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Measuring Using Disruptive Technology in the Supply Chain Context: Scale Development and Validation

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Abstract: The concept of disruptive technology has been in our lives for many years, and it is essential to measure their utilization levels to survive in the global competitive environment, to benefit from their contributions to supply chains, to examine their relations with supply chain operations and to compare them with average state of the industry. The aim of this study is to develop and validate a measurement instrument for supply chain management practices in the disruptive technology field. Accordingly, the study was carried out in five steps and the sample size consists of 47 companies as pilot data and 426 companies for the main data. These steps consist of item generation and purification, pilot test, initial identification of dimensionality, dimensionality confirmation and convergent validity assessment. As a result of the study, a new scale with a single factor structure was developed. The study ends with the evaluation of the findings. Correcting the lack of a measurement tool developed in this field in the literature is the theoretical contribution of the study. Furthermore, this study enables supply chain leaders to compare their utilization level of disruptive technology with the industries in which they operate, to associate it with operations and to enhance technology investments in practice.

Keywords: disruptive technologies; scale development; supply chain technologies; validation; using disruptive technology scale (UDTS)

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1. Introduction

Technology is a concept as old as the history of humanity and continues to maintain its existence and significance throughout our lives [1]. The birth and utilization of technology caused a revolution in businesses [2]. Thereafter, it has provided and continues to provide revolutionary contributions to businesses [3]. Nowadays, the concept of "disruptive technology (DT)" has become a widely accepted scientific term based on the commercial world and is used to describe the effect of technology on decision-making processes. The word "disruptive" refers to the interruption or disruption of the orderly progress of an event, process or activity, but also may mean a major change in structure [4].

DTs were given the title of "disruptive" because they are technologies that replace existing technologies after they are put into practice. They do this by initially outperforming technology already established in serving the mainstream market. However, they replace existing technologies over time [5]. Which technologies are disruptive have changed since the day they were introduced as a concept. DTs are typically widely focused on new and revolutionary technologies in the literature [6]. Therefore, technologies that have a disruptive effect in every period of life differ according to their era [7].

The revolutionary technologies of the current era are provided by the industrial revolutions of that era [8]. Consequently, the technologies offered by the industrial revolutions should be evaluated within the scope of DTs [9]. In the journey of industrial revolutions, which started with production using steam machines, the third industrial revolution took place with the transition of production systems from analog systems to digital systems, and the processes of companies became more complex, consumer demands and expectations changed, and the need for interdisciplinary work brought about the need for connection and communication of all objects via the internet. The need for a new industrial revolution in which the internet interacts has emerged. This need has created The Fourth Industrial Revolution (4IR) [10].

With the realization of the 4IR, new technologies and business models emerged and transformed the societies and economies in which they lived [11]. In addition to being very crucial for the modern economy, the concept of 4IR includes innovation and technological progress; it has dramatically transformed products, services, operations, and production processes [12,13]. In this context, the technologies offered by this industrial revolution, which is also called 4IR, are accepted as today's DTs, as they eliminate existing systems and provide more efficient systems to replace them [9]. This industrial revolution, unlike the other three industrial revolutions, is not a continuation of the previous one (third industrial revolution). It has been developed mainly on the basis of velocity, width/depth and system effect [14].

The supply chain (SC) is an integrated structure that includes forward and backward activities, in which many units and operations are intertwined [15]. Supply chain management (SCM) ensures the coordination of all activities in the SC by connecting suppliers, shippers, internal departments, and businesses. SCM includes coordination in SC. This coordination is the movement of products from suppliers to end users. The sharing of information such as sales forecasts, sales dates and promotional campaigns among whole members of the chain is realized through SCM [16]. 4IR is a new level of company and administration of the SC throughout the life cycle of products [17]. 4IR dramatically affects SC activities, business processes and models [18].

4IR enhances integration in the SC. It enables collaborative production and allows businesses to focus on their core competencies. In this way, businesses can develop more value-added products and complementary assets or services [19]. With this industrial revolution, SCs have become more flexible. Correspondingly, it is easier to react to changes in the market [20]. 4IR provides an unprecedented increase in operational efficiency and productivity in SCs. It enables this with production ecosystems driven by intelligent systems with autonomous features. In addition, it enables new kinds of advanced manufacturing and industrial operations to emerge [21]. Additionally, 4IR also enables mass customization. Mass customization allows businesses to address customer demands and consistently introduce new goods and services to the market in SCs. 4IR has the effect of enhancing the transparency of whole stages, from the sending of the order to the end of the product's utilization life. Furthermore, the cost, quality and competitive advantages of 4IR are some of the principal benefits of this industrial revolution [22–24].

4IR enables many competitive advantages with the dynamic structure it provides in business processes. It reduces SC risks. Besides the benefits of time and price, it is also environmentally friendly. In all these respects, it enhances economic, social, and environmental sustainability. It eliminates malfunctions. It optimizes decision making thanks to the end-to-end visibility it provides [25]. It improves the working conditions of employees with the cooperation of technology and workforce [24].

As a whole these contributions point out that 4IR is the transformation of economies and industries, and thus SCs, through a combination of technological, social, and business disruptive forces [11]. The disruptive forces that bring about the transformation referred to are DTs [26]. Consequently, the technologies with disruptive effects have emerged with 4IR in SCM. These technologies have made and continue to make dramatic contributions to SCs [27–29]. Understanding the latest trends in using DTs to shape the world is essential [30]. Nowadays, consumer habits have changed rapidly, and businesses and SCs must cope with the adversities revealed by this dynamic new environment and adapt to this change [11]. The COVID-19 pandemic has once again highlighted how significant the utilization of new DTs is to enhance SC visibility, take better action in case of SC disruptions, and build more resilient SCs [31]. For companies to benefit from the above-mentioned contributions and carry on existing in a global competitive environment, they must pursue current technological developments, current trends, innovations and research, and invest in these technologies [32].

In order to understand to what extent these facts exist in the external world and to what extent they interact, it is necessary to measure them concretely. Measuring is defined as assigning numbers to objects [33]. Scale development studies are very significant to embody the abstract and to quantify qualitative findings [34,35]. To measure the level of DT use of a company, to compare it with the average of the industry in which it operates, or to measure the level of DT use of a SC is only possible with a measurement instrument developed in this field. Measuring the level of DT use is significant and necessary both to see to what extent the company benefits from them and to compare the company with the industry in which it operates, both locally and globally. A scale developed in this field also allows the relationship of utilizing these technologies for different operations and the effect of these operations to be analyzed quantitatively in SCs, in addition to measuring the utilization level of the DTs.

In the current age, using technologies offered by the period is not a necessity, but a compulsion, for businesses to continue their operations, enhance their performance and gain a competitive advantage [36]. 4IR has many new DTs to offer [37]. The purpose of this study is to develop and validate a measurement instrument for SCM practices in the technology field. In this study, the technologies offered by 4IR within the scope of DTs within the scope of the scale development study, based specifically on those that are frequently utilized in SCs in the existing literature. The remainder of this article is developed as follows: Section 2 reviews the conceptualization of DTs, the theoretical background of the study, and explains their characteristics, opportunities and threats. Section 3 presents the empirical findings on which the scale development study is based. This scale was developed as the "Using Disruptive Technology Scale (UDTS)". In the study, the scale development steps are given separately, and the scale has validity and reliability criteria. The consequences are presented in Section 4, and it ends with the final section in Section 5.

2. Theoretical Background

2.1. Conceptualizing Disruptive Technology

The concept of "disruptive technology (DT)", which emerged with the study of Clayton Christensen and his colleagues on this subject, was not only a popular study of that period, but has continued to maintain its significance. The authors introduced the concept of DT with their book Innovator's Dilemma (1997) [5], which examines five key issues related to the impact of technological transformation on companies and industries, and were met as "gurus" in the field at that time [38,39]. DTs are technologies that dramatically change the way consumers, industry and businesses operate. A DT destroys the systems or habits it replaces. It can achieve this thanks to its recognizable superior features [40].

The condition for a technology to be called "disruptive" is not that it replaces the previous technology. For a technology to be considered disruptive, it must operate through a certain mechanism. At the same time, using this technology needs to achieve certain results. From all these perspectives, there is a technological transformation. These technologies are those that initially spread to small markets and eventually spread to the mass market. The markets where it has the most disruptive effect are the mass markets. Products produced with DTs enhance the existing product market and additionally offer new product market opportunities. They have a proactive high risk–high payoff but enable significant long-term benefits. They enable revolutionary alteration in the conduct of operations [41].

DTs have some characteristic features. Since these technologies have superior features than traditional methods, the product and service structures produced with these technologies are positively differentiated [42]. These technologies manufacture products that focus on the demands of leading utilizers [43]. They are technologies that alter the established behavior of utilizers. They enhance social welfare level, while minimizing the possibility of social harm [44]. Therefore, power and prosperity will shift in favor of SCs that can integrate and utilize them in an innovative manner [45].

DTs are technologies that affect market leaders, end users and the infrastructure used. The effects in these three fields are considered as three disruptive effects. It is through these effects that technologies can be compared amongst themselves in terms of disruptiveness. Technologies that affect market leaders, end users and infrastructure are characterized as the technologies with the highest disruptive effect [46]. This is a crucial point to be considered for companies and SCs so that managers can choose the right technology and make the right decisions. Prices are slightly higher than existing technologies for initial utilization. However, their price decreases as they spread to mass markets over time. They enable some activities to become easier to do. They are also adopted by customers because of these contributions [47].

DTs bring some opportunities and threats to companies and their SCs. While the use of DTs is increasing rapidly both on a local and global scale, it is necessary to evaluate the opportunities and threats presented by DTs while addressing the wide-ranging effects of 4IR [48]. These opportunities and challenges are given below in Section 2.2.

2.2. Opportunities and Challenges

There are many opportunities that DTs offer both to companies and their SCs. When DTs are successful, they lessen the market share and profits of large, settled companies in the upper segment. It takes several years for them to take over the market. The main advantages can be put in order as enabling a vying advantage [49], enhancing the success of the company in the industry in which it operates, improving processes and operations, contributing to the growth of the industry, creating new industries, improving the delivery of goods and services and ensuring the participation of the non-technologically advanced workforce [41]. Furthermore, it encourages disruptive innovations [50]. In other words, disruptive innovation takes place utilizing these technologies. Although the concepts of DT and disruptive innovation are considered synonymous by some researchers in the literature, they are different concepts [51].

In addition to the opportunities offered by DTs, they also bring some challenges for companies that utilize them and those that do not. Selection of these technology is a crucial challenge. They may consist of a combination of different technologies or may emerge as a completely new technology [52]. Determining the mix of technologies is complicated in terms of planning processes and performance targets. The technologies to be selected should be evaluated in terms of long-term profitability, low risk/return balance of long-term projects and their contribution to sustainability, and existing strategic planning and management processes during the selection of technology process [41]. Moreover, DTs are a threat to companies that do not utilize them because companies that adopt these technologies tend to replace established companies that do not adopt them [5]. For this reason, companies should follow the level of technologies that dominate the era utilized in the industries they are in and should bring themselves closer to this utilization level [53]. This is possible with a measurement instrument developed in this field.

Before DTs are implemented, they must be addressed in terms of legal aspects, liabilities, insurance and ethics [24]. Moreover, these technologies should be assessed in terms of security vulnerabilities and cyber risks before they are implemented. Cyber risks are risks that compromise the data records of customers, suppliers and employees, and lead to data breaches related to management and operations [54]. Additionally, cyber security precautions should be taken [21], as failure to do so leads to fraud, intellectual property theft, failure of information technology and infrastructure and unavailability of critical services [55].

While DTs promise significant opportunities for early and strong entry into existing and new markets, they can face resistance from customers. This resistance also brings with it the risk of failure that may be encountered during the implementation of technology. It should be adapted to the requirements of customers to utilize them [56]. Employee resistance poses a similar challenge. For this reason, the necessary cultural and mental transformation should be provided for the employees. The utilization of DTs should be made an integral part of company strategies. Budgeting appropriately for these technologies is another challenge. This requires a good analysis of the return-on-investment costs. Furthermore, it is crucial to be at the same technological maturity level with other SC members, as this situation leads to challenges in establishing a systemic infrastructure. Lastly, it is crucial to build a roadmap of the opportunities and challenges they enable, before implementing these technologies [57].

3. Materials and Methods

In this study, a five-step study was organized to measure, validate, and constitute the structure and predictability of using DTs. Study 1 focuses on item generation and purification. In Study 2, a draft questionnaire was prepared, the pilot study was conducted and the questionnaire was finalized. Initial identification of dimensionality was carried out in Study 3, while dimensionality confirmation was performed in Study 4. Convergent validity assessment was realized in Study 5. The micro view of the research process is given in Figure 1 below.

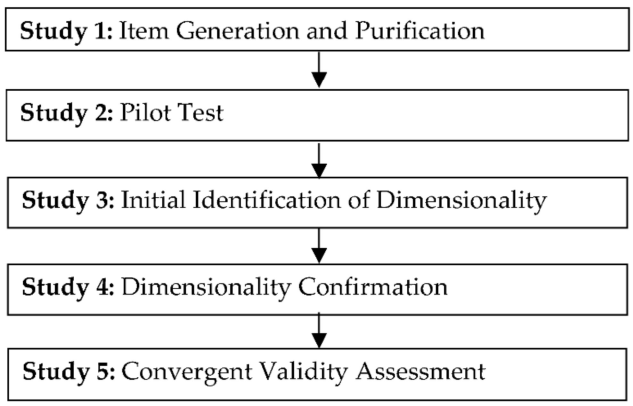

Figure 1. The micro view of research process.

In this study, data were acquired face-to-face and by e-mail, and necessary ethics committee permissions were obtained. The sample of the study consists of the data of 47 companies for the pilot study and 426 companies for the main study. SPSS V.21 for exploratory factor analysis (EFA) and controlling of bias effect, LISREL 8.51 for confirmatory factor analysis (CFA) and relationships between variables and MS Office 365 Excel for convergent validity were used. The questionnaire was generated utilizing a five-point Likert scale ranging from 1 (I totally disagree) to 5 (I totally agree).

3.1. Study 1: Item Generation and Purification

The literature review was executed by taking into account the existing academic literature in item generation and an item pool was created considering the disruptive effects of the technologies offered by 4IR. In order to negotiate the intelligibility of the items and whether there were any missing or DTs to be added, a list of expert groups to be interviewed was determined. A total of nine experts were determined, five of whom are industry professionals working in this field, and four who are previous academicians from Turkey who continue their academic studies in this field. Professionals from the industry were selected from the companies' digital transformation and SC departments. Academicians have continued to work as faculty members in these fields, and are experts in the fields of management information systems and SCM. The interviewed expert group list is given in the Appendix A of this study, Table A1. The interviews were conducted face-to-face or online by Zoom platform. In this way, the content validity of the study was performed with expert group interviews. The items generated are given in the Appendix A of this study, Table A2. In the next part of this study, the conclusions of the pilot study carried out before proceeding to the results of main study are given.

3.2. Study 2: Pilot Test

Pilot tests are studies that draw a roadmap for the study before starting the main study. A pilot study is suggested to handle the issue and predict the response rate and explore the feasibility of the study [58]. The sample size required for the pilot study in the literature differs according to the researchers. While it is accepted by a group of researchers that a sample with N's between 10 and 30 is favorable in terms of simple, easy calculation and testing ability [59], it was emphasized by another group of researchers that a pilot study should be performed with a sample of 10% of the required sample in the main study [60]. In this study, a pilot test was conducted with the data of 47 different companies, the sample size of which corresponds to approximately 10% of the targeted main sample. Internal consistency and exploratory factor analyses (EFA) of alternative models were performed in the pilot test. The conclusions of reliability analysis are given in Table 1 and conclusions of subscales and factor analysis are given in Table 2 below.

Table 1. Reliability analyses results of the pilot study.

Subscales	Number of Items	Cronbach's Alpha (α)	Inter-Item Means		Scale Statistics		
			Correlation	Covariance	Mean	Variance	Std. Deviation
UDT	16	0.944	0.516	1.117	46.96591	302.928	17.40482
UDT	10	0.901	0.478	1.016	30.30	112.752	10.61849
UDT	8	0.867	0.452	0.977	24.9574	72.085	8.49029

Note: Maximum iteration: 50.

Table 2. Subscales and factor analyses results of the pilot study.

Number of Items	Number of Factors	KMO	Bartlett's Test of Sphericity			Extraction Sums of Squared Loadings	
			Approx. Chi-Square	df	Sig. (p)	Total	Cumulative %
16 items	1 factor *	0.886	563.517	120	0.000	8.964	56.027
10 items **	1 factor *	0.892	367.347273	66	0.000	6.700	55.833096
8 items ***	2 factors	0.887	311.436	45	0.000	10.238	70.577
8 items ***	1 factor *					6.034	60.340

Note: KMO: Kaiser–Meyer–Olkin, Measure of sampling adequacy. * These structures are compressed into a factor. ** These 10 items consist of blockchain, autonomous robots, 3D printers, 5G, Cloud Computing, Horizontal and Vertical System Software Integrations, Cyber Security, Big Data Analytics, simulation and virtual reality technologies. *** These 8 items consist of blockchain, autonomous robots, 3D printers, 5G, Cloud Computing, Horizontal and Vertical System Software Integrations, Cyber Security and Big Data Analytics technologies.

KMO and Bartlett's Test of Sphericity values are values that show how convenient the data are for factor analysis. Since the KMO values for the pilot study were above 0.60 and the Barlett's Test value was found to be statistically significant ($p < 0.05$), the data were convenient for factor analysis [61,62].

When Figure 2 is examined, the eigenvalue for a single factor structure is approximately 9. Since the graph started to flatten after the second factor, it can be said that the most appropriate factor structure for the data was formed by the two-factor structure, according to the results of the pilot study. The eigenvalue for this structure is approximately 1.70. Additionally, when the structure is single factor, single factor explains 56.027% of the total variance as seen in Table 2.

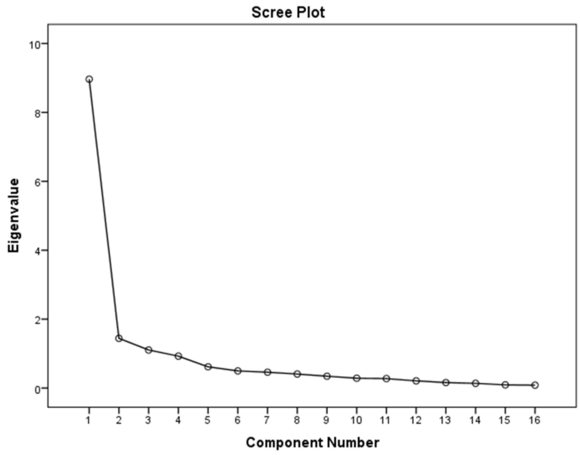

Figure 2. Scree Plot Graph for Pilot Study.

Reaching the first definition of factors with structure sub-dimensions is provided by EFA [63,64]. Varimax rotation is a type of orthogonal rotation that forces factors to be uncorrelated [65–67]. In this study, varimax rotation was used because most of the relationships between the items were below 0.30.

According to the results of EFA, the items and their factor loadings for both the single-factor structure and the two-factor structure for the pilot study are given in Tables 3 and 4 below. The factor loadings for the two-factor structure consist of 8 items ranged from 0.68 to 0.84, while the factor loadings for the single-factor structure consist of 16 items ranged from 0.60 to 0.87. DTs may fall under this grouping because technologies are grouped into hardware and software generally [68]. Hence, the factors are named as hardware and software in Table 3.

Table 3. Factor Loadings for Pilot Test.

Subscales (Factors) and Items	Factor Loadings of Items	Subscales (Factors) And Items	Factor Loadings of Items
Hardware Technologies		**Software Technologies**	
Blockchain	0.841	Cloud Computing	0.835
Autonomous Robots	0.840	Horizontal and Vertical System Software Integrations	0.806
3D Printers	0.830	Cyber Security	0.775
5G	0.757	Big Data Analytics	0.682

Note: 8 items, 2 factors, Extraction Method: Principal Component Analysis, Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 3 iterations.

Table 4. Factor Loadings for Pilot Test.

Subscales (Factors) and Items	Factor Loadings of Items	Subscales (Factors) and Items	Factor Loadings of Items
Using Disruptive Technology (UDT)			
Autonomous Robots	0.874	Augmented Reality (AR)	0.722
Artificial Intelligence	0.829	Digital Twin	0.716
Cyber Physical Systems (CPS)	0.824	Big Data Analytics	0.711
Blockchain	0.817	5G	0.705
Autonomous Driverless Vehicles	0.812	Cyber Security	0.675
Internet of Things (IoT)	0.810	Cloud Computing	0.643
Virtual Reality (VR)	0.794	3D Printers	0.632
Simulation	0.749	Horizontal and Vertical System Software Integrations	0.597

Note: 16 items, 1 factor, Extraction Method: Principal Component Analysis; 1 component extracted.

As a result of the pilot study, no items were removed from the item pool, but augmentative reality and virtual reality items were combined into a single item. Therefore, the number of items decreased from 16 in the pilot study to 15 in the main study. Accordingly, the item pool utilized in the main study, along with its references, is given in Table 5 below.

Table 5. Item Pool for the Main Study.

Item Number	Item	References
Q1	The company has used cyber physical systems (CPS) in its operations actively.	[69]
Q2	The company has used internet of things (IoT) in its operations actively.	[70]
Q3	The company has used artifical intelligence in its operations actively.	[71]
Q4	The company has used autonomous robots in its operations actively.	[72]
Q5	The company actively has used big data analitics in its operations.	[73]
Q6	The company has used blockchain technology in its operations actively.	[74,75]
Q7	The company has used cloud computing technology in its operations actively.	[76]
Q8	The company has used 3D printers (additive manufacturing) in its operations actively.	[77,78]
Q9	The company has used augmented reality (AR) and virtual reality (VR) in its operations actively.	[79,80]
Q10	The company has used autonomous (driverless) vehicles in its operations actively.	[81,82]
Q11	The company has used digital twin technology in its operations actively.	[83]
Q12	The company has used horizontal and vertical software integrations actively.	[84]
Q13	The company has used simulation technology in its operations actively.	[85,86]
Q14	The company has used cyber security (smart networks/network security) technology in its operations actively.	[84,87]
Q15	The company has used 5G technology in its operations actively.	[88]

3.3. Study 3: Initial Identification of Dimensionality

Before the initial identification of dimensionality was made, the demographic characteristics of the 426 samples collected for the main study were examined. The results are given in Table 6 below:

Table 6. Demographic characteristics of the participants.

Industry of Company	N	Percent (%)	Position in Company	N	Percent (%)
Retail and FMCG	73	17.1	Supply Chain Responsible	42	9.9
E-Trade	24	5.6	Supply Chain Executive	32	7.5
Transportation, Distribution, Warehousing	92	21.6	Supply Chain Manager	150	35.2
Import-Export	20	4.7	Digital Transformation Responsible	21	4.9
Manufacturing	151	35.4	Digital Transformation Executive	24	5.6

Table 6. *Cont.*

Service	66	15.5	Digital Transformation Manager	51	12.0
			Other	106	24.9
Total	426	100.0	Total	426	100.0
Number of Employees in Company	N	Percent (%)	Annual Turnover for Company	N	Percent (%)
Less than 250	118	27.7	Less than USD 1,000,000	118	27.7
251–999	102	23.9	USD 1,000,000–4,999,999	102	23.9
1000–1999	46	10.8	USD 5,000,000–19,999,999	46	10.8
2000–3999	43	10.1	USD 20,000,000–99,999,999	43	10.1
4000 and above	117	27.5	USD 100,000,000 and above	117	27.5
Total	426	100.0	Total	426	100.0
Activity Period of Company	N	Percent (%)	Time to Use Disruptive Technologies	N	Percent (%)
Less than 1 year	8	1.9	0–6 months	61	14.3
1–5 years	41	9.6	6 months–1 year	40	9.4
6–10 years	43	10.1	1 year–5 years	11	2.6
11–15 years	41	9.6			
16–20 years	29	6.8	5 years and above	187	43.9
20 years and above	264	61.9			
Total	426	100.0	Total	426	100.0
Field of Activity of the Company	N	Percent (%)	Status of Starting Digital Transformation	N	Percent (%)
National	77	18.1	Yes	389	91.3
International	349	81.9	No	37	8.7
Total	426	100.0	Total	426	100.0
Working with a Digital Transformation Leader	N	Percent (%)			
Yes	267	62.7			
No	159	37.3			
Total	426	100.0			

EFA was performed for the initial identification of dimensionality. In this part of the study, 3 different models were tested. These are the two-factor structure obtained by removing the 3 items caused by crossloading (EFA Model 1), the structure formed by compressing the remaining 12 items into a single factor (EFA Model 2), and the 15-item structure obtained by compressing into a single factor without removing the item (EFA Model 3). Reliability analyses and factor analysis results for these 3 constructs are given in Tables 7 and 8 below.

Table 7. Reliability analyses results.

Subscales	Number of Items	Cronbach's Alpha (α)	Inter-Item Means		Scale Statistics		
			Correlation	Covariance	Mean	Variance	Std. Deviation
UDT	12	0.896	0.420977	0.766253	35.605566	123.115817	11.095757
UDT	15	0.914	0.416523	0.756146	44.465892	186.096933	13.641735

Varimax with Kaiser Normalization was used as the rotation method since there was not a high level of relationship between the variables in the EFAs [89].

Table 8. Subscales and factor analyses results.

Number of Items	Number of Factors	KMO	Bartlett's Test of Sphericity			Extraction Sums of Squared Loadings	
			Approx. Chi-Square	df	Sig. (p)	Total	Cumulative %
12 items	2 factors	0.922	2095.989806	66	0.000	1.125999	56.458075
12 items	1 factor *					5.648970	47.074746
14 items	1 factor *	0.934	2877.906203	105	0.000	6.883	45.888865

* It is compressed into a single factor.

Principal Component Analysis (PCA) is a statistical instrument utilized to extract dominant properties, that is, principal components, from a set of multivariate data, and it was utilized as a extraction method in this study [90]. Items with a factor loading below 0.60 should be excluded from the scale [91]. Since the factor loadings of 3D Printers technology was below 0.60, compression into a single factor was carried out on 14 items. Since the KMO values were above 0.70 and Bartlett's Test of Sphericity values were statistically significant ($p < 0.05$), the data was convenient for factor analysis.

UDTS has 12 items and two factors with loading ranged from 0.545 to 0.775 (Table 9). UDTS has 12 items and one factor with loading ranged from 0.618 to 0.75 (Table 10). Since the factor loading value of the item (Q8) measuring the companies using 3D printers technology was below 0.60 ($\lambda = 0.530$), the remaining 14 items were excluded from the scale items and the remaining 14 items were compressed into a single factor. Factor loading values for this structure ranged from 0.611 to 0.754 (Table 11).

Table 9. Factor Loadings for EFA Model 1.

Subscales (Factors) and Items	Factor Loadings of Items	Subscales (Factors) and Items	Factor Loadings of Items
Hardware Technologies		**Software Technologies**	
Autonomous driverless vehicles	0.775	Cloud computing	0.755
Digital twin	0.741	Cyber security	0.741
Augmented reality (AR), Virtual reality (VR)	0.729	Horizontal and vertical system software integrations	0.694
Blockchain	0.679	Big data analytics	0.677
Autonomous robots	0.653	Cyber physical systems (CPS)	0.651
Simulation	0.585		
5G	0.545		

Note: 12 items, 2 factors.

Table 10. Factor Loadings for EFA Model 2.

Items	Factor Loadings of Items	Items	Factor Loadings of Items
Using Disruptive Technology (UDT)			
Simulation	0.750	Augmented reality (AR), Virtual reality (VR)	0.691
Digital twin	0.731	5G	0.676
Big data analytics	0.730	Cyber security	0.662
Autonomous robots	0.710	Autonomous driverless vehicles	0.632
Blockchain	0.696	Cyber physical systems (CPS)	0.628
Horizontal and vertical system software integrations	0.693	Cloud computing	0.618

Note: 12 items, 1 factor.

Table 11. Factor Loadings for EFA Model 3.

Items	Factor Loadings of Items	Items	Factor Loadings of Items
Using Disruptive Technology (UDT)			
Big data analytics	0.754	Augmented reality (AR), Virtual reality (VR)	0.686
Artificial intelligence	0.778	Internet of things (IoT)	0.684
Simulation	0.732	5G	0.659
Digital twin	0.720	Cyber security	0.641
Autonomous robots	0.712	Cyber physical systems (CPS)	0.630
Blockchain	0.699	Autonomous driverless vehicles	0.620
Horizontal and vertical system software integrations	0.687	Cloud computing	0.611

Note: 14 items, 1 factor.

When Figure 3 is examined, the eigenvalue for a single factor structure is approximately 7.00. Since the graph starts to flatten after the second factor, it is possible to say that the most appropriate factor structure for the data is the two-factor structure, according to the results of EFA of the main study. The eigenvalue for this structure is approximately 1.00.

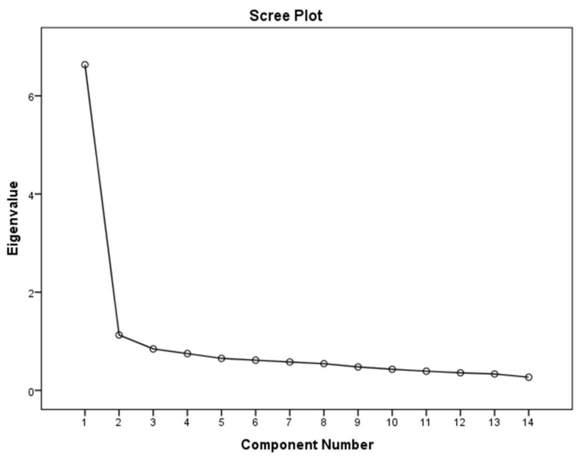

Figure 3. Scree Plot Graph for Main Study.

3.4. Study 4: Dimensionality Confirmation

CFA was utilized to ensure confirmation of dimensionality. Four alternative models were tested for construct validity. The first of these is Alternative Model 1, whose items and factor loading values are given in Table 9, which we reached with EFA. This model is given in Figure 4 below. The second tested alternative model is the single factor model. Question number Q8, which measures the utilization of 3D Printer technology in CFA, was excluded from the items because its factor loading was below 0.60 and analyzed the remaining 14 items. The resulting structure is given in Figure 5 together with its loadings. However, since the model fit values of this structure were not within the desired limits, the modifications suggested by the LISREL 8.51 package program were carried out and the alternative models given in Figures 6 and 7 were tested. Finally, the chi-square difference test was performed for the 4 models. According to the test results, these 4 models differ from each other in a statistically significant way. The most appropriate model is Alternative Model 4, which has the lowest chi-square value among these models. The final model, Alternative Model 4, is given in Figure 7 and the fit values for these models are given in Table 12.

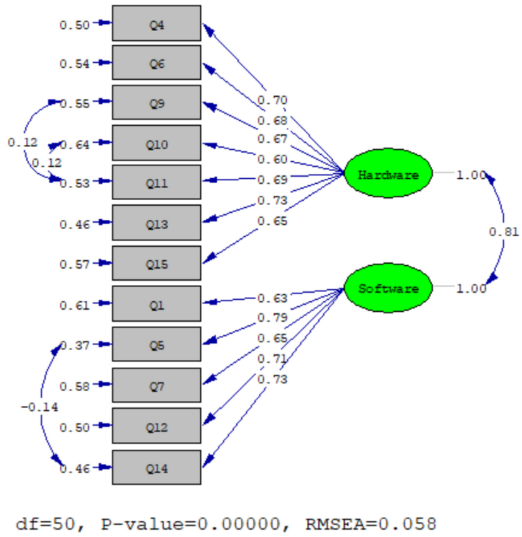

Figure 4. Alternative Model 1.

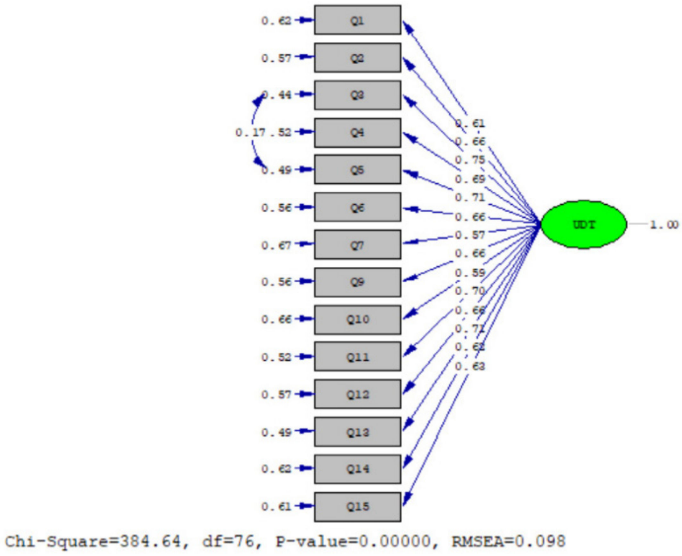

Figure 5. Alternative Model 2.

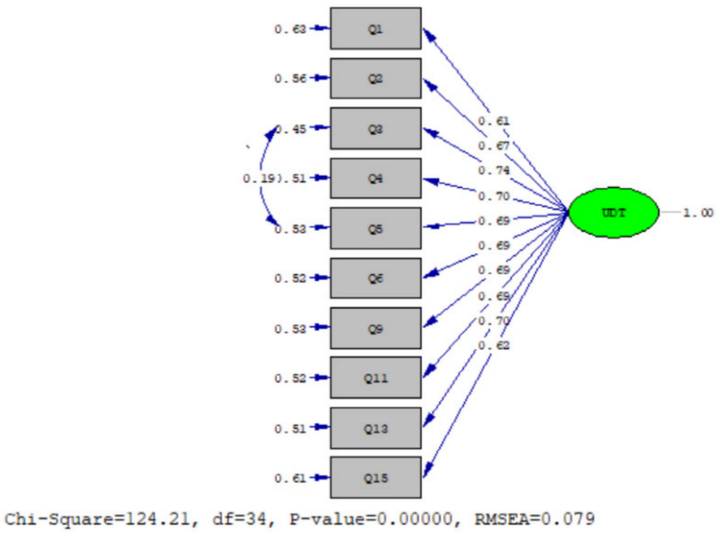

Figure 6. Alternative Model 3.

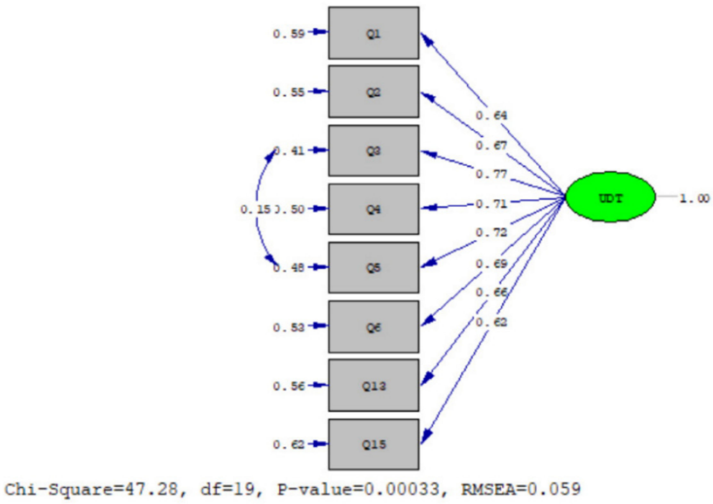

Figure 7. Alternative Model 4 (Final Model).

The existence of a relationship between the items in CFA has the effect of improving the model fit indices. However, the related items should be related in theory according to the existing literature. In Figure 4 above, Q5 and Q14, Q9 and Q11, and Q10 and Q11 are correlated in model. These relations were selected from the modification suggestions section, as they were among the relations that caused the most chi-square value decrease and based on the theoretical justification.

Big data technology requires data security [92]. Cyber security includes many different fields from information security to operational security and security of computer systems [93]. Big data analytics utilizes in cyber security [94]. Therefore, big data analytics and cyber security are related technologies, since cyber security includes data security. For this reason, Q5 and Q14 were correlated in the model. The digital twin is a technology with a virtual reality infrastructure created with simulations, which is seen as a useful tool that can be used in decision making and redesigning the system depending on the decision, supported by machine learning and artificial intelligence [95] and it can be utilized with reality technologies [96]. Therefore, Q9 and Q10 were correlated in the model. Considering the relationship between autonomous driverless vehicles and digital twin technology, for instance, by creating a digital twin of highways, autonomous vehicles can safely test different scenarios without going into traffic [97]. Therefore, Q10 and Q11 were correlated in the model. Artificial intelligence (Q3) and big data analytics (Q5) technologies were correlated with the models given in Figures 5–7 below. The reason for this is the utilization of artificial intelligence and machine learning techniques in big data analytics [98].

According to the EFA and CFA results, different factor loading values were obtained for the items. The reason for this situation is that different programs are used for these two-factor analysis. Since the loadings of item Q7, which measures companies using Cloud Computing, and Q10, which measures companies using autonomous (driverless) vehicles, are below 0.60, these items were removed from the structure and retested according to the alternative model 2 loadings for CFA. In addition, taking into account the modification indices suggestions for this model, the items Q12, which measures the utilization of horizontal and vertical system integrations, and Q14, which measures the utilization of cyber security, were removed from the structure and the model was retested. As a result of the test, the structure given has been reached in Figure 6 below. In order to improve the model fit values, new modification suggestions were fulfilled and the structure was retested by removing the items Q9, which measures the using augmented reality (AR) and virtual reality (VR), and Q11, which measures the using digital twin, which cause reduction of chi-square by removing them from the model. The model obtained is given with the loadings in Figure 7.

Table 12. The Comparison of Alternative Models.

Indices	Perfect Fit Threshold Value *	Acceptable Fit Range *	Alternative Model 1	Alternative Model 2	Alternative Model 3	Alternative Model 4
x^2/df	$1 \leq x^2/df \leq 3$	$2 \leq x^2/df \leq 5$	(122.24/50) 2.44	(384.64/76) 5.061	(124.21/34) 3.65	(47.28/19) 2.49
RMSEA	≤0.05	0.05 ≤ RMSEA ≤ 0.08	0.058	0.098	0.079	0.059
GFI	≥0.95	0.90 ≤ GFI ≤ 1	0.95	0.89	0.94	0.97
SRMR	≤0.05	0.05 ≤ SRMR ≤ 0.10	0.037	0.054	0.040	0.030
CFI	≥0.95	0.90 ≤ CFI ≤ 1	0.96	0.90	0.95	0.97
NFI	≥0.95	0.90 ≤ NFI ≤ 1	0.94	0.88	0.94	0.97
AGFI	≥0.90	0.85 ≤ AGFI ≤ 1	0.93	0.84	0.91	0.95

* Reproduced from sources: [99,100].

Chi-square difference test was performed for the 4 alternative models. These structures are different from each other, and this difference is significant statistically. The most appropriate model is Alternative Model 4 with the lowest chi-square value statistically and this model is the final model of the scale. It is the model representing the "Using Disruptive Technology Scale (UDTS)". As seen in Table 12 above, the final model has a perfect fit for the indices of x^2/df, GFI, SRMR, CFI, NFI and AGFI. The structure has an acceptable fit in terms of the RMSEA index.

Factor loadings point out the amount of relationship between the items and the latent structure [64,101]. The item with the highest loading of the scale is Q3, which measures the utilization of Artificial Intelligence with a loading of 0.74. It is followed by Q4, which measures utilizing autonomous robots, and Q13, which measures utilizing simulation technology, with loadings of 0.70. These are standardized loading values. The item with the lowest loading of the model is Q1, which measures the utilization of cyber physical systems (CPS) with a loading of 0.61. *T*-values were examined for the significance of loadings. *T*-values of the loadings are significant because they are above 1.96 at the 0.05-significance level [101]. The relevant values are given in Table 13 below:

Table 13. Factor Loading, *t*-values and R^2 for items.

Items/Variables	Factor Loadings	*t*-Values	R^2
Cyber physical systems (CPS)	0.64	13.89	0.40
Internet of things (IoT)	0.67	14.70	0.44
Artifical intelligence	0.77	17.58	0.66
Autonomous robots	0.71	15.90	0.48
Big data analitics	0.72	16.15	0.60
Blockchain	0.69	15.22	0.45
Simulation	0.66	14.47	0.42
5G	0.62	13.23	0.35

3.5. Study 5: Convergent Validity Assessment

Average variance extracted (AVE) and composite reliability (CR) values are considered for convergent validity [102]. Some researchers agree that both AVE and CR values should be within their expected limits. According to these limits, AVE should be 0.05 or higher to enable adequate convergent validity [100]. For CR, it is desirable that this value be close to 1.00 [103]. According to Fornell and Larcker (1981), in a case where AVE is lower than 0.50 but CR is greater than 0.60, the convergent validity of the construct is still adequate [104]. Therefore, this scale has provided convergent validity according to these conditions (AVE = 0.471; CR = 0.877). The condition for the scale to have internal consistency reliability is that the Cronbach's Alpha value is above 0.70 [102,105,106]. Since the scale has a value above this, it has internal consistency. The relevant values are given in Table 14 below.

Table 14. AVE, CR and Cronbach's Alpha Values.

Items/Variables	Standardized Factor Loadings	Square of Standardized Factor Loadings	Errors	AVE	CR	Cronbach's Alpha (α)
Cyber physical systems (CPS)	0.64	0.4096	0.5904	0.471	0.877	0.873
Internet of things (IoT)	0.67	0.4489	0.5511			
Artifical intelligence	0.77	0.5929	0.4071			
Autonomous robots	0.71	0.5041	0.4959			
Big data analitics	0.72	0.5184	0.4816			
Blockchain	0.69	0.4761	0.5239			
Simulation	0.66	0.4356	0.5644			
5G	0.62	0.3844	0.6156			

Discriminant validity is calculated separately for each latent variable [107]. Since the most ideal structure in this scale is a single factor structure, there is only one latent variable. Therefore, the discriminant validity could not be examined. The final form of the scale, of which whole statistical analysis results are given above, is presented in Appendix A, Table A3.

3.6. Controlling of Bias Effect

In the data obtained through the questionnaire, an issue called "bias effect" or "common method bias" may arise depending on the perception of the participants who answered the items [108]. Whether there was a response bias in the answers given by the employees was tested utilizing the MANOVA test Wilks' Lamp statistics. Wilks' Lamp is a widely utilized type of statistics that investigates whether groups differ in some way, regardless of whether they alter in at least one linear combination of dependent variables [107]. It expresses the ratio of error variance to total variance for each variable [108]. In this study, there is only one item containing information about the employees as seen in Table 6. This is the item of the position of the employees in the company. It was tested whether the eight DTs obtained in the final model differentiated according to the positions of the employees in the company, and it has been concluded that the answers given do not demonstrate a significant difference (p = 0.734). Consequently, the data collected within the scope of scale development does not have the bias effect. These findings are given in Table 15 below:

Table 15. Controlling of Bias Effect.

Effect	Value	F	df1	df2	p	Partial Eta Squared
Wilks' Lambda	0.918	0.854	42,000	1940.594	0.734	0.014

Note: Sig. value for Box's Test of Equality of Covariance Matrices: 0.366.

3.7. Relationships between Variables

The ordinal variables were taken from the variables involving the demographic characteristics of the participants given in Table 6, and the relations between the variables were examined because structural equation modeling is a type of analysis that works with categorical data [109]. First, EFA was performed for demographic variables by utilizing the PCA as extraction method and varimax rotation. The results of the analysis demonstrated that the variables of activity period, number of employees in company and annual turnover for company related to company information form a single factor structure. Since the structure obtained indicates the size of the company, this latent variable is named as CSIZE as an abbreviation of company size. The above-mentioned observed variables are named Csize1, Csize2 and Csize3 respectively. Since the variable time to use DTs emerged as a separate structure and points to the digitalization time, this latent variable was named DTIME as an abbreviation of it. The observed variable of the related factor is named Dtime1. The item numbers of the technologies obtained as a result of the developed UDTS were utilized in the model without altering. The model, in which the demographic characteristics of the participants are also reflected in the model and showing the relationships between the relevant structures, is given in Figure 8 below.

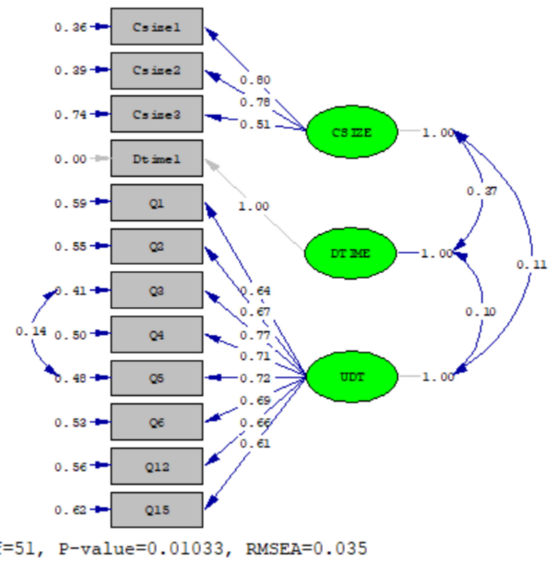

Figure 8. Relationships between Variables.

There is a low correlation between the UDT structure constituted by using DT and the CSIZE structure for company size (r = 0.11). Since the *t*-value of this relationship is greater than 1.96, this relationship is statistically significant (*t*-value = 1.97). There is low correlation between DTIME and UDT (r = 0.10), but this relationship is not statistically significant (*t*-value = 1.92). There is a moderate correlation between CSIZE and DTIME and this relationship is statistically significant (r = 0.37, *t*-value = 6.96). Therefore, it is possible to say that larger size companies have been using DTs longer than other companies. The item that best explains the company size (CSIZE) latent variable is the activity period of the company with a factor loading of 0.80. It is followed by the number of employees in the company (λ = 0.78) and company turnover (λ = 0.51). When the model fit indices of the above model are investigated, the model has perfect model fit indices in terms of whole kinds of them discussed in this study (x^2/df = 77.22/51; RMSEA = 0.035; GFI = 0.97; SRMR = 0.029; CFI = 0.98; NFI = 0.96; AGFI = 0.96).

4. Discussion

The measurement is a concept that has been the subject of discussion since ancient times [110]. It is one of the most basic concepts that enables social sciences to approach natural sciences [111]. In addition, it is the first stage encountered when a study tries to break away from theoretical context and move to the empirical level. As well as the purpose for which the measurement is made, the means by which it is made is one of the indispensable elements of the measurement methods [112].

In the current era, SCs of which they are members, not businesses, compete, and DTs have effects on SCs in many aspects, especially on SC performance [113]. In addition to enhancing SC performance, DTs have a significant role in constructing more flexible, more efficient, more visible and more resilient SCs. The COVID-19 pandemic has revealed the need to reevaluate current SC approaches and restructure SCs in recent past. This restructure requirement covers enhancing the utilization of DTs [30]. For these reasons, it is extremely critical and significant to investigate the extent to which DTs are utilized, to measure the current utilization levels of these technologies, and to examine their effects on operations in SCs. In order to determine these, it is essential to first measure their level of utilization. This can only be possible with a measurement instrument developed in this field.

Many technological changes have taken place from the past to the present [114] and DTs change according to the current era [115]. In this study, 4IR technologies were taken as DTs and current DTs that are widely used in SCs were preferred. With the inductive method, we tried to obtain information about the SCs with questionnaires collected from the companies operating in different industries. The technology that best explains the single-factor structure obtained in the final model is artificial intelligence technology, with the highest factor loading ($\lambda = 0.77$). This technology is frequently discussed today and has an enhancing utilization level in SCM. It enables machines to carry out functions that require intelligence, without humans, by offering machines the intelligence of humans [116]. It is estimated that the contribution of this technology to the global economy will be USD 15 trillion by 2030 [117].

Big data analytics is the second technology that best explains the structure ($\lambda = 0.72$). Big data technology is critical in SCs. It enables in-depth information on SCs, supports right decision making, predicts SC performance and positively affects performance [118,119]. The technology with the lowest factor loading and least explaining the structure is 5G because it is a technology that has just started to spread around the world ($\lambda = 0.72$). It refers to the fifth-generation wireless technology and has only been utilized for two years [120].

Since the scale items generated in the study focused on the level of UDT rather than agreeing with an opinion or behavior, the factor loadings obtained for the items in the study were lower than the scales in different fields. Moreover, 3D printers, a crucial technology in SCs, were excluded from the study due to their low loading ($\lambda = 0.530$). Although 3D printers are a technology that is a very high trend today and makes significant contributions to SCs, the current level of utilization of this technology is lower when it is compared with artificial intelligence and big data analytics technologies. According to a study conducted in 2020, the utilization of 3D printers will approximately triple in the next five years [121]. In other words, the loading of this technology is lower because its current utilization level is lower compared to other DTs.

The fact that the AVE value was below 0.50 in this study is due to the partially low loading values. This is due to the same reason as the utilization of 3D printer technology. Since the scale is not a measurement based on an opinion or behavior, it directly measures the level of technology use, and since companies that never use the relevant technologies answer the item as 1 (I totally disagree), it decreases the loading values of the related items. Such a strict response in items based on opinion either does not exist at whole items or is valid for very few items of the scale. It is a convergent validity value that gives results depending on the AVE factor loading values [122]. However, the scale has convergent validity when the CR value is above 0.60 according to the literature [104]. Since this scale development study is a completely new scale introduced to the SC literature, the results could not be compared with other studies.

4.1. Theoretical Contribution

The fact that a lot of study has been performed in a field so far does not mean that a new contribution cannot be made to that field. The deepest and most fundamental contribution that can be made to any field can be made in terms of measurement, because that field cannot be fully assessed when measurements cannot be made in that field [123]. Despite the enhancing emphasis on the contribution of DTs to SCM, there is a gap in enabling a measurement instrument that can evaluate their utilization. Correcting the lack of a measurement instrument developed in this field in the literature is the most crucial theoretical contribution of this study.

4.2. Managerial Implication

4IR has brought with it new DTs and digital transformation. Digital transformation is more than an essentialness; the DTs that 4IR enables are also an opportunity for countries to enhance their economic, social and environmental benefits [124]. Policy makers should engage in practices that foster the UDT and the disruptive innovation that these technologies stimulate [125].

By using the UDTS, SC managers or leaders can compare the UDT of the industries in which they operate, and with this direction they can increase their investments in the DTs in which they are behind compared to the industry. By examining the effects of DTs on SC performance, they can enhance the level of using that technology by becoming aware of which technology contributes more to SC performance. The effects of DTs on the entire SC can be examined, as well as on the basis of a specific SC operation. Improvements can be made after this study. Furthermore, UDT affects the way SC managers make strategic and operational decisions [126]. Therefore, they can measure the level of utilization of these technologies and benefit from this in their decision-making processes.

4.3. Limitations and Future Research

This study has four main limitations. First, DTs differ according to the related eras. This study deals with 4IR technologies, which are the DTs of current age. Nowadays, the concept of Industry 5.0, which is the fifth industrial revolution, has begun to be handled and discussed by many researchers [127–131]. However, before the fifth industrial revolution can be evaluated, it is necessary to have a good understanding of 4IR technologies and to reach the required level of technological maturity [132]. Measuring the 4IR maturity level is possible with the "Using Disruptive Technology Scale (UDTS)". Researchers can add different technologies to these technologies and do a scale adaptation study for further research. For instance, they can benefit from this study by adding the currently very popular metaverse technology to the item pool of this study and performing a scale adaptation study in the future. In this sense, this study will form the basis of future research.

The second limitation of the study is that it is based on perception like all other studies based on questionnaire data. Whole studies in which data were collected through questionnaires suffer from the same limitation. Third, DTs are discussed in the context of the SC, and this is a constraint. The number of these technologies used can be enhanced or lessened in different contexts by specifying their theoretical justifications. It is recommended by the authors that the scale name be altered according to that context. Finally, it involves only one type of technology. In other words, this study only contains DTs utilized in the SC. It makes a profound contribution to the literature in this respect, but for researchers and managers who want to consider the technologies utilized in the SC as a whole, they can actualize a scale adaptation study by including information systems utilized in SCs such as enterprise software and enterprise resource planning (ERP) software. In this case, it would be convenient to change the name of the scale to "using supply chain technology scale". Taking the relevant scale as a two-factor structure with information technologies and DTs factors will enable a better explanation of the structure.

5. Conclusions

SCM is the planning and coordination of whole people, processes and technology involved in constituting value. DTs have now become a part of modern SCs and make enormous contributions to them. Implementing new DTs in SCs is critical to successful SC processes. SC managers must have knowledge of these technologies and understand and know how to utilize them [133]. They must persuade managers of companies to implement these technologies or enhance their utilization level.

SC is a dynamic environment, and it has to adapt and react to the events and situations going on around it. Nowadays, there are many significant issues that SCs need to adapt to. The requirement of enhancing SC visibility and SC resilience due to the COVID-19 pandemic, and the requirement of enhancing SC sustainability performance to achieve sustainable development goals are just a few examples. DTs enable the most significant contribution to the improvement of SCs related to these issues [18,134–137]. SCs need to be improved in line with these strategic goals. Consequently, the necessity of current research in SCs is a never-ending cycle. This developed and validated scale will contribute greatly to future research and SC literature.

Explanatory and confirmatory factor analyzes show that the UDTS scale has only one dimension which consists of cyber-physical systems (CPS), internet of things (IoT), artificial intelligence, autonomous robots, big data analytics, blockchain, simulation and 5G technologies. The fact that 4IR technologies are gathered under a single roof in the literature confirms that the scale has a one-dimensional structure reached in line with the empirical results. Moreover, the technologies that explain this dimension as a result of the study are the technologies that are widely utilized in SCM and are confirmed by the theoretical background of the study. In both respects, the study is validated by the relevant literature with the theoretical justifications stated [7,11,18,24,26,31,72,121,135].

As stated above, this scale has perfect model fit values in terms of x^2/df, GFI, SRMR, CFI, NFI and AGFI indices. It also has an acceptable level of model fit index value in terms of the RMSEA. The scale also has convergent validity and data that does not have the bias effect. This scale can be utilized with confidence in research in which DT will be a variable in different fields of the social sciences in its current form. In addition, it can be utilized to determine levels of UDT. Utilizing this scale, relationships and impacts can be examined throughout the SC or within its specific operations.

Author Contributions: Conceptualization, Ö.Ö.; methodology, Ö.Ö. and F.B.; software, Ö.Ö.; validation, Ö.Ö. and F.B.; formal analysis, Ö.Ö. and F.B.; investigation, Ö.Ö.; resources, Ö.Ö.; data curation, Ö.Ö. and F.B.; writing—original draft preparation, Ö.Ö. and F.B., writing—review and editing methodology, F.B.; visualization, Ö.Ö.; supervision, F.B.; project administration, F.B.; funding acquisition, Ö.Ö. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: This study was carried out with the approval of the ethics committee received from Yeditepe University Social and Human Sciences Ethics Committee (Ethics Committee Decision No. 28/2022, Date of Approval 25.03.2022).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data can be requested from the Correspondence author when necessary.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

(DTs)	Disruptive Technologies
(4IR)	The Fourth Industrial Revolution
(SCs)	Supply Chains
(SCM)	Supply Chain Management
(UDTS)	Using Disruptive Technology Scale
(EFA)	Exploratory Factor Analysis
(CFA)	Confirmatory Factor Analysis
(UDT)	Using Disruptive Technology
(CPS)	Cyber Physical Systems
(IoT)	Internet of Things
(AR)	Augmented Reality
(VR)	Virtual Reality
(AVE)	Average Variance Extracted
(CR)	Composite Reliability

Appendix A

Table A1. List of Expert Group.

Number	Name Surname	Company, University, Position *
	Experts from Professional Life	
1	B. Mahir Yamakoğlu	Doğuş Çay, Supply Chain Manager
2	Utku Genç	Migros, Supply Chain Manager
3	Bora Tanyel	Yıldız Holding, Supply Chain Director
4	Evren Ersoy	Siemens, Digital Transformation Specialist & Business University of Costa Rica, PhD Candidate
5	Erman Keskin	Colgate-Palmolive, Supply Chain Leader (Africa Eurasia Region)
	Experts from Academia	
6	Prof. Dr. Mehmet Tanyaş	Maltepe University, Head of Logistics Management
7	Asst. Prof. Mehmet Sıtkı Saygılı	Bahçeşehir University, Faculty Member of Logistics Management
8	Asst. Prof. Özlem Sanrı	Yeditepe University, Faculty Member of Logistics Management
9	Prof. Dr. Batuhan Kocaoğlu	Piri Reis University, Head of Management Information Systems

* Consists of the knowledge of the expert group at the time of the interviews.

Table A2. Item Pool for the Pilot Study.

Item Number	Item	References
1	The company has used cyber physical systems (CPS) in its operations actively.	[69]
2	The company has used internet of things (IoT) in its operations actively.	[70]
3	The company has used artifical intelligence in its operations actively.	[71]
4	The company has used autonomous robots in its operations actively.	[72]
5	The company actively has used big data analitics in its operations.	[73]
6	The company has used blockchain technology in its operations actively.	[74,75]
7	The company has used cloud computing technology in its operations actively.	[76]
8	The company has used 3D printers (additive manufacturing) in its operations actively.	[77,78]
9	The company has used augmented reality (AR) in its operations actively.	[79,80]
10	The company has used virtual reality (VR) in its operations actively.	[79,80]
11	The company has used autonomous (driverless) vehicles in its operations actively.	[81,82]
12	The company has used digital twin technology in its operations actively.	[83]
13	The company has used horizontal and vertical software integrations actively.	[84]
14	The company has used simulation technology in its operations actively.	[85,87]
15	The company has used cyber security (smart networks/network security) technology in its operations actively.	[84,87]
16	The company has used 5G technology in its operations actively.	[88]

Table A3. The Final Form of the Scale.

Using Disruptive Technology Scale (UDTS)						
Item Number	**Item**	**1: I Totally Disagree**	**2: I Disagree**	**3: I Have No Idea**	**4: I Agree**	**5: I Totally Agree**
1	The company has used cyber physical systems (CPS) in its operations actively.					
2	The company has used internet of things (IoT) in its operations actively.					
3	The company has used artifical intelligence in its operations actively.					
4	The company has used autonomous robots in its operations actively.					
5	The company actively has used big data analitics in its operations.					
6	The company has used blockchain technology in its operations actively.					
7	The company has used simulation technology in its operations actively.					
8	The company has used 5G technology in its operations actively.					

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