative fit index (CFI) and Tucker-Lewis fit index (TLI)≥.95 (Hu & Bentler, 1999). The model fit statistics indicated an acceptable fit between the data and the measurement theory [RMSEA=.06; SRMR=.04; CFI=.95; and TLI=.94].

Additionally, the scales exhibit proper internal consistency and convergent and discriminant validity. Internal consistency was assessed by calculating Cronbach's Alpha (α), while convergent and discriminant validity were assessed via composite reliability (CR) and the average variance extracted (AVE). All Cronbach's Alphas were above .7, the recommended threshold. Furthermore, all CR and AVE values exceeded the recommended benchmark values of .7 and .5, respectively (Bagozzi & Yi, 1988). All AVE and CR confidence intervals exceeded their respective benchmarks and did not include zero, indicating precise and reliable estimates. Moreover, all items exhibited significant loadings on their intended constructs, supporting convergent validity. Finally, the scales proved acceptable discriminant validity since the correlation between constructs is smaller than the square root of the AVEs. This was further supported by the heterotrait–monotrait ratio (HTMT), with all values below the recommended threshold of .85 (Henseler et al., 2015). The standardized factor loadings (λ), standard errors, 95% confidence intervals, and Cronbach's α values for individual items and scales are presented in Table 1. Table 3 presents the composite constructs, including means, standard deviations, construct reliability, AVE estimates, and inter-construct correlations. Table 4 presents the HTMT results.

Table 3: Means, standard deviations, AVE, and correlations

Correlations	CR	CR CI	AVE	AVE CI	P	T	Y	PU	PEOU	BI
Project Communication (PC)	.84	[.744, .934]	.73	[.593, .877]	.85					
Training (T)	.94	[.909, .959]	.74	[.666, .823]	.52	.86				
Computer Playfulness (Y)	.95	[.937, .970]	.75	[.681, .821]	.40	.56	.87			
Usefulness (PU)	.96	[.950, .974]	.81	[.761, .864]	.26	.47	.41	.90		
Perceived Ease of Use (PEOU)	.94	[.905, .953]	.69	[.613, .771]	.38	.61	.49	.71	.83	
Intention to Use (BI)	.94	[.916, .973]	.90	[.845, .947]	.32	.48	.37	.77	.68	.95
Mean					5.07	5.69	6.08	6.26	5.76	6.39
Standard Deviation					1.94	1.42	1.28	1.47	1.48	1.44

Note: CR = Composite Reliability; AVE = Average Variance Extracted; CI = 95% confidence interval. All correlations are significant at the .01 level. The square root of the AVE is presented on the diagonal.

Table 4: Heterotrait–Monotrait Ratio (HTMT) Results

Constructs	P	T	Y	PU	PEOU	BI
Project Communication (PC)	-					
Training (T)	.58	-				
Computer Playfulness (Y)	.44	.60	-			
Usefulness (PU)	.28	.50	.42	-		
Perceived Ease of Use (PEOU)	.42	.66	.51	.75	-	
Intention to Use (BI)	.36	.51	.39	.81	.73	-

4.3. Structural Model

The result of the structural model indicates that the proposed model provides an acceptable fit to the data [RMSEA=.07; SRMR=.08; CFI=.95; and TLI=.94], meeting the recommended thresholds for acceptable model fit, namely, RMSEA ≤.08 (Browne & Cudeck, 1992), SRMR ≤.08, and CFI and TLI ≥.90 for acceptable fit (Hu & Bentler, 1999). The model explained a substantial proportion of variance in the endogenous constructs, with the predictors accounting for 70% of the variance in Behavioral Intention (BI), 56% in Perceived Usefulness (PU), and 48% in Perceived Ease of Use (PEOU), indicating high explanatory power. The predictors also explained 43% of the variance in Training (T), which represents a moderate level of explanatory power, while 26% of the variance in Computer Playfulness (Y) was explained by its antecedents, indicating the weakest predictive contribution among the endogenous constructs (R^2; see Figure 2). These values are consistent with the guidelines proposed by Hair et al. (2011), where R^2 values of approximately .25, .50, and .75 are considered weak, moderate, and substantial, respectively. The data provided support for $H_{1a\text{-}b,\ as}$ there is evidence that Project Communication (PC) had a positive effect on Training (T) and computer playfulness (Y) (β=.659, p<.001, f^2=.767; and β=.511, p<.001, f^2=.353). Also, the analysis revealed that there was no significant effect of Training (T) and Computer Playfulness (Y) on perceived usefulness (PU) (β=.003, p=.97, f^2=.000; β=.073, p=.32, f^2=-.005), indicating that H_{2a} and H_{3a} were not supported. However, it was found that training (T) and computer playfulness (Y) had significant positive effects on perceived ease of use (PEOU) (β=.549, p<.001, f^2=.269; β=.276, p<.001, f^2=.006), which supported H_{2b} and $H_{3b.}$

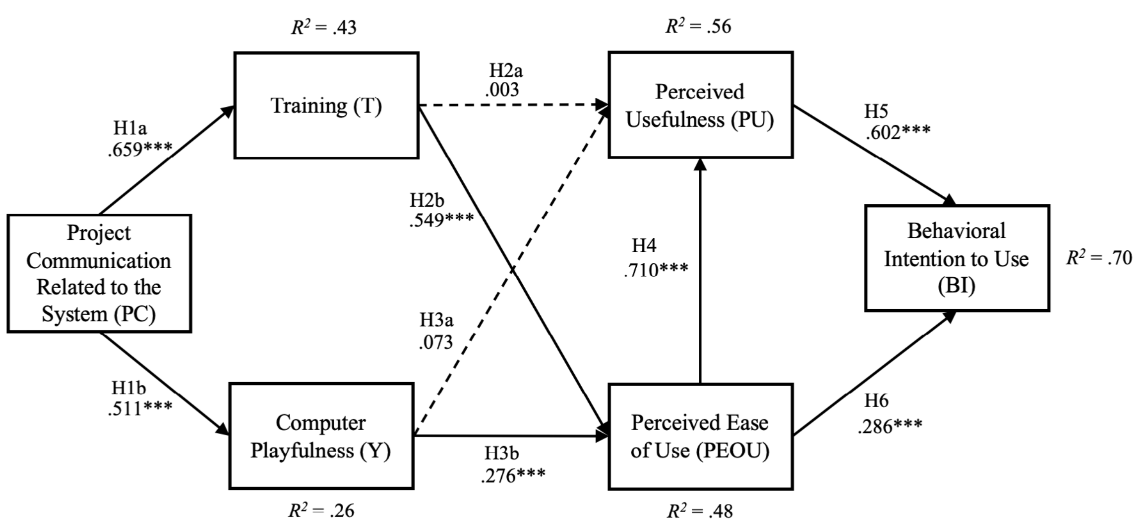
Hypothesis 4 was also supported since there was a positive effect of perceived ease of use (PEOU) on perceived usefulness (PU) (β=.710, p<.001, f^2=.417). Finally, H_5 and H_6 were supported as the effects of perceived usefulness (PU) and perceived ease of use (PEOU) on behavioral intention to use (BI) were significant (β=.602, p<.001, f^2=.370 and β=.286, p<.001, f^2=.073). Following Cohen's (1988) guidelines for evaluating effect sizes (f^2=.02 small, .15 medium, .35 large), the largest effects were observed between Project Communication (PC) and Training (T) (f^2=.767), Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) (f^2=.417), and Training (T) and Perceived Ease of Use (PEOU) (f^2=.269). Smaller effects were found for Perceived Ease of Use (PEOU) on Behavioral Intention (BI) (f^2=.073) and Computer Playfulness (Y) on Perceived Ease of Use (PEOU) (f^2=.006). As expected, no meaningful effects emerged between Training and Perceived Usefulness (f^2=.000) or between Computer Playfulness and Perceived Usefulness (f^2=–.005). A summary of the structural model results is presented in Table 5 and Figure 2.

Table 5: Summary of results of the structural model

Hypotheses	#	β	S.E.	f²	Assessment
Project Communication (PC) → Training (T)	H_{1a}	.659***	.056	.767	*Supported*
Project Communication (PC) → Computer Playfulness (Y)	H_{1b}	.511***	.064	.353	*Supported*
Training (T) → Perceived Usefulness (PU)	H_{2a}	.003	.085	.000	*Not Supported*
Training (T) → Perceived Ease of Use (PEOU)	H_{2b}	.549***	.072	.269	*Supported*
Computer Playfulness (Y) → Perceived Usefulness (PU)	H_{3a}	.073	.073	-.005	*Not Supported*
Computer Playfulness (Y) → Perceived Ease of Use (PEOU)	H_{3b}	.276***	.078	.006	*Supported*
Perceived Ease of Use (PEOU) → Perceived Usefulness (PU)	H_4	.710***	.070	.417	*Supported*
Perceived Usefulness (PU) → Behavioral Intentions to Use (BI)	H_5	.602***	.065	.370	*Supported*
Perceived Ease of Use (PEOU) → Behavioral Intentions to Use (BI)	H_6	.286***	.070	.073	*Supported*

Note: Standardized path coefficients (β) are reported; S.E. = Standard Error; *** Significant at the .001 level.

Figure 2. Structural model with coefficients



*Note: Continuous lines indicate statistically significant paths, while non-continuous (dashed) lines indicate non-significant paths; R² = Coefficient of determination; *** Significant at the .001 level.*

5. Discussion

When analyzing model results (Figure 2, Table 5), as was expected in H_1, PC had a positive effect on T (H_{1a}) and Y (H_{1b}). There can be various reasons for these statistical significances. First, these results are consistent with previous studies (e.g., Amoako-Gyampah & Salam, 2004; Bastan et al., 2022; Carter et al., 2001), especially those that present communications (PC) as the starting point of individuals valuing the benefits of the system and enabling its successful implementation (e.g., Amoako-Gyampah & Salam, 2004; Majeed et al., 2021). The positive effects of H_{1a} and H_{1b} also align with industry-wide recognition that transparent communication and a clear leadership vision are essential components of change management when adopting new technologies (BoF-McKinsey, 2026).

Relative to H_2, results indicate that training (T) did not have a positive effect on PU (H_{2a}) but did have a positive effect on PEOU (H_{2b}). H_{2b} confirms previous studies (e.g., Davis et al., 1989; Carter et al., 2001), whereas H_{2a} contradicts other TAM applications (e.g., Amoako-Gyampah & Salam, 2004). In the global fashion industry, BoF-McKinsey (2026) argues that demand for training is high, yet nearly half of consumer goods and retail employees report receiving only moderate support or less, suggesting that when adequate training is provided, it significantly reduces the perceived effort required to master new systems (H_{2b}). Even though employees report that it was easier to use the system (PEOU) after receiving information on how to use the system (T) (H_{2b}), the beliefs related to the usefulness of the system (PU) might not have been improved with training (T) (H_{2a}) and depend on whether the system improves the work efficiency in the day-to-day life of the employee. If the system does not significantly enhance their work efficiency, then the training may not effectively change their beliefs about its usefulness, leading to a disconnect between the perceived ease of use and the perceived usefulness of the system.

As for H_3, computer playfulness (Y) positively affected PEOU (H_{3b}) but not PU (H_{3a}). Results then confirm that playfulness has a positive effect on perceived ease of use (PEOU) but not on perceived usefulness (PU). As for H_{3b}, the results confirm findings reported by Salloum et al. (2019). The significant positive relationship between Y and PEOU makes sense, as an employee with high levels of Y can experience greater enjoyment when using a system. Enjoyment has been found to influence new technology adoption because when technology use is perceived as entertaining and fun, it is easier to perceive it as easy to use (Park et al., 2019). However, a system can be PEOU but not necessarily practical or helpful, and it may not provide valuable information that enables higher work performance (PU) (H_{3a}). The wide variety of systems considered by respondents in the present study may have influenced these results, as most TAM studies focus on a single system or technological product (Chan et al., 2024).

A possible explanation for the unsupported hypotheses (H_{2a} and H_{3a}) could be individual differences in training styles and preferences. While employees may find it easier to use the system (PEOU) after receiving information and training (T) (H_{2b}), beliefs about the system's usefulness (PU) might not have improved (H_{2a}) because employees vary in how they perceive and value the system's benefits. For some employees, the training may have focused primarily on technical aspects and procedural instructions, thereby enhancing their understanding of how to operate the system effectively. However, if the training inadequately demonstrated or emphasized the system's practical benefits, employees might not have developed a strong belief in its usefulness. Their evaluation of usefulness could be influenced by factors beyond training, such as prior experience with similar systems or personal expectations for improvements in work efficiency. Furthermore, employees may have varying job roles and responsibilities, and the system's impact on their day-to-day work efficiency may differ. If the system's benefits are more pronounced for specific roles or tasks, then employees who do not perceive a significant improvement in their work efficiency may not find the system highly useful, even after receiving training. It is also probable that the system/company did not offer formal training for specific individuals, or training was not purchased/accessible/available. Another possible reason for the non-significant results is that respondents selected the systems they were measuring, meaning the collected data depended on those specific systems. Refer to the Type of Software subsection in Table 2, which shows that 44.50% of the selected software was related to design and ERP, while 12.92% pertained to social media and e-commerce. This variation suggests that the level of training provided and the degree of playfulness experienced with these systems may have influenced results. As for communication, specific software selected in the survey may not have been involved in an implementation project *per se*, and the communication might have been nonexistent or informal, e.g., the boss mentioned the system in a meeting.

From an industry perspective, Fromhold-Eisebith et al. (2021) argue that Industry 4.0 technologies are transforming both the internal and external operations of textile firms. In this context, employees' behavioral intention to use technology is not simply an isolated acceptance decision but part of the firm's broader digital operational infrastructure. This perspective could also explain why the relationships described in H_{2a} (Training (T) → Perceived Usefulness (PU)) and H_{3a} (Computer Playfulness (Y) → PU) were not supported in this study. Textile firms often exhibit strong path dependency, meaning long-established practices and routines tend to persist over time. This organizational inertia can limit the ability of training or playful interaction with a system to alter employees' deeply rooted beliefs about its usefulness. This is reinforced by the structure of the textile and apparel value chain, where strong pressure from both raw material suppliers and global customers encourages firms to prioritize cost efficiency and conservative business behavior rather than experimentation or experiential engagement with technology (Fromhold-Eisebith et al., 2021). A similar pattern has been observed in developing fashion markets (Wang et al., 2022), where technology adoption tends to be driven primarily by extrinsic motivations, such as short-term financial profit and operational efficiency, rather than intrinsic enjoyment or playfulness. In these markets, perceived usefulness typically refers to the practical benefits that a technology provides for knowledge-intensive industrial activities, such as improving design quality or reducing production failure rates (Zeng et al., 2024). Consequently, if the "fun" aspects of a system do not directly support employees' daily responsibilities, they may be perceived as irrelevant to strategic or operational outcomes.

These findings also provide an important industry-specific insight regarding the unsupported H_{3a}. The result suggests that, in this context, intrinsic enjoyment does not readily translate into perceptions of professional usefulness. Wang et al. (2022) explain that while intrinsic value (including enjoyment and playfulness) can motivate technology use, it remains conceptually distinct from utility value (perceived usefulness) in the Chinese textile and apparel industry. A comparable situation may occur in developing economies such as Colombia, where textile firm managers and employees often prioritize short-term financial profit and low-cost-driven activities (Ruiz-Velásquez et al., 2020). As a result, employees are more likely to evaluate systems through a strictly utilitarian perspective, indicating that utility-value dominance also drives technology adoption. Therefore, even if respondents find a system enjoyable (or playful) to use, they may not perceive that aspect as contributing to the practical performance improvements required by their firm (Wang et al., 2022). Overall, the inability of playfulness to influence perceptions of usefulness suggests that, for these laggard firms to progress, management must move beyond designing "fun" interfaces and instead clearly demonstrate how target technologies reduce structural cost pressures and improve work quality.

As for hypotheses $H_{4\text{-}6}$, they were supported. That is, PEOU had a positive effect on PU (H_4), PU had a positive effect on BI (H_5), and PEOU had a positive effect on BI (H_6). $H_{4\text{-}6}$ results are consistent with previous studies that confirm the basic TAM structure in models without the attitude construct (e.g., Okpala et al., 2022). H_4 results explain that available technologies that are assumed to be easy to use are then perceived as being more useful and beneficial because the employee can spend their time working rather than trying to understand how to use the system (i.e., the system offers a convenience benefit to the user) (Park et al., 2019). The significance of H_4 highlights that when digital tools are easy to navigate, employees can shift their focus from understanding the system to performing higher-value tasks, such as AI-assisted design or predictive maintenance (BoF-McKinsey, 2025; Wang et al., 2022).

Reflecting on the reported software, it was foreseeable that respondents mentioned new technologies essential to everyday business needs, such as design software, ERP, social media, and e-commerce, as well as productivity-related software (Table 2). However, as Colombia is a developing country with political and economic unrest, and most companies in the fashion industry are small or medium in size and faced with the urgency of their everyday responsibilities (Ruiz-Velásquez et al., 2020), findings are far from what the most prominent fashion companies in the world are doing in terms of incorporating state-of-the-art technologies to face 4IR challenges (BoF-McKinsey, 2026; Jin & Shin, 2021) beyond basic business needs. For instance, AI is helping firms worldwide adopt technology more quickly and on lower budgets, such as AI-assisted, customized fashion design software (Zeng et al., 2024), while also extending beyond operational and logistical demands to offer digital fashion items in the Metaverse (Milanesi et al., 2024). Yet it is understandable that this labor-intensive industry, with complex production processes, mainly focuses its technological investments on processes that must be constantly adjusted in day-to-day operations and in response to fashion cycles and market/legal demands. Findings in this study are consistent with the Fobiri et al. (2024) systematic literature review, which indicates that technology adoption is prevalent in the textile and fashion industry; digitalization has been key to sustaining the industry and meeting market demands, but small-scale producers appear to be laggards in this adoption.

Market information could also provide context for the relevance of findings in this study. BoF-McKinsey (2026) global report argues that developing and integrating AI, digital, and technology-related capabilities into fashion business operations is crucial. This offers the most significant opportunity to address the difficult industry outlook for 2026 and beyond. In Colombia, Inexmoda (2025) also emphasizes the importance of technology in preparing firms for the sector's uncertain future, especially by improving their ability to gain market knowledge, which is fundamental for sound strategic decisions, including how to incorporate sustainability. This is especially relevant for enhancing brand-consumer interactions across systems managed by the firm, such as social media, e-commerce, and notably, AI-assisted front-office systems (e.g., chatbots). Despite the urgency, Inexmoda also notes that only 42% of fashion firms have implemented AI in consumer communication. However, the type of software reported in this study also indicates a possible limitation for creating innovations and achieving competitiveness in the national and international arena. Systems reported mainly focus on the production, administration, and sales aspects of the business, rather than new industry demands related to sustainability, transparency, and other areas (cf. BoF-McKinsey, 2025). This reality confirms that, to this day, only "few brands or retailers have embraced technology with a truly competitive mindset" (BoF-McKinsey, 2022, p.8). Anyhow, specific essential software (e.g., design software for prototyping) can also be creatively used to generate, for example, product innovation. Evidence of this is Colombian designers such as Amalia Toro and Silvia Tcherassi, who, despite multiple budget constraints, limited governmental support, and low-skilled labor, among many other challenges, have attained trendsetter status worldwide (Procolombia, 2023). Hence, designers and companies must be more creative during technology adoption in Colombia than in other contexts with better conditions for adapting to their environments, persevering, staying relevant, and competing.

Interpreting the overall findings in light of Fromhold-Eisebith et al. (2021), we conclude that behavioral intention (BI) is the foundation of organizational readiness in Colombia's fashion industry, as firms cannot build the digital operational infrastructure needed for Industry 4.0 without employees' individual intention to adopt systems. Beyond individual acceptance, our findings highlight the strategic role of communication in developing organizational capabilities. In our model, communication acted as the foundational catalyst shaping employees' beliefs about technology adoption. However, the lack of support for H_{2a} and H_{3a} suggests that, while communication effectively reduced the perceived mental effort associated with using the technology, it has not yet fully bridged the gap toward establishing perceived utility value. In the context of a strong path dependency and a historically context-development trajectory (Fromhold-Eisebith et al., 2021), simply training employees on procedural tasks is insufficient. To move the fashion industry toward an Industry 4.0 transformation, firms must use communication not only to explain how systems work but also to align employees' cognitive drivers with the technology's strategic utility value, thereby framing digital adoption as a business necessity for long-term competitiveness and survival (Wang et al., 2022).

5.1. Theoretical Implications

Findings provide theoretical contributions in several ways. First, this study advances the Technology Acceptance Model (TAM) conceptually by moving beyond simple contextual application to uncover new insights into the belief-formation process within a traditional industrial setting. We advance the model by introducing Project Communication (PC) as a foundational catalyst for belief formation, aligning organizational narratives before employees interact with the technology itself. In this way, internal communication becomes a primary driver of employee acceptance of new systems. This finding suggests that PC shapes the effectiveness of subsequent interventions, such as training and computer playfulness, serving as an anchor for employee acceptance prior to technical interaction. Second, the pattern of unsupported relationships (H2a and H3a) offers an additional theoretical insight. In this context, employees distinguish between their belief that a system is easy to use (Ease of Use) and their belief about its professional value (Perceived Usefulness). In other words, employees may separate intrinsic enjoyment and procedural mastery from utilitarian productivity outcomes. This finding extends TAM by suggesting that the persistence of traditional routines in the fashion industry may act as a boundary condition for belief conversion, limiting the extent to which ease of use or playfulness translates into perceived usefulness.

Third, by identifying behavioral intention as a critical link in building a firm's digital operational infrastructure, this research situates TAM within the broader framework of organizational capability development. Specifically, we conceptually link individual-level cognitive drivers to the firm's ability to achieve organizational readiness for Industry 4.0. This extension suggests that individual technology acceptance is not merely a psychological endpoint but a micro-foundation for firms' strategic adaptation and survival. Finally, the findings also extend the application of TAM by testing these relationships among variables in an uncharted business environment and geographic context. The results demonstrate that the TAM structure is crucial in shaping technology adoption in this setting. Moreover, the TAM modifications proved appropriate for measuring adoption beyond consumers, explaining user acceptance among employees and managers, and assessing adoption in non-student populations. Unlike much prior research focused on consumers in Western, Educated, Industrialized, and Democratic (WEIRD) societies, this work examines technology adoption among employees in a specific industry outside such contexts. Importantly, the findings and discussion also explain key antecedents of employee technology adoption, which could help companies translate theory into practice. These implications are especially important for the Colombian fashion industry, where adoption of technology is vital for strengthening capabilities amid challenging prospects for 2026 and beyond.

5.2. Managerial Implications

Results shed light on factors influencing the adoption of new technology in the fashion industry, specifically within a developing-country context. Implementing IT systems requires investments of resources beyond financial resources, so findings can be helpful to managers aiming to increase the use of newly implemented technology, better plan future system implementations, and, therefore, improve their innovation performance. However, as employees reported using new technologies in their everyday work, these efforts may not be enough to stay afloat and remain competitive, especially as the fashion tech acceleration is digitalizing the entire value chain and creating a fast-evolving, hyper-connected industry (BoF-McKinsey, 2022; 2025). Nevertheless, the rise of more accessible emerging technologies, such as Artificial Intelligence (AI), offers new opportunities to implement technology that improves all aspects of the fashion value chain and increases innovation with lower budgets and effort.

Furthermore, findings suggest that managers must lead the creation/reinforcement of a continuous learning digital culture within their companies. There is a need to consistently communicate the benefits of emerging tech, encourage reflection on how these information systems can improve everyday processes within the value chain, and promote employees' playfulness with these systems. As training alone cannot sustain steady adoption (Bastan et al., 2022), managers must also empower employees to learn independently about process digitalization and technology integration. Nevertheless, managers may encounter employees with negative attitudes toward technology, which can make these communication efforts daunting.

Thus, new hires should prioritize candidates with technology skills and a positive attitude toward emerging technologies. As resources are scarce, caution is warranted, and priorities should be established to optimize individual and group efforts.

6. Conclusions

Due to the tech acceleration in the 4IR, the fashion industry is experiencing exciting and thought-provoking times. Now, more than ever, a company's capacity to adopt new information technology will be a critical factor in its success. Despite this scenario, the models that have studied information technology adoption still need to be tested beyond the US context and beyond specific products and consumer populations. This study explained user acceptance of technology in the understudied, complex context of the fashion industry in a developing country. Overall, the findings indicate that the first step in a fashion company's technology adoption process is sharing information about the new technologies to be implemented and used by employees. Internal communication about the benefits of new systems catalyzes user acceptance of information technology in Colombian fashion businesses. Results are limited to Colombia, but they may also apply to other emerging countries with a similar fashion industry landscape. Survey results may have been influenced by the definition of information systems and by the systems respondents selected for data collection. Future studies can focus on certain types of software to yield more consistent results. Additionally, potential individual differences among users, such as gender, may warrant further investigation. Future studies on technology adoption may adopt a comprehensive, process-oriented approach, recognizing that adoption processes are not purely functional but are also shaped by ethical, cultural, and cognitive dimensions (Martinez & Montoya, 2023).

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