

Factors Influencing the Willingness to Adopt Internet of Things in Supply Chain Management: A Study on Bangladeshi Manufacturing Firms

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Abstract: This study explores the factors influencing the willingness to adopt the Internet of Things (IoT) in Bangladeshi manufacturing firms' supply chain management (SCM). Using a quantitative research approach, data is collected from 162 firm-specific SCM professionals through purposive sampling. Applying the partial least squares structural equation modeling (PLS-SEM), the four primary constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT) model- performance expectancy, effort expectancy, social influence, and facilitating conditions are examined to find their influence on the willingness to adopt IoT in the SCM of Bangladeshi manufacturing firms. Findings enumerate that these four constructs explain 42% of the variance in the willingness to adopt IoT. Performance expectancy, social influence, and facilitating conditions are statistically significant, while effort expectancy is insignificant in influencing the willingness to adopt IoT in the SCM. These findings bring several theoretical and practical contributions and suggest scope for future research.

Keywords: Bangladesh; Internet of Things (IoT); Supply chain management; behavioral intentions

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1. Introduction

The supply chain, an integrated and extensive system of operations within an organization, received attention in prior research as an important business domain (Agrawal & Narain, 2018). Supply chain management (SCM) is a crucial business domain that involves diligently managing an organization's supply chain components to achieve higher performance, optimize costs, reduce risks, and achieve higher profits (Ghadge et al., 2020). Scientific investigations constantly taking place in SCM to identify practical, effective, and strategic ways to improve the entire supply chain ecosystem (Martins & Pato, 2019). Manufacturing firms often consider SCM as a separate department that includes demand forecasting, sourcing raw materials and logistics, production scheduling, inventory and warehouse management, distribution, asset tracking, and customer management.

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Manufacturing firms also rely on various technologies, such as transport and logistical management software, blockchain, big data, IT, and artificial intelligence, to enhance their supply chain performance (Fatorachian & Kazemi, 2021).

IT has significantly influenced supply networks by integrating multiple activities with suppliers and consumers, making it a critical enabler for efficient SCM (Ben-Daya et al., 2019). The Internet of Things (IoT) an advent of IT is causing a paradigm shift in various business domains, including SCM, by enabling human-to-thing interaction and automatic coordination among 'things'. This new capability provides enormous opportunities in dealing SCM difficulties efficiently (Khan et al., 2022). The impact of IoT adoption on organizations is multifaceted, positively influencing every area of the value chain (Palmaccio et al., 2021). Empirical research has shown that IoT in SCM can provide major advantages to customers and organizations, such as greater visibility, real-time tracking, and decision-making capabilities (Palmaccio et al., 2021). These advantages can result in lower costs, enhanced productivity, and more customer satisfaction, guiding a company toward a competitive edge (Dymitrowski & Mielcarek, 2021). However, as a relatively new field, more scholarly works on IoT in SCM can help firms learn and develop strategies for better performance using IoT (Fatorachian & Kazemi, 2021).

The adoption of IoT in SCM is crucial, but the factors influencing decisions are still underexplored (Kasilingam & Krishna, 2022). Developed and developing countries have been the focus of previous studies, while emerging countries have received less attention (Shi et al., 2022). Moreover, while a few previous studies have explored the causes of lower IoT adoption rates, they have limited their findings to niche contexts and lack theoretical underpinning and generalizability, particularly emerging economies (Khan et al., 2023). In addition to this scarcity, a sample of previous studies (see Table A1 in the appendix) clearly shows that no studies in Bangladesh have attempted to investigate IoT adoption in SCM. As a result, this study aims to address this gap by examining factors that contribute to Bangladeshi manufacturing firms' willingness to adopt IoT in their SCM by considering the following research question: What factors influence Bangladeshi manufacturing firms' willingness to adopt IoT in their SCM?

In emerging economies such as Bangladesh, the use of IoT in SCM is a key driver of Industry 4.0. The IoT expansion in Bangladesh is similar to that in other emerging economies around the world. The adoption was primarily for business-to-business (B2B) purposes by mobile providers. However, in 2018, the Bangladesh Telecommunication Regulatory Commission (BTRC) declared IoT lawful in the country. In March 2020, the Information and Communication Technology (ICT) Division developed the National IoT Strategy, aiming to turn Bangladesh into a technologically driven country by 2030. The

National IoT Strategy contains a vision, mission, goals, objectives, prospects, difficulties, procedures, regulations, and action plan. The plan prioritizes industrial IoT services first for upgrading RMG facilities in Bangladesh, providing real-time insights to manufacturers, and expanding to other business areas.

This study has several notable theoretical and practical contributions. First, in terms of theory, this study extended the existing literature by incorporating Bangladesh into its study context, which had never been explored before. Second, in terms of policy, this study urges increased focus on IoT at both firm and government levels to bring sustainable development to firms, the economy, and the nation. The Bangladesh government's current policy aims to transform the country into a "Digital Bangladesh," where IoT-enabled SCM would be revolutionary. This study's findings will benefit firms and stakeholders, including government bodies and end consumers. In practical use, it outlines managerial implications for widespread IoT adoption in SCM activities in Bangladesh, including enabling supportive technological infrastructure, investing in networking, ensuring proper training, and shifting from traditional SCM to updated management aligned with digitalization efforts. Users are more likely to adopt IoT when perceived as improving performance, having favorable influence, and receiving adequate support for technological infrastructure.

The remainder of the paper is structured as follows. Section 2 discusses the theoretical background and hypotheses of the study. Section 3 describes the methods followed in the study. The results are presented in Section 4, followed by a relevant discussion in Section 5. Finally, Section 6 concludes the paper by summarizing the study and finding the study's limitations and scope of further research.

2. Literature Review

2.1 IoT applications in SCM

The "Internet" or network component is the primary focus of the first vision of the IoT, while the "things" component is the focus of the second (Atzori, et al., 2010). Initial definitions of the Internet of Things (IoT) primarily focus on "things," specifically addressing radio frequency identification (RFID) tags that connect to a network to provide identifying data (Xu et al., 2014). Subsequently, more "things"—sensors and actuators—appear, including the entirety of modern mobile devices (Ben-Daya et al., 2019). An IoT network typically consists of four primary layers: (1) a sensing layer, which integrates various "things" such as actuators, sensors, and RFID tags; (2) a networking layer, which facilitates information transfer via wired or wireless networks; (3) a service layer, which unifies applications and services via middleware technology; and (4) an interface layer, which presents data to the user and permits interaction by users with the system (Xu et al.,

2014). Additionally, Lee and Lee (2015), in their study, suggested five key IoT technologies: (1) radio-frequency identification (RFID), (2) wireless sensor networks (WSN), (3) middleware, (4) cloud computing, and (5) IoT applications.

SCM concepts, strategies, and definitions are constantly evolving, such as through modern information and communication technology. These changes impact the structure, maintenance, and control and planning procedures within supply chains (Olhager & Selldin, 2004). The term SCM has gained momentum in the last decade of the twentieth century, where it has been defined and researched in different areas of business, i.e., manufacturing, distribution, marketing, customer management, or transportation. The definition of SCM has a number of trajectories; some researchers label it in operational terms, including material and product flow, while others comprehend it as a management philosophy or a management process (Olhager & Selldin, 2004). Taking into account the growing body of research going these different ways, SCM is "the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a company and across businesses within the supply chain, with the goal of improving the long-term performance of both the individual companies and the supply chain as a whole" (Xu et al., 2014). Therefore, SCM is crucial for achieving and sustaining the competitive positions of manufacturing firms (Olhager & Selldin, 2004).

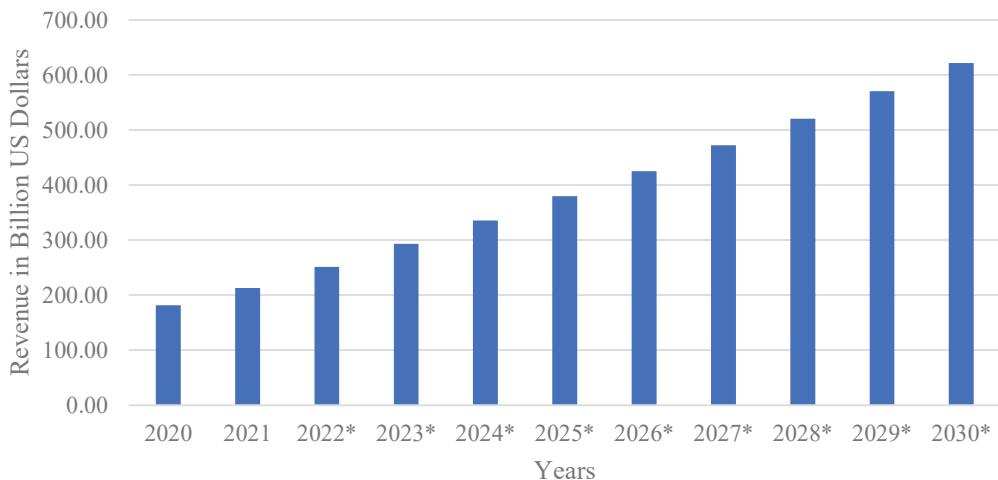
Many business areas, including agriculture, smart homes and cities, manufacturing, services, enterprise solutions, and SCM, can apply IoT. Table 1 presents a list of possible IoT applications in different industries and their associated benefits. In a manufacturing context, IoT can be articulated as the basic network of sensors and equipment that are connected to one another, collect, and transmit data, which allows managers to make more informed decisions about manufacturing solutions. IoT in manufacturing is a way to turn both established and emerging industries into creative, cost-efficient sectors. The IoT helps manufacturing organizations because it allows them to gather data and improve most operations in order to become as efficient as possible. Besides, in SCM, IoT benefits a manufacturing firm by optimizing production, improving customer service, tracking assets and resources, forecasting demand, and managing inventory. Comprising the benefits of IoT in different industries signposts a gradual upward trend in the total annual revenue from the IoT. Figure 1 depicts IoT's total worldwide annual revenue from 2020 to 2030 in billions of U.S. dollars.

Table 1: Application of IoT in different industries with benefits

Industry	Benefits
Smart cities	Water and waste management, energy management, public safety, pollution monitoring
Smart homes	Energy efficiency, security, convenience, smart lighting
Supply chain management	Optimize production, improve customer service, asset tracking, inventory management
Agriculture	Smart irrigation systems, livestock tracking, equipment monitoring, soil moisture monitoring, precision farming, soil chemistry and fertilizer profiles
Enterprise solutions	Workforce management, building management, mitigation tactics, customer analytics, information technology infrastructure library (ITIL)
Wearables	Smartwatches, virtual and augmented reality, elderly care, less workplace accidents
Connected factories with industrial IoT	Maintenance management, predictive maintenance, process automation, safety and security, product development and quality testing
Retail	Cashless shopping, inventory management, data-driven marketing
Hospitality	In-room controls, housekeeping and room service, electronic keys, energy management, check-in/check-out
Traffic	Smart parking, traffic light control, public safety
Fleet management	Vehicle tracking, performance monitoring, maintenance schedule
Energy and utilities	Smart grids
Healthcare	Monitor patients, contact tracing apps, medical record keeping, monitor blood sugar levels accurately, upgraded pharmaceutical manufacturing

Source: Author's compilation based on the Chataut et al. (2023)

Figure 1: The total worldwide annual revenue of IoT from 2020 to 2030 in billion U.S. dollars



Source: Author's compilation based on the data provided by the Statista Search Department (2024)

To enable a manufacturing firm to be an IoT-enabled advanced business unit, supporting advanced technology and infrastructure is required, which includes but is not limited to IoT sensors, satellite networks, RFID, Bluetooth low energy (BLE), application programming interfaces (APIs), cloud computing, and security infrastructure. Table 2 presents descriptive statistics of different IoT technologies with current and expected market sizes. IoT sensors are electrical chipsets or devices that use a gateway to send data they detect about the environment or system conditions to the Internet. While magnetic fields, radiation, or physical contact can trigger these various sensors, RFID is a more integrated technology for asset tracking and identification (Landaluce et al., 2020). This is because there are more and more tags available in the interrogation zone. The satellite network is the alignment of different components that create communication between two points on Earth via different nodes, whereas the term satellite network in IoT describes how IoT devices and satellite networks are combined to provide streamlined data exchange and communication (Centenaro et al., 2021).

Besides, using the 2.4 GHz ISM band, BLE is a low-power wireless personal area network that aims to connect devices over a comparatively small range, and the design of BLE is structured by keeping the application of it in IoT-enabled devices. A means of communication between two or more computer programs or components is an API, an

important route for developing and implementing IoT in specific manufacturing firms (Landaluce et al., 2020). Cloud computing is a term used for an online platform that allows users to share and access a variety of computing resources (computers, networks, storage, software, etc.) as needed. Because of the massive amount of data created by IoT devices and the requirement for it to be analyzed using high-speed processing machines to enable real-time and efficient decision-making, cloud computing is essential to the implementation of IoT (Lee & Lee, 2015). Finally, IoT security is the technology segment focused on safeguarding connected devices and networks in IoT. Authentication and authorization of devices, data encryption, secure communication protocols, frequent software upgrades, network segmentation, and strong access restrictions are some examples of IoT security types. The goal of these actions taken together is to guarantee the availability, confidentiality, and integrity of IoT systems (Ben-Daya et al., 2019).

Table 2: Descriptive statistics of different IoT technologies with current and expected market size

IoT Technologies	Current market size (in 2023)	Expected market size (in 2030)
IoT Sensors	34.48 Billion USD	94.82 Billion USD
RFID	14.98 Billion USD	26.01 Billion USD
Satellite Network	1.87 Billion USD	4.61 Billion USD
Bluetooth Low Energy	23.20 Billion USD	43.34 Billion USD
Application Programming Interface	3.89 Billion USD	12.99 Billion USD
Cloud Computing	680 Billion USD	1440 Billion USD
Security Infrastructure	148.5 Billion USD	191.83 Billion USD

Source: Author's compilation based on the Mordor Intelligence IoT global report (2024)

2.2 Theoretical Background

The factors affecting the behavioral intention, usage, and post-usage outcome of adopting a technology are multifaceted and complex, and they continue to challenge researchers across several disciplines (Venkatesh et al., 2003). Furthermore, in SCM, various psychological factors, including external entities and persons, contribute to this complication (Katoch, 2022). Several conceptual models are available to understand these technology-related, psychology-laden events similar to those in SCM (Taherdoost, 2018). Some of these theories and models are the Technology Acceptance Model (TAM), Extended TAM (ETAM), Theory of Planned Behavior (TBP), Theory of Reasoned Action (TRA), Theory

of Interpersonal Behavior (TIB), Social Cognitive Theory (SCT), and Diffusion of Innovations Theory (DOI) (Davis et al., 2023). However, Venkatesh et al. (2003) proposed a more robust model, UTAUT, based on the previous eight commonly used frameworks of technology adoption. The UTAUT also overcomes the limitations of those previous models, i.e., insufficient precision and reliability. Because of its superiority, the UTAUT gained appeal, resulting in broad acceptance of the model in various scholarly domains, including IT, e-learning, the Internet, online shopping, and social media platforms.

However, previous studies emphasized the necessity of validating UTAUT in diverse business contexts to better suit the research environment (Yee & Abdullah, 2021). As a result, numerous studies have employed the UTAUT model to elucidate behavioral intentions and actual usage of various business technologies, such as IoT (Shi et al., 2022), and even to examine SCM (Sharma et al., 2023). Table A1 in the appendix presents a summary of the several previous studies that were reviewed in this research, majority of which used the UTAUT model. Therefore, this study adopts the UTAUT model as the theoretical framework because of its broad applicability in examining users' behavioral intentions towards IoT in SCM. The four main elements of the UTAUT model—performance expectancy, effort expectancy, social influence, and facilitating conditions—are considered in this study without any changes. Venkatesh et al. (2003) also argued that when applied independently, these constructs may predict 70% of the variation in user motivation, 17% greater than the eight integrated models developed before UTAUT. The following sections present the reasons for considering these variables, hypotheses based on the relationships between variables, and the study's theoretical model.

2.3 Hypotheses Development

Venkatesh et al. (2003) describe performance expectancy as the degree to which a technology apparatus or system is perceived to improve performance, solve a specific problem, or complete any task with a specified level of efficiency and effectiveness. In this study, performance expectancy is referred to as the extent to which IoT is anticipated to be beneficial in improving the performance of the SCM of manufacturing firms. Several studies on different technology adoptions, including IoT, contended that performance expectancy is the most reliable predictor and has a statistically significant impact on the users' willingness to adopt the technology (Ronaghi & Forouharfar, 2020). Therefore, this research hypothesized that,

H₁: Performance expectancy positively influences the willingness to adopt IoT in the SCM of Bangladeshi manufacturing firms

Venkatesh et al. (2003) further described effort expectancy as the perceived ease of utilizing a technology instrument or system. The authors merged the concepts of perceived ease of use, complexities, and ease of use across three distinct models to develop a single measuring unit. In this research, the effort expectancy is characterized as the degree to which SCM professionals perceive the implementation and usage of IoT technology to be simple. Previous studies that considered effort expectancy as a predictor variable to the user's behavioral intention found mixed results. While a few numbers of studies concluded that effort expectancy has a statistically insignificant impact on the intention to adopt a technology (Andrews et al., 2021), several others contended that effort expectancy significantly influences the behavioral intention of the users toward a new technology (Yee & Abdullah, 2021). Therefore, this study hypothesized that,

H₂: Effort expectancy positively influences the willingness to adopt IoT in the SCM of Bangladeshi manufacturing firms

Venkatesh et al. (2003) developed the construct of social influence from subjective norms derived from four previously developed technology adoption models. The authors described this social influence as the users' evaluation of their social environment, including relatives, peers, and relevant outside people, regarding using a new system's ability to improve performance in the job atmosphere and their willingness to use the new system. In this research, social influence is characterized as the degree to which a person with the capacity for decision-making within the SCM believes that crucial people, such as their peers, value IoT in the SCM and anticipate the individual to use it to improve efficiency. Previous research has already proven the significance of social influence as a predictor of the willingness to adopt new technology (Yee & Abdullah, 2021). Therefore, this study hypothesized that,

H₃: Social influence positively influences the willingness to adopt IoT in the SCM of Bangladeshi manufacturing firms

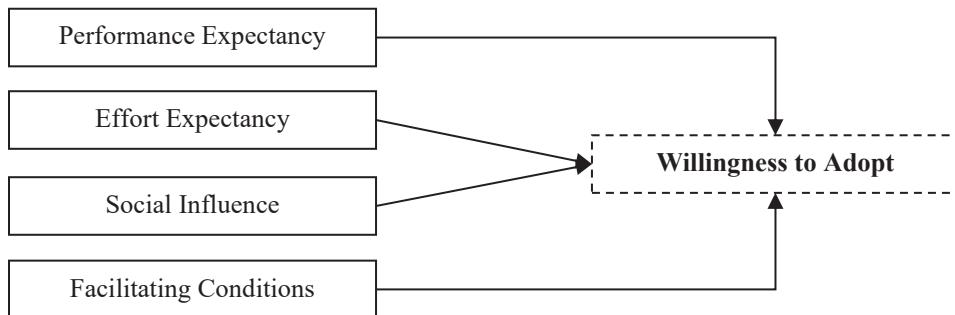
Venkatesh et al. (2003) described the facilitating conditions as how a person views the technological and organizational framework necessary to use the proposed system that is now accessible. The author developed this construct considering three different previously developed variables, named compatibility, behavioral control, and facilitating conditions and argued that facilitating conditions can enable the implementation of new systems or technologies. Considering this definition, this study defines facilitating conditions as the degree to which a person believes their company has adequate institutional and technological capacity to facilitate the use of IoT to improve overall SCM performance. Several previous studies argued that facilitating conditions significantly influence the

behavioral intention of the users toward a technology (Andrews et al., 2021; Williams et al., 2015). Therefore, this study hypothesized that,

H₄: Facilitating conditions positively influences the willingness to adopt IoT in the SCM of Bangladeshi manufacturing firms

Considering these four constructs of the UTAUT model and their associated hypothesized relationship with the dependent variable, the theoretical model of this study is developed. Figure 2 presents the theoretical model of this study, adapted from Venkatesh et al. (2003).

Figure 2: The theoretical model of the study



Source: Adapted from Venkatesh et al. (2003)

3. Methods

3.1 Research Design

In accordance with positivist principles, the researcher examined the hypothesized relationship through the application of deductive reasoning. When researchers want to investigate a theory, the deductive method, consistent with positivist philosophy, appears justifiable (Saunders et al., 2009). Consequently, the study is quantitative. A cross-sectional survey is used to collect data from respondents between May and September 2023.

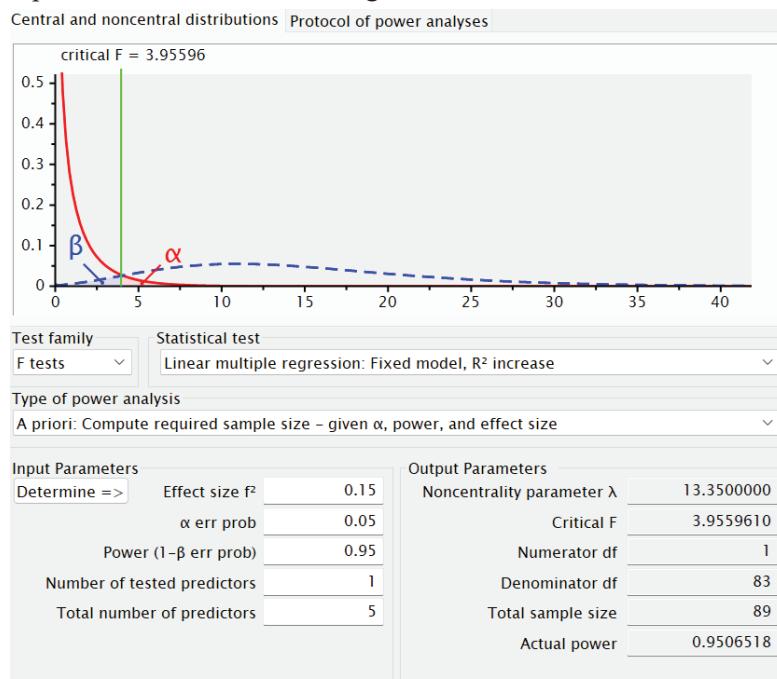
3.2 Participants, Sampling and Data Collection Procedure

The study participants are SCM specialists or professionals working in Bangladeshi manufacturing firms who have some familiarity with IoT activities. Only manufacturing firms with distinct supply chain departments were considered for the data collection in this study. Once the organizations have been identified, data has been collected from one specific respondent from each organization. This process of limiting one participant from each organization represents organizational-unit data. This type of data is considered an organizational response through the lens of individuals involved in the SCM process. While

choosing the respondents for each of the companies surveyed, responses from SCM specialists or professionals affiliated with each organization are encouraged. The organizations that responded were chosen using purposive sampling, a non-probability technique, focusing on organizations with a certain level of familiarity with IoT in their supply chain activities.

Hair Jr et al. (2013) recommendations are followed to determine the minimal sample size. Therefore, the sample size is adequate for subsequent analysis. According to Hair Jr et al. (2013), the sufficient sample size to run a model is 91 with a statistical power of 0.80, R^2 of 0.25, at the 1% significance level where the maximum number of arrows pointing at a construct is four. G*power software is also utilized to validate the sample size for this study. With $f^2=0.15$ (medium), $\alpha=0.01$, 80% power, and the number of predictors = 4, 89 sample size is adequate for the study (See figure 3). The researcher considered the Dhaka Stock Exchange (DSE) database to choose the organizations, and the questionnaire was initially sent to more than double than the minimum required number of organizations- 240 manufacturing firms. However, 162 responses were obtained following multiple follow-up contacts, representing a response rate of 68%. Therefore, the sample size of this study is higher than the minimum required for completing the further analysis.

Figure 3: Sample Size Determination Using G*Power



Source: Author's calculation using G*Power software

Table 3 shows the demographic information of the respondents. Among the 162 respondents, 94% are male and 6% are female. The majority of respondents (51 percent) are under 30, followed by 30-35 (40 percent) and above 35 (9 percent). Regarding employment duration, 43% of the participants reported having less than five years of experience, while 47% reported having between five and ten years of experience. The remaining 10% have more than ten years of experience. Furthermore, 71% of the respondents held a master's degree, whereas 29% held a bachelor's degree.

Table 3: Participants' demographic profile

		N	%
Gender	Male	153	94%
	Female	9	6%
Age	Below 30	82	51%
	30-35	64	40%
	Above 35	16	9%
Tenure	Below 5	69	43%
	5-10 Years	76	47%
	Above 10	17	10%
Education	Bachelors	47	29%
	Masters	115	71%

Source: Primary data collection, 2023

3.3 Measures

The questionnaire is divided into two sections (please see the detailed questionnaire in the appendix). The first included demographic questions such as gender, age, tenure and education. The remaining sections include measures that assess performance expectancy, effort expectancy, social influence, facilitating conditions and the willingness to adopt IoT.

A well-established and valid scale is used to measure all the relevant constructs. Performance expectancy was measured with a three-item scale by Alam et al. (2020). Example item includes "Using an IoT system will assist in forecasting the demand for the inventory". Likewise, the three-item scale of Alam et al. (2020) was utilized to measure effort expectancy. An example item is "The IoT is easy to learn for me." Social influence was assessed by Alkawssi et al. (2021) with three items, and facilitating conditions were evaluated by Sheel and Nath (2020) with three items. Items such as "People who matter to me suggest I should utilize the IoT in the SC" and "I know how to apply IoT in the SC" are examples of social influence and facilitating conditions, respectively. Lastly, three-item scale of Sheel and Nath (2020) is utilized to assess willingness to adopt. Finally, the three-item scale of Sheel and Nath (2020) measured willingness to adopt. The exemplary

statement is "I intend to use the IoT system in SCM operation." Each item was evaluated using a five-point Likert scale, with five indicating strong agreement and one indicating strong disagreement.

3.4 Data Normality and Bias Issues

The researcher looked at the multivariate skewness and kurtosis features included in the web power software program, following the advice of (Hair Jr et al., 2017). The data obtained for this research did not conform to multivariate normality, as indicated by Mardia's multivariate skewness ($\beta = 28.953$, $p < 0.01$) and kurtosis ($\beta = 73.718$, $p < 0.01$). Consequently, the researcher switched from CB-SEM to PLS-SEM and employed Smart PLS software.

Since participants were required to complete the questionnaire independently, the study may have suffered from a typical bias method problem (Fuller et al., 2016). In order to address the concerns raised by common method bias (CMB), the researchers employ Harman's single-factor test. The CMB relates to whether the relationship between the underlying constructs caused any variance between two variables to overlap. Harman's single-factor test posits that studies are susceptible to CMB when the variance exceeds 50% (Podsakoff et al., 2003). In this investigation, the result of Harman's single factor test is 31.05% of the total variance, which is below 50%. In this investigation, the result of Harman's single factor test is 27.05% of the total variance, which is below 50%. Therefore, it can be inferred that the study lacks common method bias.

3.5 Data Analysis

The data is analyzed using the SPSS (Statistical Package for Social Sciences) and Smart PLS (version 4.0.8.9). This study uses the Partial Least Squares (PLS) method for performing Structural Equation Modeling (SEM). The PLS is currently considered a well-known methodology in business management (Garces-Ayerbe et al., 2012). PLS-SEM facilitates analysis where the relationship among the variables seems complex and can run the analysis with a minimal number of samples.

The data analysis with PLS-SEM includes contains two sub-processes. The first one is the measurement model, where the indicators' reliability and model validity are assessed. Another is the structural model, where the examination of the proposed hypotheses, coefficient of determination (R^2), predictive relevance (Q^2), effect size (f^2), and other goodness of model fit is checked. SPSS was employed to evaluate the descriptive analysis (Table 4).

Table 4: Descriptive Analysis of the constructs

	Mean	Std. Dev	PE	EE	SI	FC	WTA
PE	4.128	0.479	1.000				
EE	3.860	0.556	0.438	1.000			
SI	3.864	0.495	0.470	0.470	1.000		
FC	3.646	0.542	0.313	0.371	0.252	1.000	
WTA	4.080	0.643	0.326	0.326	0.485	0.438	1.000

Source: Primary data collection, 2023

4. Results

4.1 Measurement Model Evaluation

Measurement models are concerned with the constructs' reliability and validity. Construct reliability is assessed through Cronbach Alpha and composite reliability (Islam et al., 2022). For both cases, a score of 0.7 or higher demonstrates adequate construct reliability (Hair Jr et al., 2017). In this study, the Cronbach alpha values for the five constructs varied between 0.700 and 0.851. Similarly, the composite reliabilities spanned from 0.817 to 0.909 (Table 5). Hence, the constructs used in this research are entirely reliable.

Table 5: Alpha value, CR & AVE

Constructs	Items	Loadings	α	CR	AVE
Performance Expectancy	PE1	0.724	0.705	0.817	0.599
	PE2	0.831			
	PE3	0.763			
Effort Expectancy	EE1	0.857	0.749	0.857	0.666
	EE2	0.793			
	EE3	0.797			
Social Influence	SI1	0.748	0.736	0.847	0.649
	SI2	0.812			
	SI3	0.852			
Facilitating Condition	FC1	0.712	0.700	0.820	0.606
	FC2	0.882			
	FC3	0.730			
Willingness to Adopt	WTA1	0.883	0.851	0.909	0.768
	WTA2	0.860			
	WTA3	0.886			

Source: Primary data collection, 2023

On the other hand, the validity of the constructs must be confirmed through the evaluation of convergent and discriminant validity. Convergent validity refers to the items of a construct being identical, whereas discriminant validity means that all constructs are distinct. A value greater than 0.50 for the average variance extracted (AVE) is required for convergent validity (Hair Jr et al., 2017). According to Table 5, the AVE in this study ranged between 0.599 and 0.768, more significant than 0.50, indicating that all constructs exhibit convergent validity. Likewise, discriminant validity can be assessed using the heterotrait-monotrait ratio of correlations (HTMT) ratio. An effective way for assessing discriminant validity is the HTMT, which is a measure of similarity between latent variables. Any HTMT value less than 0.85 provides sufficient proof of discriminant validity (Henseler et al., 2015). Table 6 illustrates all the HTMT values < 0.85 ; thereby, the constructs have discriminant validity.

Table 6: HTMT Ratio for Discriminant Validity

	PE	EE	SI	FC	WTA
PE					
EE	0.714				
SI	0.878	0.627			
FC	0.528	0.556	0.443		
WTA	0.721	0.419	0.576	0.540	

Source: Primary data collection, 2023

4.2 Structural Model Evaluation

Evaluation of the structural model includes five aspects: collinearity assessment, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and structural model path coefficients (Hair Jr, 2019; Hair Jr, 2021). Collinearity or multicollinearity issues have been checked through the inner VIF. According to Hair Jr (2021), the construct's tolerance (VIF) value should be higher than 0.20 and lower than 5 to avoid the collinearity issue. In this study, as evident in Table 7, the inner VIF ranges between 1.199 and 1.625, demonstrating that this study is free from multicollinearity problems. Moreover, the coefficient of determination or R^2 value determines the model's explanatory power. A higher R^2 value between 0 and 1 suggests higher explanatory power. Cohen (1977) suggested that a R^2 value more excellent than 0.30 indicates high predictability. The current study's R^2 value is $0.418 > 0.30$, indicating the model has significant predictability power. The explanatory power is acceptable compared to different studies in similar contexts (Hair Jr, 2021).

Effect size or f^2 is used to assess the relative impact of the independent variables on the dependent variable. According to Hair Jr et al. (2021), the f^2 values of 0.02, 0.15, and 0.35

are considered independent variables with small, medium, and large effects, respectively, on a dependent variable. Table 7 displays that PE and SI have a medium effect on WTA, while FC has a small effect. However, EE does not affect WTA. Besides, the study used predictive relevance (Q^2) using the blindfolding procedure to obtain the cross-validated redundancy measure for the dependent variable. Hair Jr et al. (2019) recommended that a Q^2 value larger than zero indicates the model's predictive relevance. Table 7 reported that Q^2 equals 0.368, concluding that the model has sufficient predictive relevance.

Table 7: Structural model fit indices

	f^2	VIF	R^2	Q^2
PE	0.116	1.456	0.418	0.368
EE	0.002	1.199		
SI	0.131	1.604		
FC	0.058	1.625		

Source: Primary data collection, 2023

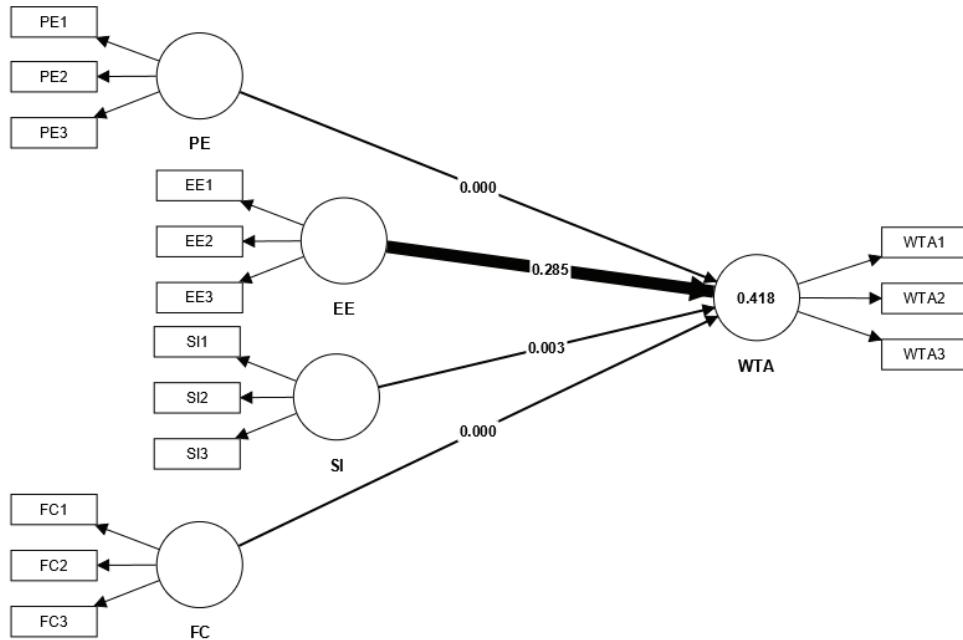
Path coefficients of the structured model were assessed by employing the bootstrapping with 5000 sub-samples, a one-tailed test, and a 0.05 significance level. As presented in Table 8 and Figure 4, all the hypothesized relationships are observed to be statistically significant except H_2 . Thus, the present study found a significant positive relationship between PE and WTA ($\beta=0.350$; $p=000$), SI and WTA ($\beta=0.230$; $p=003$), and FC and WTA ($\beta=0.290$; $p=000$). However, the study found an insignificant relationship between EE and WTA ($\beta=-0.040$; $p=0.285$). It implies that effort expectancy or perceived ease of use of IOT does not necessarily influence supply chain professionals' willingness to adopt it.

Table 8: Summary of Hypotheses

Hypothesis	Path Relations	β	Std. Dev	t values	P values	LLCI (5.00%)	ULCI (95.00%)	Decision
H1	PE \rightarrow WTA	0.35	0.080	4.250	0.000	0.217	0.486	Supported
	-	0						
H2	EE \rightarrow WTA	0.04	0.080	0.570	0.285	-0.172	0.072	Not Supported
	-	0						
H3	SI \rightarrow WTA	0.23	0.090	2.760	0.003	0.09	0.366	Supported
	-	0						
H4	FC \rightarrow WTA	0.29	0.070	4.410	0.000	0.169	0.379	Supported
	-	0						

Source: Primary data collection, 2023

Figure 4: Structural Model



Source: Primary data collection, 2023

5. Discussion

This study explores the factors influencing the willingness to adopt IoT in the SCM of Bangladeshi manufacturing firms using one of the well-established technology adoption models- the UTAUT. Because of its economic trajectory, digitalization efforts, sustainable development, and the quest for excellence in firm management, Bangladesh has been selected as a case study in this study. Findings show that the four primary constructs of the original UTAUT model- performance expectancy, effort expectancy, social influence, and facilitating condition, explain 42% of the variance in the willingness to adopt IoT in SCM in Bangladesh. However, among these four predictors, performance expectancy, social influence, and facilitating condition are significant in predicting the behavioral intention to adopt IoT in SCM in Bangladeshi manufacturing firms. In contrast, only effort expectancy found statistically insignificant. These findings are enumerated through the four major hypotheses of this study, which are discussed below.

Hypothesis one predicted that performance expectancy positively influences the willingness to adopt IoT in the SCM in Bangladeshi manufacturing firms. Similar to some of the previous studies in other country contexts (Ronaghi & Forouharfar, 2020), this study also

concluded that performance expectancy significantly influences the willingness to adopt IoT in firms' SCM. IoT is one of the latest advances of fourth industrial revolution that is expected to increase performance and coordination among each component of the firm's total supply chain. Consequently, firms interested in increasing their productivity and market position and achieving competitive advantage are willing to adopt IoT in the firm's overall SCM. IoT in SCM is also expected to improve warehouse management, greater visibility in transportation, materials management and waste reduction, coordination among productions, storage and distribution, and last-mile delivery (Núñez-Merino et al., 2020; Palmaccio et al., 2021). Therefore, it can be summarized that implementing IoT in the SCM may help improve Bangladeshi manufacturing firms' performance and operational productivity.

However, this study does not support hypothesis two, which assumes that effort expectancy significantly influences the willingness to adopt IoT in SCM. No significant association is observed between effort expectancy and the willingness to adopt IoT in the SCM of Bangladeshi manufacturing firms. The degree of easiness associated with using IoT in SCM activities was expected to improve the willingness to adopt IoT favorably. However, the lack of evidence to support this hypothesis is likely due to the pervasiveness of IoT technology. Perceived ease of use had little influence on the behavioral intention to use a new technology, which requires widespread familiarity before accepting it (Chong, 2013). This may explain why the influence of effort expectation in willingness to adopt is more relevant for non-users unfamiliar with IoT than individuals who are already familiar with IoT and will likely be acquainted with the functioning of IoT in SCM (Slade et al., 2015). Moreover, adopting a new technology, i.e., IoT, is the discretion of the firm's top management and their philosophy, which results in fewer opportunities for the end-users in SCM activities to decide their choice of adopting the technology. These end-users are bound to adapt to changes in the firms even if it requires adopting a complex technology.

The third hypothesis of the study assumes that social influence has a significant favorable influence on the willingness to adopt IoT in the SCM in Bangladeshi manufacturing firms. The SCM is the field of business that connects different actors at both vertical and horizontal levels of operations. Consequently, firms in any particular context are influenced by their external and internal partners, i.e., suppliers, distributors, competitors, regulators, and customers. The adoption of IoT in the organizational SCM will result in the active engagement and collaboration of workers, colleagues, and other stakeholders in the organizational framework. The findings of this study support that social influence significantly affects the willingness of SCM users to adopt IoT in their organizations. This result matches several previous studies (Ronaghi & Forouharfar, 2020; Williams et al.,

2015; Yee & Abdullah, 2021). Therefore, findings imply that influences from society, both internal (workers and managers) and external (stakeholders outside the business), positively facilitate the willingness to adopt IoT in SCM activities of Bangladeshi manufacturing firms.

Finally, hypothesis four predicts that facilitating conditions positively influence the willingness to adopt IoT in SCM of Bangladeshi manufacturing firms. Similar to previous studies, this research also observed a significant positive association between facilitating conditions and willingness to adopt IoT in SCM (Al-Saedi et al., 2019; Williams et al., 2015). Firms interested in adopting IoT in their traditional SCM activities require a radical shift toward advanced technological and infrastructural support, including but not limited to IoT sensors, satellite networks, radio frequency identification (RFID), Bluetooth low energy (BLE), application programming interface (APIs), cloud computing and security infrastructure. A details of these technologies and their applications are discussed in the literature review section. Such technologies require a significant financial commitment from the firms but, once presented, enable users to use IoT in SCM activities and enhance performance regularly (Ben-Daya et al., 2019). Therefore, the findings of this study suggest that improving an organization's technical facilities and supportive infrastructure can enhance employee behavior while increasing their ability to adapt to shifting technological and environmental situations.

In summary, the findings of this study suggest that users in SCM are willing to adopt IoT in their organization when they have a positive perception of IoT in improving their performance, favorable influence from peers and close people and adequate supporting technological infrastructure. These findings are useful for practitioners, decision-making authorities of the firms and policymakers, as all of these parties and other stakeholders can contribute to developing IoT-enabled SCM ecosystems. An IoT-enabled SCM ecosystem ensures more coordination among SCM parties, visibility in material processing and output deliveries, waste management and cost reductions, and improved data-driven decision-making. Besides, firms must invest in developing IoT-supporting technological infrastructure, offering IoT-supporting devices and training for SCM users. Such a holistic effort from all the parties involved in SCM is expected to offer a positive perception of the benefits of IoT in SCM of Bangladeshi manufacturing firms and increase the willingness of firms and their users to adopt IoT in their respective SCM activities.

6. Conclusion and Recommendation

Among different technologies, IoT elevates firms to a new level by enabling human-to-thing interaction and automatic coordination among 'things'. However, research on users' willingness to adopt IoT in supply chain management (SCM) of firms in emerging

economies like Bangladesh is lacking. This study fills this gap by investigating how performance expectations, effort expectations, social influence, and enabling conditions affect Bangladeshi manufacturing firms' willingness to use IoT in their supply chains. Data were collected from 162 supply chain practitioners using purposive sampling and analyzed using PLS-SEM. The findings show that performance expectancy, social influence, and facilitating conditions are statistically significant in influencing the willingness to adopt IoT in the SCM of Bangladeshi manufacturing firms. These findings have significant theoretical and practical contributions, particularly in developing an IoT-enabled SCM ecosystem in Bangladesh's manufacturing sector by incorporating a holistic effort from all stakeholders.

Despite these notable contributions, this study is not without its limits. This study is a pioneer in exploring the factors influencing Bangladeshi firms' willingness to adopt IoT in SCM activities. However, further studies should be initiated to explore other possible variables that contribute to the supply chain users' willingness to adopt IoT. Future studies can extend the existing UTAUT model by incorporating other constructs or blending more than one technology adoption theory. Furthermore, the current study focuses solely on Bangladesh's manufacturing sector. Future studies might include Bangladeshi service organizations to have a more comprehensive view of the users. Future studies could explore other business domains and conduct cross-country comparisons, allowing for the comparison of one country's results with those of other nations.

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References

Agrawal, P., & Narain, R. (2018). *Digital SC management: An Overview*. Paper presented at the IOP Conference Series: Materials Science and Engineering.

Alam, M. Z., Hu, W., Karium, M. A., Hoque, M. R., & Alam, M. M. D. (2020). Understanding the determinants of mHealth apps adoption in Bangladesh: A SEM-Neural network approach. *Technology in Society*, 61(1), 101255.

Alkawsi, G., Ali, N. a., & Baashar, Y. (2021). The moderating role of personal innovativeness and users experience in accepting the smart meter technology. *Applied Sciences*, 11(8), 3297.

Al-Saedi, K., Al-Emran, M., Abusham, E., & El Rahman, S. A. (2019). *Mobile payment adoption: a systematic review of the UTAUT model*. Paper presented at the 2019 International Conference on Fourth Industrial Revolution (ICFIR).

Andrews, J. E., Ward, H., & Yoon, J. (2021). UTAUT as a model for understanding intention to adopt AI and related technologies among librarians. *The Journal of Academic Librarianship*, 47(6), 102437.

Atzori, L., Iera A., & Morabito, G. (2010). The internet of things: A survey. *Computer Networks*, 54(15), 2787-2805

Ben-Daya, M., Hassini, E., & Bahroun, Z. (2019). Internet of things and SC management: a literature review. *International Journal of Production Research*, 57(15-16), 4719-4742.

Centenaro M., Costa C. E., Granelli F., Sacchi C., & Vangelista, L. A. (2021). Survey on technologies, standards and open challenges in satellite IoT. *IEEE Communications Surveys and Tutorials*, 23(3), 1693–1720. <https://doi.org/10.1109/COMST.2021.3078433>.

Chataut, R., Phoummalayvane, A., & Akl, R. (2023). Unleashing the Power of IoT: A Comprehensive Review of IoT Applications and Future Prospects in Healthcare, Agriculture, Smart Homes, Smart Cities, and Industry 4.0. *Journal of Sensors*, 23, 7194.

Chong, A. (2013). A two-staged SEM-neural network approach for understanding and predicting the determinants of m-commerce adoption. *Expert Systems with Applications*, 40, 1240–1247.

Cohen, J. (1977). *Statistical Power Analysis for the Behavioral Sciences*. New York, NY: Academic Press.

Davis, F. D., Granić, A., & Marangunić, N. (2023). The technology acceptance model 30 years of TAM. *Technology*.

Dymitrowski, A., & Mielcarek, P. (2021). Business model innovation based on new technologies and its influence on a company's competitive advantage. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(6), 2110-2128.

Fatorachian, H., & Kazemi, H. (2021). Impact of Industry 4.0 on SC performance. *Production Planning & Control*, 32(1), 63-81

Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. *Journal of Business Research*, 69(8), 3192–3198.

Ghadge, A., Er Kara, M., Moradlou, H., & Goswami, M. (2020). The impact of Industry 4.0 implementation on SCs. *Journal of Manufacturing Technology Management*, 31(4), 669-686.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2013). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.

Hair Jr, J., Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review*, 31(1), 2-24.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.

Islam, M., Mamun, A. A., Afrin, S., Ali Quaosar, G. A., & Uddin, M. A. (2022). Technology Adoption and Human Resource Management Practices: The Use of Artificial Intelligence for

Recruitment in Bangladesh. *South Asian Journal of Human Resources Management*, 9(2), 324-349.

Kasilingam, D., & Krishna, R. (2022). Understanding the adoption and willingness to pay for internet of things services. *International Journal of Consumer Studies*, 46(1): 102-131.

Katoch, R. (2022). IoT research in SC management and logistics: A bibliometric analysis using vosviewer software. *Materials Today: Proceedings*, 56: 2505-2515.

Khan, S., Singh, R., Khan, S., & Ngah, A. H. (2023). Unearthing the barriers of Internet of Things adoption in food SC: A developing country perspective. *Green Technologies and Sustainability*, 1(2), 100023.

Khan, Y., Su'ud, M. B. M., Alam, M. M., Ahmad, S. F., Ahmad, A. Y. B., & Khan, N. (2022). Application of Internet of Things (IoT) in Sustainable SC Management. *Sustainability*, 15(1), 694.

Landaluce, H., Arjona, L., Perallos, A., Falcone, F., Angulo, I., & Muralter, F. (2020). A review of IoT sensing applications and challenges using RFID and wireless sensor networks. *Journal of Sensors*, 20, 2495.

Lee, I., & K. Lee. (2015). The Internet of Things (IoT): Applications, Investments, and Challenges for Enterprises. *Business Horizons*, 58 (4), 431–440, DOI: 10.1016/j.bushor.2015.03.008

Martins, C., & Pato, M. (2019). SC sustainability: A tertiary literature review. *Journal of cleaner production*, 225, 995-1016.

Núñez-Merino, M., Maqueira-Marín, J. M., Moyano-Fuentes, J., & Martínez-Jurado, P. J. (2020). Information and digital technologies of Industry 4.0 and Lean SC management: a systematic literature review. *International Journal of Production Research*, 58(16), 5034-5061.

Olhager, J., & Selldin, E. (2004). Supply chain management survey of Swedish manufacturing firms, *International Journal of Production Economics*, 89(3), 353-361.

Palmaccio, M., Dicuonzo, G., & Belyaeva, Z. S. (2021). The internet of things and corporate business models: A systematic literature review. *Journal of Business Research*, 131, 610-618.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *Journal of Applied Psychology*, 88(5), 879–903.

Ronaghi, M. H., & Forouharfar, A. (2020). A contextualized study of the usage of the Internet of things (IoTs) in smart farming in a typical Middle Eastern country within the context of Unified Theory of Acceptance and Use of Technology model (UTAUT). *Technology in Society*, 63, 101415.

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students*. Pearson education.

Sharma, A., Sharma, A., Singh, R. K., & Bhatia, T. (2023). Blockchain adoption in agri-food SC management: an empirical study of the main drivers using extended UTAUT. *Business Process Management Journal*, 29(3), 737-756.

Sheel, A., & Nath, V. (2020). Antecedents of blockchain technology adoption intentions in the SC. *International Journal of Business Innovation and Research*, 21(4), 564-584.

Shi, Y., Siddik, A. B., Masukujjaman, M., Zheng, G., Hamayun, M., & Ibrahim, A. M. (2022). The antecedents of willingness to adopt and pay for the IoT in the agricultural industry: An application of the UTAUT 2 theory. *Sustainability*, 14(11), 6640.

Slade, E. L., Dwivedi, Y. K., Piercy, N. C. & Williams, M. D. (2015). Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: extending UTAUT with innovativeness, risk, and trust. *Psychology & marketing*, 32 (8), 860-873

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia manufacturing*, 22, 960-967.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*: 425-478.

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): a literature review. *Journal of enterprise information management*, 28(3), 443-488.

Xu, L. D. , W. He , and S. Li. (2014). Internet of Things in Industries: A Survey. *IEEE Transactions on Industrial Informatics*, 10 (4): 2233–2243, DOI: 10.1109/TII.2014.2300753

Yee, M. L. S., & Abdullah, M. S. (2021). A review of UTAUT and extended model as a conceptual framework in education research. *Jurnal Pendidikan Sains Dan Matematik Malaysia*, 11(1), 1-20.

Appendix

Sl.	Study	Constructs	Industry/focus	Target variable(s)	Research approach	Model applied	Major Findings
1	Aamer et al. (2021)	IoT adoption challenges	Food SC	IoT adoption	Systematic literature review	N/A	There are 5 principal domains, namely technical, financial, social, operational, and educational & governmental, that present 15 obstacles to the implementation of IoT in the food SC.
2	Mengru (2018)	Perceived cost, external pressure, perceived benefits, and perceived trustworthiness of technology	Multiple	IoT adoption intention, perceived benefits	Mixed method	Technology, organization, and environment (TOE)	The study found that benefits, cost, trustworthiness, and external motivating factors influence IoT adoption decisions in SC management. Quantitative findings confirmed these findings, identifying perceived costs, benefits, and external pressure as determinants of IoT adoption, and highlighting the impact of perceived trustworthiness on benefits.
3	Haddud et al. (2017)	Benefits to individual organizations, benefits to entire SC, challenges to individual organizations, and challenges to entire SC	Multiple	Potential benefits and challenges of IoT adoption	Quantitative	Self-developed framework	The adoption of IoT influences 12 key SC management success factors and challenge 3 different domains, namely technological, organizational, and resource availability.
4	Kamble et al. (2019)	lack of regulations and governance, lack of internet infrastructure, complex architecture, lack of human skills, lack of standards,	Food Retail	IoT adoption barriers	Two-phase hybrid methodology	ISM and DEMATEL	12 different factors (mentioned constructs) that act as barriers to IoT adoption have been classified into four categories based on their sensitivity, which allows prioritization of the

Sl.	Study	Constructs	Industry/focus	Target variable(s)	Research approach	Model applied	Major Findings	
5	Celia et al., (2020)	scalability issues, integration and compatibility issues, security and privacy issues, high energy consumption, high operating costs, long payback period, and lack of validations.	IoT adoption, circular SC	Electric Battery	Digital Circular SC (CSC) information infrastructure	Qualitative & case study	N/A	The adoption of IoT in the circular SC (CSC) framework to recover WEEE can strengthen SCM information infrastructure.
6	Manavalan & Jayakrishna (2019)	Business-based smart operations, technology-based smart products, sustainable development, collaboration, and management strategy & organization	Industry 4.0	IoT embedded sustainable SC	Literature review	N/A	Implementation of IoT enhances the outcomes, guarantees wide prospects to gain competitive advantage, and guides sustainable SC practices.	
7	Theofilos et al. (2020)	IoT Adoption	Industry 4.0, waste management sector	Sustainable SC management	Case study	N/A	The Adoption of IoT enables efficient decisions and facilitates the reduction of non-renewable energy sources and CO2 emissions.	
8	Zhang et al. (2022)	Economic factors, organizational factors, environmental factors, and technological factors	Sustainable SC	Barriers to IoT adoption	Qualitative and Quantitative	Fuzzy multi criteria decision-making (MCDM)	Among the four identified factors of barriers (i.e., economic, organizational, environmental, and technological), the economic	

Sl.	Study	Constructs	Industry/focus	Target variable(s)	Research approach	Model applied	Major Findings
9	Ronaghi et al. (2020)	Performance expectancy, effort expectancy, social influence, individual factors, and facilitating conditions	Smart Firming	Behavioral intention, use behavior	Quantitative	UTAUT	All the constructs impose a factor is the most influential to IoT adoption.
10	Yawised et al. (2022)	Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, price value, habit behaviour, age, gender, experience, business transformation capabilities, digital transformation capabilities	Hospitality and tourism; SME	Behavioral intention, use behavior	Comprehensive literature analysis and synthesis	UTAUT 2	The UTAUT 2 model can be expanded by considering business transformation capabilities, digital transformation capabilities, and personal innovativeness as mediators and moderating variables, with age, gender, and experience also playing significant roles in determining behavioral intention and use behavior.
11	Nikbin & Ahmad (2019)	Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, price value, experience & habit, and personal innovativeness	Entrepreneurs	Adoption of IoT	Quantitative	UTAUT 2	The UTAUT 2 constructs, except price value and effort expectancy, significantly influence IoT adoption, with personal innovativeness showing a significant relationship with new technology adoption.

A2. Questionnaire of the study

[1. Strongly disagree, 2. Disagree, 3. Neutral, 4. Agree, and 5. Strongly agree.]

Statements	Responses
Performance Expectancy	
(PE1) I find IoT systems useful in Improving the productivity of physical and human resources of the firm	(1) (2) (3) (4) (5)
(PE2) Using an IoT system will assist in forecasting the demand for the inventory	(1) (2) (3) (4) (5)
(PE3) Improving the productivity of physical and human resources of the firm	(1) (2) (3) (4) (5)
Effort Expectancy	
(EE1) The IoT is easy to learn for me.	(1) (2) (3) (4) (5)
(EE2) It is simple to become skillful at using the IoT.	(1) (2) (3) (4) (5)
(EE3) I find the IoT simple to use.	(1) (2) (3) (4) (5)
Social Influence	
(SI1) People who matter to me suggest I should utilize the IoT in the supply chain	(1) (2) (3) (4) (5)
(SI2) People who shape my behavior suggest I should utilize the IoT in the supply chain	(1) (2) (3) (4) (5)
(SI3) People I respect desire that I employ the IoT in the supply chain	(1) (2) (3) (4) (5)
Facilitating Condition	
(FC1) I am well-equipped to put the IoT to work in the supply chain	(1) (2) (3) (4) (5)
(FC2) I know how to apply IoT in the supply chain	(1) (2) (3) (4) (5)
(FC3) When I encounter challenges in implementing IoT in supply chain operations, I can ask for assistance from others.	(1) (2) (3) (4) (5)
Hedonic Motivation	
(HM1) IoT system usage is fun.	(1) (2) (3) (4) (5)
(HM2) IoT system usage is enjoyable.	(1) (2) (3) (4) (5)
(HM3) IoT system usage is entertaining.	(1) (2) (3) (4) (5)

Trust	
(T1) I believe that using the IoT is safe.	(1) (2) (3) (4) (5)
(T2) I do not doubt the security of the IoT.	(1) (2) (3) (4) (5)
(T3) The IoT can fulfill its task.	(1) (2) (3) (4) (5)
Price Value	
(PV1) The IoT system is reasonably priced	
(PV2) Usually, IoT systems are good value for the money.	(1) (2) (3) (4) (5)
(PV3) With the current price, the IoT system provides good value.	(1) (2) (3) (4) (5)
(1) (2) (3) (4) (5)	
Reliability	
(R1) I believe IoT will operate reliably	
(R2) I believe IoT will perform reliably	(1) (2) (3) (4) (5)
(R3) I believe the operation of IoT is dependable	(1) (2) (3) (4) (5)
(1) (2) (3) (4) (5)	
Hedonic Motivation	
(PFC1) I believe the cost of using IoT services is higher than other supply chain technologies	(1) (2) (3) (4) (5)
(PFC2) The installation cost of IoT technology in firm's supply chain is expensive	(1) (2) (3) (4) (5)
(PFC3) Using IoT can be a cost burden to me.	(1) (2) (3) (4) (5)
(1) (2) (3) (4) (5)	
Perceived Self-Efficacy	
(PSE1) I believe it will be easy for me to use IOT services.	(1) (2) (3) (4) (5)
(PSE2) I have the capability to use IOT in supply chain operations.	(1) (2) (3) (4) (5)
(PSE3) I am able to use IOT without much effort.	(1) (2) (3) (4) (5)
(1) (2) (3) (4) (5)	
Willingness to Adopt	
(WTA1) I intend to use the IoT system in supply chain operation.	(1) (2) (3) (4) (5)
(WTA2) I plan to use IoT systems in supply chain operation in the future.	(1) (2) (3) (4) (5)
(WTA3) In the future, I believe I will employ an IoT system in supply chain operation.	(1) (2) (3) (4) (5)

Willingness to Pay	
(WTP1) I will use IoT services in the supply chain operation, even if the price increases somewhat.	(1) (2) (3) (4) (5)
(WTP2) I am interested to pay a higher price for IoT services than Traditional technologies used in supply chain	(1) (2) (3) (4) (5)
(WTP3) I will use IoT services via information technology devices, even if the price increases.	(1) (2) (3) (4) (5)

1. Age of Respondent:

2. Tenure:

3. Education: i. Bachelor ; ii. Master ; iii. Others

4. Size of the firm: i. Small ii. Medium iii. Large;

5. Gender: i. Male ; ii. Female
