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THE ADOPTION OF LOGISTICS 4.0 TECHNOLOGIES BY WAREHOUSE EMPLOYEES AND ITS IMPACT ON JOB SATISFACTION[1]

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ABSTRACT

Focusing on a smart warehouse in Turkey that serves global clients, this research investigates how warehouse employees adopt Logistics 4.0 tools and the subsequent impact on their job satisfaction. Conducted within the framework of the widely used Technology Acceptance Model (TAM), the research evaluated the relationships between the dimensions of perceived usefulness (PU), perceived ease of use (PEOU), behavioral intention (BI) and actual behavior (AB), and job satisfaction. Data were collected via face-to-face surveys of 70 warehouse employees and analyzed using the SPSS 27.0 program. Reliability analyses showed that the scales were generally acceptable. The findings showed that employees found Logistics 4.0 technologies useful and easy to use. It was determined that PU and PEOU had a significant positive effect on BI and that PU, PEOU and BI increased job satisfaction. However, the study's most striking finding is that there is no significant relationship between BI and AB. Although employees express a strong BI to use the technology, this does not always translate into AB. Consequently, although Logistics 4.0 technologies have the potential to increase job satisfaction, closing the BI-AB gap requires investment in infrastructure, confidence-building communication strategies and continuous training programmes.

Keywords: Logistics 4.0, Technology Adoption, Technology Acceptance Model, Job Satisfaction, Behavioral Intention-Actual Behavior Gap

JEL Codes: M11, L23

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1. INTRODUCTION

With the widespread adoption of digital technologies today, the logistics sector is evolving into a new paradigm known as "Smart Logistics" or "Logistics 4.0". The concept of Logistics 4.0 signifies a shift towards autonomous supply chains, where digitalization permeates essential functions ranging from procurement to warehousing. This system delivers high-quality service at lower costs.

The adoption of digital technologies in logistics involves more than just transitioning from analog to digital; it also requires a fundamental socio-technical transformation in how businesses and employees work (Legner et al., 2017). This transformation requires businesses to develop innovative business models to optimize performance and implement changes using digital technology opportunities (Brennen & Kreiss, 2016). The Logistics 4.0 paradigm is based on integrating the Internet of Things (IoT), big data analytics, cloud logistics, augmented reality, robotic systems, autonomous vehicles, and blockchain technologies. Implementing these technologies aims to increase cost efficiency by minimizing error and waste rates in logistics operations. Efficiency and profitability optimization in transportation and warehouse management processes improves customer service levels and, consequently, customer satisfaction (Erdal & Saygılı, 2007). Integrating these technologies into supply and distribution channels is expected to significantly contribute to the development of fundamental logistics processes, such as autonomous transportation, supply, and warehouse management.

As an integral part of modern logistics processes, warehouses play a critical role in the integration of Logistics 4.0 technologies. Smart warehouses accelerate operational processes, increase accuracy, and transform flexibility through automation systems, autonomous transport vehicles, wearable technologies, and other innovative solutions. However, the successful implementation of these technologies depends on warehouse personnel embracing and effectively using these innovations.

To understand the drivers behind user technology adoption, researchers frequently utilize the Technology Acceptance Model (TAM) as a foundational theoretical lens. According to TAM, individuals' tendencies to adopt technology are shaped by two factors: perceived usefulness (PU) and perceived ease of use (PEOU). PU reflects the belief that a technology will improve job performance, and PEOU reflects the belief that using the technology is simple. These two factors directly influence the intention to use technology, which translates into actual behavior. In this context, new technological transformations and employees' perceptions of these technologies influence job satisfaction and play an important role in business efficiency.

This study aims to determine warehouse workers' adoption levels of Logistics 4.0 technologies within the framework of the TAM and examine how these levels affect employee job satisfaction. To this end, we will measure and analyze key TAM variables, such as PU, PEOU, behavioral intention(BI), and actual behavior(AB) regarding Logistics

4.0 technologies. Then, the direct impact of employees' adoption of these technologies on job satisfaction will be evaluated.

2. CONCEPTUAL FRAMEWORK

Logistics 4.0 is defined as the integration of smart systems and innovative applications in logistics operations (Barreto et al., 2017). It signifies a shift in logistics processes from a hardware-centric approach to a software-centric one (Timm & Lorig, 2015). Logistics 4.0 encompasses a network of machines and hardware that can interact with each other and humans. This network is supported by smart sensors and objects that collect data via the internet. The data is then recorded, processed through software, and shared in databases. The goal is to enable autonomous processes (Domingo Galindo, 2016). In this context, Logistics 4.0 is considered a complex structure composed of independent subsystems that exchange information (Timm & Lorig, 2015).

Technological transformation is happening fastest in warehouses within the logistics system. Logistics 4.0 technologies are making warehouse operations more efficient, reducing error rates, and resulting in significant cost savings.

Inventory management has been revolutionized by tools such as UAVs and RFID, which facilitate rapid and precise stock quantification. These technologies ensure the real-time detection of products reaching the reorder point and the execution of real-time supply activities (Shariatzadeh et al., 2016). This minimizes excess inventory costs and customer losses due to stock shortages.

The use of material handling equipment and personnel movement in warehouses can be monitored through sensors to minimize the risk of accidents (Lee, 2011). Additionally, handling operations become more efficient, and losses are detected to prevent theft (Meydanoğlu & Klein, 2013). Warehouse heating and lighting systems minimize energy losses by adapting to changing conditions. Conveyor systems guided by sensors can be used to transport and classify products within the facility more quickly (Lee, 2011).

Order picking, often cited as a high-cost operation, sees significant efficiency gains through the deployment of augmented reality solutions. Smart glasses applications reduce error rates and boost the efficiency of order picking activities (DHL, n.d.). Augmented reality glasses support minimizing human error by communicating work orders, providing in-warehouse navigation, performing barcode reading, and enabling hands-free operation. Additionally, using forklift windshields as computer screens allows operators to perform handling operations more safely and efficiently.

Various operations in storage facilities, from product acceptance to shipment, require human intervention. Standardized processes, in particular, can be automated through robotic systems and autonomous vehicles. This integration equips storage areas with smart systems and increases process efficiency. Automated Storage and Retrieval Systems (AS/RS) contribute significantly to operational performance by automating the processes of placing loads on shelves, storing them, and preparing them for shipment according to orders. Robotic systems are also used in palletizing and packaging processes to optimize processing times. Smart conveyor systems equipped with sensors and image processing

technologies can rapidly and accurately transport and sort packages within the facility. Although autonomous vehicles can perform full pallet preparation processes in order picking operations,

Although Logistics 4.0 offers significant efficiency gains through its technologies, it is not yet possible to transition to a fully autonomous system due to the technologies' lack of maturity. In operations requiring articulated movements and cognitive skills, humans are far superior to machines. Conversely, even with the use of Logistics 4.0 technologies, humans still play an important role in monitoring and controlling activities. These technologies enhance human-machine interaction, supporting the workforce and decision-making processes (Lagorio et al., 2021). Therefore, how the workforce perceives these technologies, the degree to which they are adopted, and their impact on job satisfaction are important questions that must be addressed.

TAM was developed by (Davis, 1989) and has been an effective model used in research on how users perceive new technologies for many years. The Technology Acceptance Model is a framework that aims to predict the future roles of these technologies in users' lives by analyzing individuals' attitudes toward new technologies, their adoption and usage behaviors (Yıldırır & Kaplan, 2019). TAM consists of three elements: perceived usefulness (PU), perceived ease of use (PEOU), and behavioral intention (BI).

PU is defined as the extent to which individuals believe that using technology will improve their job performance (Davis, 1989). In this context, a positive correlation between technology use and performance indicates a high level of perceived usefulness. For instance, if one software application operating under equivalent conditions produces superior results compared to another, it suggests that the former has higher PU (Turan, 2011).

PEOU reflects users' subjective belief that they will expend minimal effort when using a technology. According to research findings, perceived ease of use indirectly affects PU(Davis, 1989). When individuals perceive that new technologies are relatively simple to use, they are more willing to adopt and use these technologies (Saadé & Bahli, 2005).

BI is the measurement of an individual's effort and willingness to perform a specific behavior. According to the TAM, BI represents the process that precedes behavior and is the fundamental determinant of technology adoption and use (Bayraktar, 2019).

Job satisfaction is defined as the positive emotional responses employees exhibit toward their jobs as a result of their experiences (Locke, 1976). In this context, financial gain and the ability to express oneself by working synergistically with colleagues to produce a collective product are key factors influencing job satisfaction (Bingöl, 1996). Low job satisfaction can result in psychological and mental exhaustion, a lack of motivation, burnout, poor performance, and general dissatisfaction. Job satisfaction plays a critical role in optimizing businesses' effectiveness and efficiency. Thus, analyzing factors that determine job satisfaction is important from academic and practical perspectives. These factors can be examined under two main categories: individual and organizational (Çolak Alsat, 2018). Individual factors include age, gender, education, status, and personality. Organizational factors include salary, job structure, work environment, and work group.

Technological innovations implemented in businesses have the potential to affect employee job satisfaction levels directly or indirectly by profoundly influencing organizational structures and processes. For example, the integration of automation into work processes can lead to a decrease in labor demand. This may result in increased remuneration policies for qualified technology specialists and decreased policies for unqualified labor. Advanced data analytics tools can make performance-based remuneration systems more applicable. Technological applications can eliminate routine processes, enabling employees to take on more complex, creative tasks and increasing satisfaction. Sensor technologies and artificial intelligence-based systems can minimize occupational safety risks and improve workplace safety. Technological platforms can facilitate the formation of more synergistic work groups by optimizing information sharing and collaboration among employees. Therefore, how employees perceive and adopt technological applications is critical to job satisfaction and organizational efficiency.

3. LITERATURE REVIEW

In recent years, the adoption of Logistics 4.0 technologies in the logistics sector and the multidimensional effects of this transformation on the human factor have become the focus of academic interest (Winkelhaus et al., 2022). This section will critically evaluate the impact of digital transformation processes on acceptance factors, employee experience and job satisfaction, drawing on Davis's TAM model and its expanded theoretical frameworks.

3.1. Technology adoption and key determinants of Logistics 4.0

The academic literature commonly employs the TAM and its extensions to explain the intention to adopt new technologies (Davis, 1989; Tung et al., 2008; Liu et al., 2025). Studies in the logistics and supply chain context consistently demonstrate that TAM's key variables, PEOU and PU, play a pivotal role in technology adoption. PEOU and PU have a positive influence on the BI to adopt various logistics technologies, including electronic logistics information systems (Tung et al., 2008), electric cargo vehicles (Ngoc et al., 2022), and delivery drones used in humanitarian aid operations (Edwards et al., 2024). A common finding is that PEOU indirectly influences PU by facilitating user perception (Toraman & Öz, 2023). For instance, Wolff & Madlener (2019) discovered that the perception among commercial vehicle drivers of electric vehicle features, such as automatic transmission, as enhancing efficiency (PU) and being effortless (PEOU) resulted in high satisfaction. Other important external factors that affect the acceptance process include trust and perceived risk (Tan & Sundarakani, 2021). Nguyen et al. (2025) found that the level of trust of operators is a critical factor in the acceptance of logistics robots and that PEOU and PU also positively influence overall trust. Edwards et al. (2024) observed that perceptions of safety (with regard to both drones and packages) play a vital role in the acceptance of drone deliveries. Conversely, Ngoc et al. (2022) emphasized that perceived risk relating to safety, performance and a lack of charging infrastructure is one of the biggest barriers to the adoption of electric cargo vehicles. In their study examining

social, environmental, and technological barriers to the acceptance of last-mile logistics applications in Egypt, Sultan et al. (2023) found that, beyond individual perceptions, a lack of government support, legal uncertainties, and deficiencies in technological infrastructure were the strongest barriers.

3.2 The impact of Logistics 4.0 on employees

The adoption of Logistics 4.0 technologies brings about systemic changes that affect employees' work experiences and, consequently, their JS, either directly or indirectly (Winkelhaus et al., 2022). The literature critically examines this impact in two main scenarios: technology replacing employees (automation), or supporting it (augmentation) (Sgarbossa et al., 2020). In this context, the importance of human-centred approaches to the adoption of Logistics 4.0 technologies is highlighted (Kadir et al., 2019; Cimini et al., 2021; Lagorio et al., 2021; Cimini et al., 2022).

3.2.1 Positive effects and employee-centred support approaches

As with many new technologies, Logistics 4.0 has the potential to enhance work quality and job satisfaction by alleviating ergonomic and cognitive strain. Automation-based systems, such as cobots and wearable technologies, along with ergonomic systems, can reduce physical strain and the risk of human error. Jacob et al. (2023) state that human–robot collaboration increases efficiency, quality and performance, while also providing ergonomic benefits. Cimini et al. (2019) reported that Logistics 4.0 technologies free operators from dangerous and low-value tasks through automation, enabling them to play a more active role in cognitive processes such as decision-making and process improvement by providing real-time access to information via mobile devices. Winkelhaus et al. (2022) found that Logistics 4.0 technologies positively impact job satisfaction by increasing task variety and autonomy for employees. However, Wang et al. (2025) reported that job satisfaction does not directly affect logistics performance, but this effect is strongly mediated through competencies such as logistics innovation and customer responsiveness. This finding shows that it is not the technology itself, but rather the new competencies offered by technology to employees, that are decisive for satisfaction.

3.2.2 Negative effects and barriers to acceptance

Organizational and operational changes brought about by digitalization and automation also have the potential to cause negative psychosocial outcomes. According to Winkelhaus et al. (2022), advanced automation systems narrow employees' roles, making them feel like 'part of the machine', reducing task variety and social interaction. Issantu (2021) and Jacob et al. (2023) emphasize that psychosocial factors such as fears about job security, resistance to change, job loss, stress and a lack of motivation regarding robotic systems can negatively affect employees' acceptance of technology. Studies such as those by Perotti et al. (2022) and Fahmi et al. (2024) indicate that a lack of training and competence can

lead to technologies being used incorrectly or inadequately, thereby reducing operational efficiency.

3.3. Gaps in the Literature and Originality of this Study

Traditional TAM models generally assume that BI has a positive and significant influence on AB (Davis, 1989). There are numerous studies investigating the relationship between technology acceptance and job satisfaction. However, the existing literature has not adequately explored the discrepancy between positive technology perceptions (PU, PEOU, and BI) and low AB (the behavioral intention–actual behavior gap).

While many TAM studies in logistics have found that the impact of BI on AB is significant (Gündoğan & Keçeci, 2024; Fahmi et al., 2024), there are few studies that have thoroughly examined the reasons for this gap at an organizational level. For example, why does AB remain low despite high BI? This study relates the fundamental reasons for this gap to the following theoretical arguments:

1. Although employees are willing to use technology, they are unable to do so in practice due to difficulties with system integration (Tan & Sundarakani, 2021) and inadequate infrastructure (Sultan et al., 2023).

2. Although employees have positive perceptions of technology (PU/PEOU), strong psychosocial factors such as fear of job loss or lack of trust (Jacob et al., 2023) prevent these BI from being translated into AB.

3. An employee with high BI may lack the practical knowledge or digital competencies required to use the technology (Gündoğan & Keçeci, 2024), which creates this gap.

The primary objective of this study is to empirically examine and analyze the adoption process of Logistics 4.0 technologies in smart warehouse environments, focusing on the direct relationship between TAM structures and job satisfaction. The study's original contribution to the literature is its empirical evidence of the potential gap between BI and AB. This study aims to provide unique insight into technology acceptance literature by demonstrating that, although acceptance of Logistics 4.0 technology and job satisfaction are positively correlated at the intention level, organizational and psychosocial barriers prevent this positive BI from being fully translated into AB.

4. MATERIAL METHOD

This quantitative study aims to examine the level of adoption of Logistics 4.0 technologies by workers in a smart warehouse that serves international customers on a contractual basis in Turkey, as well as the impact of these technologies on job satisfaction.

Data for the study were collected using a face-to-face survey, a quantitative research method. The data were analyzed using SPSS 27.0, a statistical analysis program for the

social sciences. The study population includes all employees working in the relevant smart warehouse. Since there are 70 employees in the warehouse, the entire population was included in the sample.

The demographic questions used in this study were designed based on a review of similar studies in the relevant literature and in accordance with the study's purpose. The study's primary data collection tools were developed by combining the TAM, which was developed by Davis (1989), with the Job Satisfaction Scale, which was adapted into Turkish by Başol & Çömlekçi (2020).

This study examined the four dimensions of TAM—PU (four statements), PEOU (four statements), BI (four statements), and AB (three statements)—together with the five-statement Job Satisfaction Scale. The study analyzes how technology adoption processes affect job satisfaction. The conceptual model is presented in detail in Figure 1.

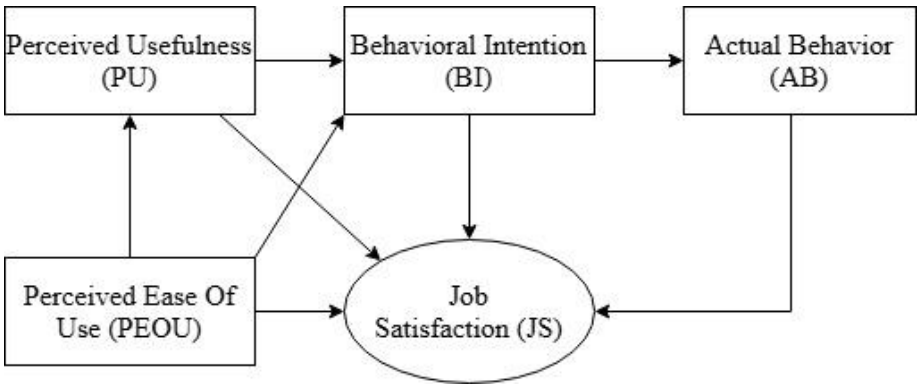

Figure 1. Research Model

Within the scope of the research model, the existence of the specified relationships has been assumed. These assumptions form the basic hypotheses of the research.

H_1: The PEOU of Logistics 4.0 technologies by warehouse employees positively impacts PU.

H_2: The PEOU of Logistics 4.0 technologies by warehouse employees positively impacts BI.

H_3: The PU of Logistics 4.0 technologies by warehouse employees positively impacts BI.

H_4: The BI of Logistics 4.0 technologies by warehouse employees positively impacts AB.

H_5: The PEOU of Logistics 4.0 technologies by warehouse employees positively impacts JS.

H_6: The PU of Logistics 4.0 technologies by warehouse employees positively impacts JS.

H_7: The BI of Logistics 4.0 technologies by warehouse employees positively impacts JS.

H_8: The AB of Logistics 4.0 technologies by warehouse employees positively impacts JS.

These hypotheses define the fundamental relationships that the research model will test.

4.1. Reliability and Validity Analysis

To evaluate scale reliability and internal consistency, we calculated Cronbach's alpha (α) coefficients for the dataset. The analysis revealed that the Cronbach's Alpha value for the entire model was α = 0.802, and the coefficients for the subscales are presented in table 1.

Table 1. Cronbach's Alpha Values of Scales

Scales	Cronbach's alpha (α) coefficient
PU	.922
PEOU	.625
BI	.900
AB	.530
JS	.659
General Total	.802

These values were examined in light of the reliability assessment criteria specified by Özdamar (2013). Accordingly, α = 0.802 indicates that the model as a whole is highly reliable. The PU and BI scales are highly reliable (α = 0.80–1.00), while the PEOU and JS scales are acceptable reliability (α = 0.60–0.80). However, the AB scale was found to be low but marginally acceptable reliability ($0.40<\alpha\leq0.60$). These findings suggest that all the scales meet the reliability criteria.

5. RESULTS

5.1. Demographic Information about Participants

Table 2 shows the demographic characteristics of the 70 warehouse employees who completed the survey.

Examining the gender distribution of participants revealed that 91.4% were male and 8.6% were female. In terms of age, 10.0% of participants were in the 18–24 age group, 55.7% were in the 25–34 age group, and 32.9% were in the 35–44 age group. Because there were insufficient participants in the 45-54 age range, this category was included in the 35-44 age range. There were no participants in the 55-and-older category, so this group was excluded from the analysis.

Table 2. Demographic Data on Participants

Variable		N	%
Gender	Male	64	91,4%
	Female	6	8,6%
Age	18-24	7	10,0%
	25-34	39	55,7%
	35-44	23	32,9%
	45-54	1	1,4%
Educational Status	Elementary School Graduate	9	12,9%
	High School Graduate	45	64,3%
	University Graduate	14	20,0%
	Master's Degree	1	1,4%
	Doctorate Degree	1	1,4%
Work experience in logistics	0-1	19	27,1%
	2-5	30	42,9%
	6-10	18	25,7%
	11-15	1	1,4%
	>15	2	2,9%
Work experience in this warehouse	0-1	27	38,6%
	2-5	22	31,4%
	6-10	21	30,0%

According to the education status variable, 12.9% of participants are elementary school graduates, 64.3% are high school graduates, and 20.0% are university graduates. Since there were insufficient participants with master's and doctoral degrees, these groups were combined under the university graduate category.

Of the total work experience in the logistics sector, 27.1% of participants had 0–1 years, 42.9% had 2–5 years, and 25.7% had 6–10 years. Since there were insufficient participants with 11-15 and over 15 years of experience, these categories were included in the 6-10 years range.

Regarding current warehouse work experience, 38.6% of participants have 0–1 years of experience, 31.4% have 2–5 years, and 30.0% have 6–10 years. There were no participants with 11-15 or more than 15 years of experience, so these categories were excluded from the analysis.

5.2. Normality Tests

In order to determine whether the data set shows a normal distribution, the skewness and kurtosis values frequently used in the literature were examined. The normality of data collected with Likert-type scales is critical for obtaining reliable statistical results. In

accordance with the criteria proposed by Tabachnick et al. (2007), who suggested that values should fall between -1.5 and +1.5, and George (2011), who stated that values between -2.0 and +2.0 are acceptable, the skewness and kurtosis values are presented in Table 3.

Table 3. Tests of Normality

Scales	Skewness	Kurtosis
PU	-2,024	3,062
PEOU	-0,355	-0,749
BI	-1,044	1,33
AB	0,097	-1,266
JS	-0,977	0,025

The analysis results showed that the skewness and kurtosis values of the PU scale were outside the limits specified in the literature. Therefore, nonparametric tests were applied to this scale. Since the skewness and kurtosis values of the other scales were within acceptable limits, parametric tests will be used for them.

5.3. Findings Regarding the Descriptive Statistics of the Scales

Table 4 presents descriptive statistics of participants' opinions regarding the statements on the study's scales.

Table 4. Findings Regarding the Descriptive Statistics of the Scales

Factors	Loads	Mean	Std. Dev.
Perceived usefulness (PU)			
Using Logistics 4.0 technologies increases my performance.	0,813	4,7	0,645
Using Logistics 4.0 technologies increases my productivity.	0,91	4,71	0,593
Using Logistics 4.0 technologies increases my efficiency.	0,85	4,67	0,675
I find Logistics 4.0 technologies useful.	0,676	4,69	0,649
Explained Variance = %81			
Perceived ease of use (PEOU)			
Using Logistics 4.0 technologies is straightforward and clear.	0,821	4,56	0,715
Using Logistics 4.0 technologies does not require much mental effort.	0,831	3,54	1,224
Using Logistics 4.0 technologies are easy	0,799	3,97	1,116
I find it easy to use Logistics 4.0 technologies to do what I want	0,829	4,46	0,716
Explained Variance = %49			
Behavioral Intention (BI)			
I intend to use Logistics 4.0 technologies in the future.	0,835	4,13	0,931
I plan to use Logistics 4.0 technologies in the future.	0,912	4,21	0,883
I predict that I will use Logistics 4.0 technologies in the future.	0,776	4,04	1,028
Explained Variance = %84			

Actual Behavior (AB)			
I can frequently use Logistics 4.0 technologies.	0,644	4,37	0,783
I cannot work efficiently without Logistics 4.0 technologies.	0,624	3,76	1,398
I do not use Logistics 4.0 technologies.	0,786	3,73	1,403
I rarely use Logistics 4.0 technologies.	0,767	3,31	1,440
Explained Variance = %42			
Job Satisfaction (JS)			
I find my job enjoyable.	0,730	4,73	0,536
I am satisfied with my current job.	0,718	4,73	0,679
I enjoy doing my job.	0,754	4,84	0,367
Time passes well at work.	0,608	4,71	0,486
I find happiness in my work.	0,587	4,70	0,462
Explained Variance = %67			

Factor analysis was applied in this study to test the construct validity of the scales. The analysis revealed that the dimensions of PU, PEOU, BI, and AB were grouped under a single factor. Due to the negative wording of items 13 and 14 on the AB scale, these items were reverse coded prior to analysis.

Factor analysis produces coefficients known as factor loadings, which indicate the relationship between variables and factors. Higher absolute factor loadings imply a more robust association between the variable and its underlying factor (Altunışık et al., 2005). Tabachnick et al. (2007) state that the minimum factor loading value for an item to be assigned to a factor is 0.32.

To determine the factor distribution of the scale items, the varimax rotation method was used. The resulting factor loadings and percentages of variance explained by the variables are presented in Table 4.

According to the results of the analysis, the total variance percentages explained by the scales are as follows: PU(81%), PEOU(49%), BI(84%), AB(42%), JS(67%).

5.4. Relationship between Scale Statements

Correlation analysis was performed to determine the direction and strength of the relationship between the subscales of the TAM and job satisfaction. The results of the analysis are presented in Table 5.

This study employed correlation analysis to determine the strength and direction of relationships between variables. According to Kalaycı (2010), the Pearson correlation coefficient (r) ranges from −1 to +1. This coefficient indicates the following: $r > 0$ indicates a positive relationship; $r < 0$ indicates a negative relationship; and $r = 0$ indicates no relationship.

Table 5 presents the correlation coefficients between the variables. Due to the skewed distribution of the PU scale, the relationship between this scale and the others was examined using the Spearman correlation coefficient. The relationships between all other variables were analyzed using the Pearson correlation coefficient.

Table 5. Relationship between Scale Statements

		PU	PEOU	BI	AB	JS
PU	r	1				
	p					
	N	70				
PEOU	r	,337**	1			
	p	0,004				
	N	70	70			
BI	r	,410**	,493**	1		
	p	<,001	<,001			
	N	70	70	70		
AB	r	,352**	-0,014	0,001	1	
	p	0,003	0,907	0,995		
	N	70	70	70	70	
JS	r	,414**	,384**	0,087	,322**	1
	p	<,001	0,001	0,476	0,007	
	N	70	70	70	70	70

According to the results of the analysis, no statistically significant relationship was found between the AB scale and the other scales. The strongest relationship among the variables was found between PEOU and BI (r = 0.49).

5.5. Findings Related to the Research Hypotheses

This section summarizes the results of the regression and correlation analyses for the hypotheses examining the adoption process of Logistics 4.0 technologies by smart warehouse employees and its effects on JS.

5.5.1 TAM Constructs Findings (H_1, H_2, H_3)

Regression analysis results indicate that PEOU has a significant and positive effect on both PU and BI,

H_1 (PEOU → PU): PEOU has a significant and positive effect on PU (F = 26.246; p = 0.001). The effect is strong (β = 0.610), explaining 26.8% of the variance in PU (R^2= 0.268). **H_1** was accepted.

H_2 (PEOU → BI): PEOU has a significant and positive effect on BI (F = 21.867; p = 0.001). The effect coefficient is β = 0.505, with PEOU explaining 23.2% of the variance in BI (R^2= 0.232). **H_2** was accepted**.**

H_3 (PU → BI): Similarly, PU has a significant and positive effect on BI (F = 12.008; p = 0.001). The effect coefficient is β = 0.343, with PU explaining 13.8% of the variance in BI (R^2= 0.138). **H_3** was accepted.

H_4 (BI → AB): Correlation analysis revealed no significant relationship between employees' BI and their AB (r = 0.019; p = 0.876). Due to statistical insignificance (p > 0.05), **H_4** was rejected**.** This finding empirically confirms the existence of the BI–AB gap.

5.5.2 TAM Constructs and JS (H_5, H_6, H_7, H_8)

Regression analyses demonstrated significant and positive relationships between the TAM constructs and JS.

H_5 (PEOU → JS): PEOU has a significant and positive effect on JS (F = 11.785; p = 0.001). The effect coefficient is β = 0.437, explaining 13.5% of the variance (R^2 = 0.135). **H_5** was accepted.

H_6 (PU → JS): PU has a significant and positive effect on JS (F = 10.235; p = 0.002). The effect coefficient is β = 0.356, explaining 11.8% of the variance (R^2 = 0.118). **H_6** was accepted.

H_7 (BI → JS): BI has a significant and positive effect on JS (F = 7.864; p = 0.007). The effect coefficient is β = 0.357, explaining 9% of the variance (R^2 = 0.09). **H_7** was accepted.

H_8 (AB → JS): Correlation analysis showed no significant relationship between AB and JS (r = 0.071; p = 0.562). Due to statistical insignificance (p > 0.05), **H_8** was rejected. This situation implies that actual behavior has no effect on job satisfaction.

6. DISCUSSION AND CONCLUSION

This study used data collected via a quantitative survey of 70 warehouse employees working in a smart warehouse that serves international customers in Turkey. The study aimed to examine the adoption levels of Logistics 4.0 technologies within the framework of the TAM and investigate its effect on job satisfaction. According to the study's demographic findings, most participants were male (91.4%), aged 25–34 (55.7%), and high school graduates (64.3%). Participants had 2-5 years of experience in the logistics sector (42.9%), and 38.6% had worked at their current company for 0-1 years. This demographic structure may limit the generalizability of the findings. Given this specific profile, the findings of this study should be interpreted with caution due to several limitations regarding generalizability. First, the data were collected from a single smart warehouse operating in Turkey, which may reflect specific organizational and cultural characteristics not present in other settings. Second, the relatively small sample size (N=70) and the male-dominated demographic profile (91.4%) limit the extent to which these results can be extrapolated to the broader logistics workforce. Consequently, the observed relationships between behavioral intention and actual behavior might be influenced by the specific context of this case study.

Reliability and validity analyses show that the Cronbach's alpha value of the general model is 0.802, indicating high reliability. Among the subscales, PU (α = 0.922) and BI (α = 0.900) are highly reliable, while PEOU (α = 0.625) and JS (α = 0.659) are acceptable reliable. However, the reliability coefficient of the "actual behavior" scale was found to be low (α = 0.530). While this value is below the traditional threshold, it can be considered marginally acceptable for exploratory research using scales with few items. Crucially, despite this psychometric limitation, the scale empirically highlighted the 'intention-behavior gap,' which stands as one of the study's most striking findings. Therefore, while results related to this variable should be interpreted with caution due to the reliability constraint, they provide valid and critical insights into the barriers preventing technology adoption.

The hypothesis tests largely support the basic assumptions of the TAM. Studies have shown that PEOU positively effects PU and BI, and that PU also positively effects BI. These findings show that when employees find technology easy and useful, their BI increases. Additionally, PEOU, PU, and BI were found to positively and significantly affect JS. These results align with studies by Winkelhaus et al. (2022) and Gruchmann et al. (2021). The former suggests that digital technologies can positively influence JS by increasing task variety and autonomy. The latter shows that ergonomic technologies increase acceptance by reducing physical difficulties.

Contrary to the foundational premises of TAM, our analysis necessitated the rejection of H4, as no statistical link was found between BI and AB. This contradicts the assumption that positive BI leads directly to AB, a fundamental premise of technology adoption models such as TAM. Our findings also contradict those of Torun & Cengiz (2019), who suggested that BI has a positive effect on AB. Similarly, our study rejected hypothesis H8 by revealing that BI had no significant effect on employee JS. These findings demonstrate that, despite positive perceptions and BI towards technology among employees, these do not always translate into AB, nor does usage directly determine JS.

This observed situation confirms the frequently discussed BI-AB gap. Although employees report finding Logistics 4.0 technologies useful and easy to use, and intend to continue using them, the failure to translate this positive BI into AB poses a significant productivity problem for companies. This gap is caused by two main categories of barriers: organizational (systemic) and individual (employee-related) factors.

At the organizational level, the infrastructure deficiencies and integration issues highlighted by Tan & Sundarakani (2021) and Sultan et al. (2023) can be considered fundamental systemic barriers that prevent BI from being translated into AB. Disruptions to technology access, integration and operation will render even the strongest intention to use ineffective in practice.

At the individual level, psychosocial and cognitive barriers are prevalent. As emphasized by Jacob et al. (2023), psychosocial factors, such as concerns about the security risks associated with Logistics 4.0 technologies and fears that these technologies will lead to

job losses in the future, prevent positive BI from being translated into AB. Issantu (2021) supports this view, noting that employees resist changes related to robotic systems due to concerns about job security. Therefore, the BI- AB gap observed in this study may reflect employees' caution and distrust towards technological change. Furthermore, Gündoğan & Keçeci (2024) point out that a lack of practical knowledge or digital literacy among employees is also a significant cognitive barrier. Studies by Perotti et al. (2022) and Fahmi et al. (2024) strongly emphasize the critical importance of developing digital skills and implementing continuous education programmes to close this gap.

In light of these findings, comprehensive interventions are required to bridge the BI– AB gap and ensure the adoption of Logistics 4.0 technology. Firstly, the company must promptly address infrastructure improvements by identifying deficiencies in the technical infrastructure and integration issues. Employees' concerns about security risks should be addressed by taking the necessary precautions and adopting a transparent communication strategy that conveys the message that Logistics 4.0 technologies support and empower employees rather than replacing them. Finally, to address the knowledge and skill gaps identified by Gündoğan & Keçeci (2024), the company should provide continuous training programmes that focus on both theory and practice to encourage employees to use these technologies. This holistic approach will ensure positive BI translates into high AB, maximizing the contribution of Logistics 4.0 investments to organizational benefits.

Future studies should use qualitative research methods, such as in-depth interviews and focus groups, to support quantitative findings. To better understand the reasons behind the relationship between behavioral intention and actual usage behavior, for example, the effects of individual differences, social interactions, and environmental conditions on employee productivity can be examined, as in the study by Aloini et al. (2022). Since this study was limited to 70 warehouse workers, the generalizability of the findings is constrained. To overcome these limitations and validate the identified 'intention-behavior gap,' future research is strongly encouraged to employ larger and more diverse samples. Specifically, comparative studies across different logistics sub-sectors (e.g., transportation vs. warehousing) and cultural contexts would provide deeper insights. Furthermore, ensuring a more balanced gender distribution and including employees from multiple organizations in future samples will be crucial to increasing the external validity of the TAM in the context of Logistics 4.0. As in Nguyen et al.'s (2025) study, future research on the adoption of Logistics 4.0 technologies can include variables such as the trust factor and managerial support in the model.

COMPLIANCE WITH ETHICAL STANDARD

Conflict of Interests: There is no conflict of interest between the authors or any third party individuals or institutions.

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