VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

Adoption of Industry 4.0 in Developing Countries: Scale Development and Empirical Validation

Sayıl Saçak Düzgün[1], Üstün Özen[2], Derya Fındık[3]

ABSTRACT
Purpose: The primary aim of this study is to develop a valid and reliable scale for measuring the factors influencing the adoption of Industry 4.0 technologies in developing countries. By identifying these factors, the study seeks to provide a comprehensive understanding of how developing economies can more effectively manage their transition processes towards Industry 4.0.
Methodology: A systematic scale development process was followed in the study. In the initial phase, scale items were generated based on a comprehensive literature review and expert opinions. Subsequently, preliminary tests and pilot applications were conducted to assess the face validity of the scale. In the final phase, survey data collected from a large sample were analyzed using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to evaluate the construct validity properties of the scale.
Findings: The analysis revealed that the factors influencing the adoption of Industry 4.0 could be categorized into eight distinct dimensions. The developed scale demonstrated high validity and reliability, and its factor structure was confirmed to be robust.
Originality: This study represents one of the first systematically developed scales to measure the factors influencing Industry 4.0 adoption in developing countries. Given that the literature on scale development is largely confined to developed nations or specific sectors, this research fills a significant gap within the context of developing countries.
Keywords: Industry 4.0, Developing Countries, Scale Development, Digital Transformation, Factor Analysis.
JEL Codes: L6, M11, M15, O3.

Endüstri 4.0’ın Gelişmekte Olan Ülkelerde Benimsenmesi: Ölçek Geliştirme ve Ampirik Doğrulama

ÖZET
Amaç: Bu çalışmanın temel amacı, gelişmekte olan ülkelerde Endüstri 4.0 teknolojilerinin benimsenmesini etkileyen faktörleri ölçmek üzere geçerli ve güvenilir bir ölçek geliştirmektir. Söz konusu faktörlerin tespit edilmesiyle, gelişmekte olan ekonomilerin Endüstri 4.0'a yönelik geçiş süreçlerini daha etkin bir şekilde nasıl yönetebileceklerine dair kapsamlı bir anlayış sunulması hedeflenmektedir.
Yöntem: Çalışmada sistematik bir ölçek geliştirme süreci izlenmiştir. İlk aşamada, kapsamlı bir literatür taraması ve uzman görüşleri doğrultusunda ölçek maddeleri oluşturulmuştur. Ardından, ön test ve pilot uygulamalar gerçekleştirilerek ölçeğin görünüş geçerliliği değerlendirilmiştir. Son aşamada, geniş bir katılımcı kitlesine uygulanan anket verileri açımlayıcı faktör analizi (AFA) ve doğrulayıcı faktör analizi (DFA) ile incelenerek ölçeğin yapı geçerliliği özellikleri test edilmiştir.
Bulgular: Analizler sonucunda, Endüstri 4.0’ın benimsenmesini etkileyen faktörlerin sekiz farklı boyuta ayrıldığı belirlenmiştir. Geliştirilen ölçeğin geçerlilik ve güvenilirlik değerleri yüksek bulunmuş ve faktör yapısının güçlü olduğu doğrulanmıştır.
Özgünlük: Bu çalışma, gelişmekte olan ülkelerde Endüstri 4.0'ın benimsenmesini etkileyen faktörleri ölçen ilk sistematik ölçeklerden biridir. Gelişmiş ülkeler veya belirli sektörlerle sınırlı alan yazın göz önüne alındığında, bu araştırma gelişmekte olan ülkeler bağlamında önemli bir boşluğu doldurmaktadır.
Anahtar Kelimeler: Endüstri 4.0, Gelişmekte Olan Ülkeler, Ölçek Geliştirme, Dijital Dönüşüm, Faktör Analizi.
JEL Kodları: L6, M11, M15, O3.

[1] Atatürk Üniversitesi, Sosyal Bilimler Enstitüsü, Yönetim Bilişim Sistemleri Bölümü, Erzurum, Türkiye,
[2] Atatürk Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, Yönetim Bilişim Sistemleri Bölümü, Erzurum, Türkiye
[3] Ankara Yıldırım Beyazıt Üniversitesi, İşletme Fakültesi, Yönetim Bilişim Sistemleri Bölümü, Ankara, Türkiye

Corresponding Author: Sayıl Saçak Düzgün, sayil@atauni.edu.tr
DOI: 10.51551/verimlilik.1647544
Research Article | Submitted: 26.02.2025 | Accepted: 23.06.2025
Atıf/Cite: Saçak Düzgün, S., Özen, Ü. and Fındık, D. (2025). “Adoption of Industry 4.0 in Developing Countries: Scale Development and Empirical Validation”, *Verimlilik Dergisi,* 59(3), 682-700.

1. INTRODUCTION

Industry 4.0 represents the digital transformation of manufacturing processes and is considered an industrial revolution driven by advanced technologies such as artificial intelligence, big data analytics, the Internet of Things (IoT), cloud computing, and cyber-physical systems (Pattanapairoj et al., 2021; Bonekamp and Sure, 2015; Lasi et al., 2014). Industry 4.0 transformation enables the establishment of smart factories through innovative technologies such as smart logistics, integrated decision-making mechanisms, advanced sensors, and big data analytics (Kang et al., 2016; Lee, 2015; Wang et al., 2016). The primary objective of Industry 4.0 is to enhance flexibility, efficiency, and competitiveness in manufacturing processes. Advanced economies which are ready for this transformation have swiftly embraced this transformation, strengthening their global competitive advantage (Aygün and Satı, 2022; Sarvari et al., 2018). However, for developing countries, this transformation process presents numerous challenges.

The adoption of Industry 4.0 in developing countries faces several obstacles, including infrastructure deficiencies, the need for a skilled workforce, investment costs, and technological adaptation (Aygün and Satı, 2022; Horváth and Szabó, 2019). While large-scale firms lead the transformation, the cost-benefit analysis of this process is critical, especially for small and medium-sized enterprises (SMEs) (Jovanovski et al., 2019).

The adoption of Industry 4.0 in developing countries is closely linked not only to economic factors but also to workforce transformation and social change. Digitalization automates traditional manufacturing processes, necessitating the acquisition of new skills by employees. This situation requires workforce retraining and the enhancement of digital competencies (Pessl et al., 2017). Moreover, for developing countries, defining digitalization strategies, restructuring industrial policies, and increasing international competitiveness have become significant issues (Slusarczyk et al., 2021; Grabowska, 2018).

This study aims to develop a valid and reliable scale to measure the factors influencing the adoption of Industry 4.0 in developing countries. Existing literature primarily focuses on developed economies, and comprehensive scale studies evaluating the adaptation of developing countries to Industry 4.0 are quite limited (Aygün and Satı, 2022; Horváth and Szabó, 2019). Therefore, this study will identify the key determinants of Industry 4.0 adoption in developing countries and create a scale suitable for measuring these factors. By obtaining more robust data in critical areas such as industrial policies, business strategies, and workforce transformation, this study aims to provide decision-makers with a useful tool for policy and strategy formulation.

Measurement can be defined as the assignment of numbers to objects (Aygün and Satı, 2022; Wu et al., 2016). In social sciences, scale development is an essential method used to systematically measure individuals' attitudes, beliefs, and behaviors (DeVellis, 2012). Developing reliable and valid scales is crucial for collecting accurate data and making sound inferences in social sciences. Additionally, measurement studies prevent research from remaining purely theoretical by elevating it to an empirical level (Hays, 1973). Such scale development efforts bring social sciences closer to natural sciences (Greer, 1989). By quantifying qualitative findings, scale development plays a significant role in concretizing abstract concepts (DeVellis and Thorpe, 2021; DeVellis, 2012).

Several scale development studies related to Industry 4.0 exist in the literature. Ghlolami et al. (2025) developed a multi-item scale to measure Green Lean Six Sigma applications in the Industry 4.0 era. Sözbilir (2021) designed a scale to assess employees' adaptation potential to Industry 4.0. Mishra et al. (2024) conducted a scale development study to evaluate digitalization practices in supply chains. Pinto et al. (2025) focused on collaborative robots and validated a scale designed to measure acceptance in the context of human-robot interaction (HRI). Özkanlısoy & Bulutlar (2022) developed a measurement tool for assessing supply chain management practices in the field of disruptive technology. Leichtmann et al. (2023) designed material to measure employees' attitudes toward mobile production robots working in collaboration with humans. Şimşek Demirbağ (2021) examined the current state of Industry 4.0 in the literature, identify research trends and gaps through thematic analysis, and assess the Industry 4.0 maturity levels, current practices, advantages, and challenges faced by both main and subcontractor companies in Türkiye's white goods industry. While all these studies are connected to Industry 4.0, none specifically address the factors influencing its adoption in developing countries.

Without a reliable and well-validated scale, it becomes challenging to adequately assess the adoption of Industry 4.0 technologies in developing countries, compare the digitalization levels of different industrial sectors, and understand the impact of Industry 4.0 applications on performance. Our study aims to fill this critical gap in literature.

The research questions that this study seeks to address are as follows:

RQ1: What are the subdimensions affecting the adoption of Industry 4.0 in developing countries?

RQ2: How can we measure the different dimensions influencing the adoption of Industry 4.0 in developing countries?

RQ3: How can a valid and reliable scale be developed to measure the factors influencing the adoption of Industry 4.0 in developing countries?

Therefore, this study aims to identify the subdimensions affecting the adoption of Industry 4.0 in developing countries and develop a valid and reliable scale to measure these dimensions.

The subsequent sections of this study are structured as follows: The literature review section provides the requisite theoretical and empirical background; the methodology section delineates the research design and analytical procedures; the findings section present the empirical results derived from the data analysis; and finally, the conclusion synthesizes the study's key contributions, implications, and limitations.

2. LITERATURE REVIEW

Industry 4.0 refers to intelligent production systems integrated with information technologies, placing digitalization at the center of manufacturing processes (Yin et al., 2017; Reischauer, 2018; Baio Junior and Carrer, 2022). Today, this transformation enhances the efficient use of production factors, helping businesses gain a competitive advantage in terms of flexibility, speed, and quality (Dalenogare et al., 2018). Industry 4.0 transforms traditional manufacturing methods through integrated technologies. The key components of this transformation include:

2.1. Cyber-Physical Systems (CPS)

CPS synchronizes physical production processes with digital networks, enabling real-time control and digital modeling of machines and production equipment (Zezulka et al., 2016; Baio Junior and Carrer, 2022). CPS is indispensable for transitioning to Industry 4.0, integrating information technologies with physical operations (Lu, 2017; Wang and Wang, 2016; Duman and Akdemir, 2021). By enabling real-time decision-making, CPS reduces resource consumption, increases efficiency, and supports sustainability (Prinz et al., 2016). These systems enhance automation rates, improve monitoring, and optimize business processes (Dey et al., 2018; Baio Junior and Carrer, 2022).

2.2. Internet of Things (IoT)

IoT enables machines and sensors in factories to share data over the internet, making production processes more autonomous and efficient (Wang et al., 2016). For example, IoT sensors in smart factories optimize energy consumption, supporting sustainable production systems (Lu, 2017; Duman and Akdemir, 2021). IoT has broad applications in service industries (Rha and Lee, 2022), and studies highlight the importance of network architectures in healthcare services (Dhanvijay and Patil, 2019; Pandya and Kumar, 2023). Ghosh et al. (2016) propose an IoT-based system for remote patient monitoring, improving healthcare services. IoT enhances interoperability, security, and operational efficiency by connecting objects through unique identities and network protocols (Greengard, 2017; Xu et al., 2014). Additionally, IoT reduces carbon emissions, increases energy efficiency, and facilitates resource sharing (Atzori et al., 2017; Çevik Onar and Ustundag, 2018).

2.3. Big Data and Analytics

Analyzing data from production processes enhances decision-making mechanisms and reduces error rates (Raguseo, 2018). Predictive maintenance algorithms, for instance, minimize failure risks in production facilities, increasing operational efficiency (Dalenogare et al., 2018). Big Data and Analytics (BDA) techniques, such as text mining and analytics, help firms extract meaningful insights from customer data. Studies by Schaeffer et al. (2014) and Donnelly et al. (2015: 422–442) emphasize that BDA enables SMEs to derive value from collected data. Another critical application of BDA is detecting fraudulent activities in online banking. Wongchinsri and Kuratach (2016) provide a detailed framework for using BDA techniques to detect credit card fraud. Thus, BDA significantly enhances the sustainability of SMEs in the service sector. Moreover, big data technologies transform large and complex datasets into valuable insights, offering businesses real-time analytics and competitive advantages (Banger, 2017; Santos et al., 2017). The integration of cloud computing further strengthens big data applications by providing scalable, cost-effective, and efficient data management solutions (Basl, 2016).

2.4. Cloud Computing

Storing, analyzing, and sharing production data on cloud-based platforms enhances businesses’ remote management capabilities (Frank et al., 2019; Baio Junior and Carrer, 2022). This allows production processes to be synchronized across geographically dispersed facilities (Bag et al., 2021). Cloud

Computing (CC) enables high-speed data access remotely and is increasingly adopted in the service sector due to its scalability, mobility, and security advantages (Riazul Islam et al., 2015; Pandya and Kumar, 2023). In the healthcare sector, CC facilitates efficient information dissemination and reduces medical record errors.

2.5. 3D Printing

3D printing transforms digital 3D data into physical objects, reducing production costs and providing a competitive advantage (Onday, 2017; Duman and Akdemir, 2021). It lowers costs for small-scale production and allows for on-demand manufacturing of spare parts, enhancing production flexibility (Dopico et al., 2016). Additionally, it accelerates prototyping and testing, facilitating product development (Popovich et al., 2017). By enabling customized mass production, 3D printing shortens production times, reduces costs, and fosters innovation while promoting eco-friendly manufacturing processes (Schwab, 2016). Widely used in healthcare, education, industry, and services, 3D printing plays a crucial role in business sustainability within Industry 4.0.

2.6. Robotics Applications

Advancements in robotics have enabled machines to provide services. The COVID-19 pandemic accelerated the adoption of robotic solutions in hospitality and healthcare, reducing frontline workloads and minimizing infection risks (Belanche et al., 2020). Humanoid robots enhance customer satisfaction and comfort (Becker et al., 2022). Additionally, robots lower labor costs, increase efficiency, and improve workplace safety (Gorçun, 2017; Salkın et al., 2018; Duman and Akdemir, 2021). Their integration allows businesses to operate independently, improving operational efficiency under challenging conditions (Banger, 2017; Richert et al., 2016).

2.7. Augmented Reality (AR) & Virtual Reality (VR)

AR and VR technologies, used in industrial training, maintenance, and remote support systems, enhance workers' technical skills and improve production efficiency (Tortorella et al., 2020). AR integrates virtual and physical environments, improving interactions and training experiences (Vaidya et al., 2018). In education, AR is used for pilot training (Schaffernak et al., 2020), while in tourism and hospitality, it enhances customer engagement (Flavián et al., 2021). Furthermore, AR improves product design, reduces costs, and shortens development cycles (Mourtzis et al., 2020).

2.8. Artificial Intelligence (AI)

The use of AI-powered systems in production lines accelerates defect detection in quality control processes and enhances robotic automation systems (Bag et al., 2020). AI-driven automated quality control systems detect defects that are difficult for the human eye to identify, reducing error rates (Büchi et al., 2020). AI enables precise diagnostics and intelligent decision-making, transforming industries such as healthcare, banking, and e-commerce (Flavián and Casaló, 2021; Giger, 2018). AI-powered smart medical devices monitor and regulate health metrics (Metcalf et al., 2016; Pandya and Kumar, 2023). AI-based automation boosts efficiency across industries, supporting sustainability.

2.9. Industry 4.0 Technologies and Productivity

Industry 4.0 technologies have both direct and indirect impacts on productivity. Smart manufacturing systems reduce error rates, optimize processes, and shorten production times. Research suggests that Industry 4.0 applications can increase factory productivity and reduce production costs (Baur and Wee, 2015).

The most frequently mentioned benefit of Industry 4.0 in the literature is increased productivity (Saçak Düzgün et al., 2024). Industry 4.0 also enhances workforce productivity. AI-powered robots collaborate with human workers, handling repetitive tasks while employees focus on high-value activities (Horváth and Szabó, 2019). Additionally, smart supply chain management reduces inventory costs and optimizes logistics processes (Bag et al., 2020).

3. METHODOLOGY

The primary aim of this study is to develop a measurement tool that assesses the impact of factors influencing digital transformation on the adoption of Industry 4.0 in developing countries. This tool is designed to be applicable across multiple developing nations, independent of country-specific conditions.

To develop a scale, Carpenter (2018) proposed a ten-step scale development method. The first step involves reviewing the theoretical background and establishing the conceptual framework. Next, the sampling method and sample size must be determined. Ensuring the quality of collected data is also essential. Following this, a statistical evaluation should be conducted to determine whether factor analysis can be performed on the dataset. Once this is confirmed, factor analysis is carried out, requiring decisions on the factor extraction method and the number of factors to be retained. Additionally, the appropriate rotation method must be selected. The scale items should then be evaluated based on predefined criteria, and finally, the results must be reported.

Boateng et al. (2018) proposed an alternative nine-step scale development methodology. According to this approach, the first step is defining the research domain and generating scale items. The next step is ensuring content validity. This is followed by a pre-testing phase for the survey items. Once these steps are completed, the study moves on to sampling and survey administration. The subsequent stages involve item reduction and factor extraction. Next, dimensionality tests are conducted, followed by reliability testing. Finally, the validity of the scale is assessed. In this study, the scale was developed through six main steps, as illustrated in Figure 1.

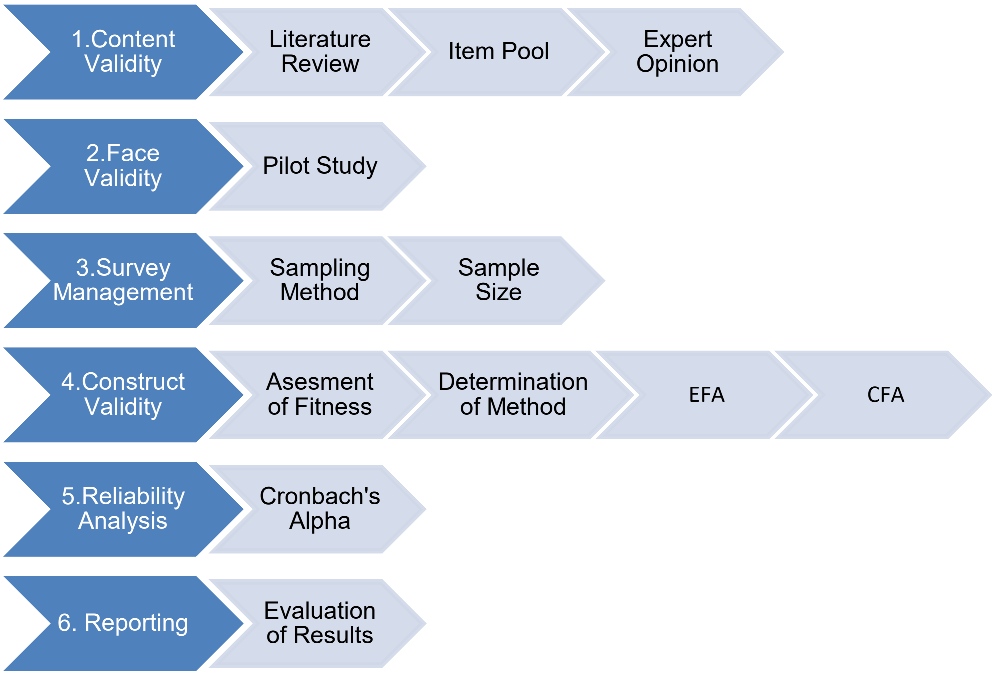

Figure 1. Scale development methodology applied in the study

This study represents one of the first systematically developed scales to measure the factors influencing Industry 4.0 adoption in developing countries. Given that the literature on scale development is largely confined to developed nations or specific sectors, this research fills a significant gap within the context of developing countries.

4. FINDINGS

4.1. Ensuring Content Validity

As observed in similar studies, the first step in a scale development study is to define the scope and establish the conceptual framework. The most appropriate method for this purpose is a systematic literature review (Mishra et al., 2024; Özkanlısoy and Bulutlar, 2022). In this study, the systematic literature review was conducted following internationally recognized methodological steps in academic research.

In the initial phase of the literature review, known as the planning stage, search queries were defined, and screening criteria were established. In this context, the term "Industry 4.0" was used as a keyword, along with the names of countries classified as developing economies by the International Monetary Fund (IMF, 2021), including Argentina, Brazil, Chile, China, Colombia, Egypt, Hungary, India, Indonesia, Iran, Malaysia, Mexico, the Philippines, Poland, Russia, Saudi Arabia, South Africa, Thailand, Turkey, and the United Arab Emirates. Separate queries were conducted for each country. The scope of the search was set to begin from 2011, the year the concept of Industry 4.0 was introduced, and only academic journal articles written in English were included. The academic databases Scopus and Web of Science, which are widely recognized in the literature, were chosen for the study.

The implementation phase of the systematic literature review was carried out in March and April 2023. Initially, searches were conducted in the Scopus database, where country names were queried in the title, keywords, and abstract sections of the articles. The term "Industry 4.0" was searched only in the keywords and abstract sections. A similar search strategy was applied in the Web of Science database, and the retrieved publications were recorded.

In the final evaluation stage of the retrieved articles, duplicate records were removed by identifying publications that appeared in both databases and those returned in multiple country queries. Next, the abstracts of the articles were reviewed, and publications that did not meet the following criteria were excluded:

- Articles published in languages other than English,
- Articles focusing solely on a specific disruptive technology rather than the general concept of Industry 4.0,
- Technically focused articles,
- Publications not centered on Industry 4.0,
- Studies that did not examine developing countries,
- Articles containing only bibliometric analysis,
- Publications retracted by the authors.

Finally, the included articles were analyzed in detail using the document analysis method, and factors influencing the adoption of Industry 4.0 in developing countries were identified based on the conceptual framework. A 44-item item pool was then created in alignment with this framework.

To confirm the alignment of the prepared item pool with the study's objectives, it was shared with three professors and one associate professor specializing in both industry and academia, as well as a business owner with expertise in survey research. Based on expert opinions, the number of items was reduced to 41. Through this process, content validity for the scale was ensured.

At the end of this phase results of revealed 10 distinct constructs namely “Perceived Technological Usefulness in Achieving Sustainability”, “Perceived Technological Usefulness in Achieving a Circular Economy”, “Perceived Technological Usefulness in Supply Chain Performance”, “Readiness”, “Innovation”, “Awareness”, “Quality Management”, “Education System”, “Competencies”, “Plan, Policy, and Strategy Studies”.

4.2. Establishing Face Validity

Before the large-scale administration of the survey, a pilot study was conducted with 61 participants to assess the adequacy of the scale (Isaac and Michael, 1995; Hertzog, 2008; Johanson and Brooks, 2010; Chahal et al., 2018). The pilot study employed a five-point Likert scale consisting of items deemed appropriate in the previous phase. The scale ranged from 1 (strongly disagree) to 5 (strongly agree). The five-point Likert scale has been frequently preferred in similar studies in the literature (Sözbilir, 2021: 704-721; Gholami et al., 2025: 179-202). Participants were asked to provide feedback on the clarity of the included items, the appropriateness of their order and length, and the adequacy and meaningfulness of the response options.

Although some participants expressed negative feedback regarding the measurement adequacy of items related to quality management and maturity/readiness levels, these items were not removed from the survey as they did not compromise its face validity. The reliability coefficient calculated from the 61 responses obtained in the pilot study was 0.954. At this stage, face validity was confirmed, and the survey was deemed suitable for the data collection process.

4.3. Survey Implementation

After finalizing the survey form, an online survey was conducted to collect data from relevant sectors to test the validity of the scale. Before implementation, approval for the study was obtained from the Ethics Committee of Atatürk University.

The study participants were employees working in firms operating in the manufacturing and industry, information technology, energy and infrastructure, healthcare and medical technology, logistics and transportation, and finance and banking sectors in Turkey. Participants were selected using purposive sampling and convenience sampling methods.

Purposive sampling is a method that involves the deliberate selection of participants most relevant to the research topic and objectives. This approach is widely used in qualitative research and allows researchers to select individuals or groups that best represent a particular phenomenon (Patton, 2002). Convenience sampling, on the other hand, involves selecting participants who are most easily accessible to the researcher. This method was preferred due to its advantages in terms of time and cost (Etikan et al., 2016). The target participants included white-collar employees in decision-making positions and those directly influencing the technical aspects of the transition to Industry 4.0, such as senior executives (CEOs, general managers, directors), mid-level managers (department heads, branch managers, team leaders), specialists/engineers (technical experts, project managers, consultants), and operational-level employees (technicians, operators, analysts). The study aimed to assess factors influencing the adoption of Industry 4.0 technologies. Therefore, gathering the perspectives of decision-makers, experts, engineers, and operational employees was deemed more appropriate (Rogers, 2003). The focus of the research was to evaluate the views of professionals who directly interact with and drive the digitalization process. Since blue-collar employees are generally not involved in strategic decision-making and digital transformation initiatives, their data may not sufficiently contribute to the study's objectives (Venkatesh et al., 2003: 425-478). For this reason, blue-collar workers were not included in the sample.

Various approaches exist in the literature regarding the determination of sample size. Comrey and Lee (1992) provided the following guidelines for sample sizes in exploratory factor analysis: 50 (very poor), 100 (poor), 200 (fair), 300 (good), 500 (very good), and 1000 (excellent). Guadagnoli and Velicer (1988), based on their simulation studies with different sample sizes, suggested that a minimum of 300–450 participants is necessary to observe an acceptable pattern comparability. Tabachnick and Fidell (2013) recommended a 5:1 ratio for factor analysis. The research data were collected from 400 participants via an online survey in November and December 2024. The online survey was distributed to participants using Google Forms.

Table 1. Demographic Statistics

Demographic		*Frequency*	*Percentage*
Gender	Female	232	58
	Male	168	42
Age	18-29	119	29,8
	30-39	177	44,3
	40-49	80	20
	50 and over	24	6,1
Position	Senior Executives	30	7,5
	Mid-Level Managers	107	26,8
	Specialists/Engineers	112	28
	Operational-Level Employees	151	37,8
Business Sector	Manufacturing Industry	161	40,3
	Information Technology	78	19,5
	Energy and Infrastructure	19	4,8
	Health and Medical Technology	65	16,3
	Logistics and Transportation	46	11,5
	Finance and Banking	31	7,8
Business Scale	Small	128	32
	Medium	116	29
	Large	156	39

The demographic characteristics of the 400 participants in this study are presented in Table 1. In terms of gender distribution, 58% of the respondents were female, while 42% were male. Regarding age groups, the majority of participants were between 30-39 years old (44.3%), followed by those aged 18-29 (29.8%), 40-49 (20%), and 50 and over (6.1%).

In terms of professional positions, 37.8% of respondents were operational-level employees, 28% were specialists or engineers, 26.8% were mid-level managers, and 7.5% were senior executives. The business sector distribution indicated that the highest proportion of participants worked in the manufacturing industry (40.3%), followed by information technology (19.5%), health and medical technology (16.3%), logistics and transportation (11.5%), finance and banking (7.8%), and energy and infrastructure (4.8%).

Lastly, business scale analysis showed that 39% of the participants were employed in large enterprises, 32% in small enterprises, and 29% in medium-sized enterprises. These demographic findings provide a comprehensive overview of the sample composition, ensuring a diverse representation across different sectors, job positions, and company sizes.

4.4. Establishing Construct Validity

Exploratory Factor Analysis (EFA) was employed to establish the construct validity of the developed scale. Factor analysis is a statistical technique aimed at reducing a set of related variables into a smaller number of uncorrelated and conceptually meaningful factors (Leech et al., 2005).

Researchers utilize EFA during scale development to mitigate the possibility of errors in their assumptions about the dimensions of the construct and to ensure item quality (Gholami et al., 2025; Sözbilir, 2021;

Mishra et al., 2024; Pinto et al., 2025; Özkanlısoy and Bulutlar, 2022; Jamwal et al., 2023; Leichtmann et al., 2023).

A common error in EFA is the use of Principal Component Analysis (PCA), which differs conceptually and mathematically from common factor analysis. Instead, Principal Axis Factoring (PAF) or Maximum Likelihood (ML) should be selected (Carpenter, 2018).

Rotation is essential for clarifying the factors (or dimensions) of the scale. Two types of rotation are available: oblique and orthogonal. Orthogonal rotation produces uncorrelated factors, but in social sciences, factors are rarely uncorrelated. Oblique rotation options include Direct Oblimin and Promax, both allowing factors to correlate. Promax is suggested to yield more robust results (Thompson, 2004).

For the above reasons, Principal Axis Factoring and Promax rotation were used to test the construct validity of the scale in this study. The EFA was conducted using IBM SPSS Statistics 20. The fitness of the sample for factor analysis was assessed initially. According to Field (2013), Bartlett's test of sphericity should yield $p < 0.01$, and the minimum recommended Kaiser-Meyer-Olkin (KMO) value should be 0.60. For the sample of 400, the KMO value was 0.944, indicating sufficient sample size for EFA. Bartlett's test yielded $\chi2$ (276) = 4987.351, $p < 0.05$, demonstrating adequate inter-item correlation for EFA.

The initial stage of the study, involving a literature review and content analysis, revealed 10 distinct constructions, each potentially representing a separate factor. To examine this 10-factor structure, an Exploratory Factor Analysis (EFA) was conducted on 40 items with a suppression value of 0.30, forcing a 10-factor solution. This approach is supported by prior research where a predetermined number of factors were specified (Pinto et al., 2025; Krägeloh et al., 2019, 88; Nomura et al., 2012, 242). In the Scale an additional item (item 41) was included to directly assess Industry 4.0 adoption. However, due to its single-item nature, it was excluded from the factor analysis. Instead, the EFA focused solely on items representing the multidimensional construction.

The initial EFA revealed cross-loadings and misplacements among items related to Readiness and Maturity Levels, consistent with feedback from the pilot survey. Consequently, these 8 items were removed due to compromised construct validity. A subsequent EFA, forcing an 8-factor solution, led to the removal of 8 more cross-loading items. The final EFA resulted in a 25-item scale loading onto 8 factors, explaining 59.22% of the total variance. Table 2 shows the factors loadings of the items. Since the original survey is in Turkish, the final version of the items in Turkish can be found in the appendix. The first factor represents perceived technological benefits in achieving a circular economy. The second factor is planning, the third factor is perceived technological benefits in supply chain performance, and the fourth factor is perceived technological benefits in sustainability. The remaining factors are awareness, education system, workforce qualifications, and innovation, respectively.

To validate the factor structure identified through Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA) was conducted using IBM SPSS AMOS Version 20, as is common practice in similar studies (Gholami et al., 2025; Sözbilir, 2021; Mishra et al., 2024; Pinto et al., 2025; Özkanlısoy and Bulutlar, 2022; Jamwal et al., 2023; Leichtmann et al., 2023). Confirmatory Factor Analysis is an evaluation method that allows for the comparison of a predetermined factor structure based on systematic goodness-of-fit evaluation procedures and estimates the relationship between latent constructs free from measurement errors. In this process, the extent to which the model explains the obtained data is determined by goodness-of-fit indices. Goodness-of-fit tests enable the decision to accept or reject the model.

The 8-factor, 24-item scale structure derived from the EFA was used as input for the Confirmatory Factor Analysis (CFA). Based on this EFA model, a measurement model (Figure 2) was developed for the CFA, and the goodness-of-fit index values of this measurement model were examined and evaluated. The Maximum Likelihood method was employed as the estimation method. To utilize the Maximum Likelihood estimation method, the data must exhibit a normal distribution (Tabachnick and Fidell, 2013). They stated that skewness and kurtosis values should be between -1.5 and +1.5 to ensure the normality assumption. In the research model, these values ranged between -1.103 and +1.259, thus the normality condition was satisfied.

The standardized factor loadings of all items in the CFA were found to be greater than 0.6, and as shown in Table 3, the goodness-of-fit indices of the measurement model indicate an excellent fit. At this stage, there was no need to make any modifications to the scale, such as removing items. Thus, the fit criteria for the measurement model of Industry 4.0 adoption in developing countries were met.

Table 2. Factors and Factor Loadings

Item No	*Factor Loading* *F1*	*F2*	*F3*	*F4*	*F5*	*F6*	*F7*	*F8*	*Item*
1				0,462					The digital transformation targeted by Industry 4.0 in the field of industry, supports society and industry in achieving sustainability goals.
2				0,834					In a developing country, Industry 4.0 applications provide benefits on social sustainability issues such as meeting the basic needs of people like health, education, food, water and shelter.
3				0,547					In a developing country, Industry 4.0 applications provide benefits on economic sustainability issues such as ensuring a long-term perspective in the economy, regulating the finance industry, reducing national debt, etc.
4				0,354					In a developing country, Industry 4.0 applications provide benefits on environmental sustainability issues such as global warming, climate change, etc.
5	0,506								In developing countries, Industry 4.0 applications are beneficial for the transition from a linear economy to a circular economy.
6	0,780								In developing countries, Industry 4.0 technologies increase the efficiency of circular economy applications.
7	0,955								In developing countries, Industry 4.0 supports the transition to a circular economy.
8	0,815								The adoption of Industry 4.0 helps to improve the circular economy by providing operational and strategic information on time.
9				0,489					Industry 4.0, by making the entire supply chain smarter, enables the rapid production of products needed by customers.
10				0,789					Industry 4.0 facilitates information sharing in supply chains digitally through horizontal and vertical integrations.
11				0,707					Industry 4.0 applications provide agility and flexibility in supply chain management.
12				0,496					Using digitalized solutions helps firms cope with internal and external changes and uncertainties and succeed in a competitive environment.
19								0,651	Disruptive technologies such as artificial intelligence, which Industry 4.0 is based on, offer businesses the opportunity to create new business opportunities with the innovation support they provide.
20								0,472	The technologies provided by Industry 4.0 play a critical role in establishing mutual trust, which is a key challenge in the open innovation process.
22					0,473				In order to reach the determined level of digitalization, firms must first be aware of the innovations brought by Industry 4.0 and the advantages and disadvantages provided by this phenomenon.
23					0,690				The lack of awareness regarding the requirements and impact of Industry 4.0 technologies in firms reduces their chances of exploring opportunities related to Industry 4.0.
24					0,601				Lack of information is one of the inhibiting factors in the transition to Industry 4.0.
29						0,575			In developing countries, the preparation of the workforce for the future by education systems affects the transition to Industry 4.0.
30						0,923			Increasing the competencies of teachers in vocational schools and universities regarding Industry 4.0 affects the transition of developing countries to Industry 4.0.

Table 2. (*Continued*)

Item No	*Factor Loading F1*	*F2*	*F3*	*F4*	*F5*	*F6*	*F7*	*F8*	*Item*
35							0,498		In the transition to Industry 4.0, leaders must possess technical and digital skills that enable them to navigate and communicate in the digital world while adapting to disruptive technologies.
36							0,509		The gap between the competencies possessed by the current workforce and the competencies associated with Industry 4.0 creates a significant obstacle to the economic development of developing countries.
37		0,763							A comprehensive industrial policy is necessary for the sustainability of advancements like Industry 4.0.
38		0,850							Organizations need innovative strategies and government policies to successfully implement Industry 4.0.
39		0,664							To foster the development of necessary technologies for Industry 4.0 adoption, enabling regulations should be implemented for innovation and entrepreneurship ecosystems.

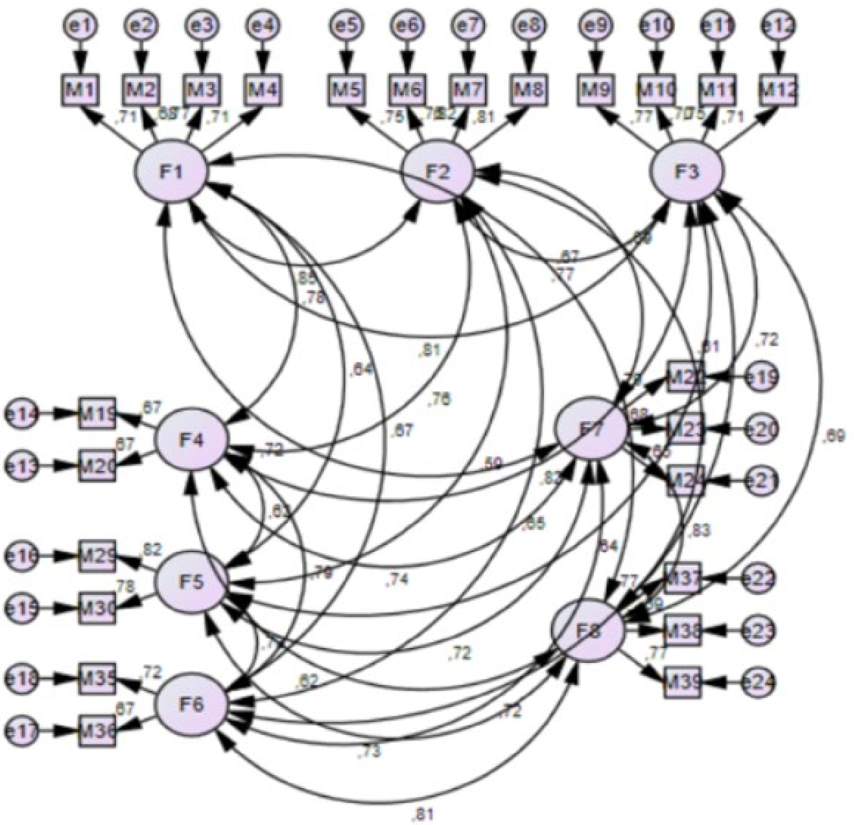

Figure 2. CFA measurement model

Table 3. DFA Fit Indices

İndices	*Referans Value*	*Measured Value*
CMIN/DF	< 3	2,211
NFI	> 0.90	0,903
CFI	> 0,90	0,944
GFI	> 0,90	0,905
RMSEA	< 0,07	0,055

Source: The reference values were obtained from the studies by Gholami (2024: 179-202) and Mishra et al. (2024:1278-1297).

4.5. Reliability Analysis

Evaluating reliability is a critical step in determining the psychometric properties of a scale (Churchill, 1979). In this study, item-total correlations and Cronbach's alpha coefficient were calculated to measure the internal consistency of the digitalization scales (Nunnally and Bernstein, 1994).

The analysis revealed that all item-total correlations were above the threshold value of 0.30. The lowest item-total correlation value was calculated as 0.514, which indicates sufficient internal consistency of the scale (Hair et al., 2014). Furthermore, the Cronbach's alpha coefficient was found to be 0.942, demonstrating that the scale possesses excellent internal consistency (Nunnally and Bernstein, 1994).

Reliability analysis was used to identify inconsistent items at the item level and to evaluate the quality of the scale (Hair et al., 2014). The scale's reliability is supported by item-total correlations exceeding the threshold of 0.50 and item-item correlations being higher than 0.30, which are among the most common methods for assessing internal consistency (Hair et al., 2014). Additionally, due to the Cronbach's alpha coefficient being significantly above the threshold of 0.70, there was no need to make any changes to the scale (Nunnally, 1978).

In conclusion, the calculated Cronbach's alpha and item-total correlation values demonstrate that the current dataset is highly reliable (Hair et al., 2009; Nunnally and Bernstein, 1994).

5. CONCLUSION and EVALUATION of FINDINGS

This study conducted a comprehensive scale development process to identify and measure the factors influencing the adoption of Industry 4.0 in developing countries. Utilizing rigorous methodological approaches such as systematic literature reviews, expert opinions, pilot studies, and factor analyses, this scale aims to understand the key variables affecting Industry 4.0 adoption at both academic and practical levels.

Altough the initial stage of the study, involving a literature review and content analysis, revealed 10 distinct constructs namely “Perceived Technological Usefulness in Achieving Sustainability”, “Perceived Technological Usefulness in Achieving a Circular Economy”, “Perceived Technological Usefulness in Supply Chain Performance”, “Readiness”, “Innovation”, “Awareness”, “Quality Management”, “Education System”, “Competencies”, “Plan, Policy, and Strategy Studies”. In this study, the developed dimensions are generally consistent with the existing literature. However, while some studies in the literature support the inclusion of "Readiness and Maturity Levels" (Ávila Bohórquez and Gil Herrera, 2022; Brodny and Tutak 2023, Stawiarska et al. 2021) and "Quality Management"(Ganjavi and Fazlollahtabar, 2021; Kannan and Garad, 2020) as distinct dimensions, the results of the Exploratory Factor Analysis (EFA) do not support these structures within the context of this research.

Numerous studies have shown that Industry 4.0 technologies can increase production efficiency, reduce costs, and enhance labor productivity by reallocating human effort to higher value-added tasks (Baur and Wee, 2015; Rikalovic et al., 2021; Saçak Düzgün et al., 2024). Therfore it is important for emerging countries to investigate how to apply Industry 4.0 widely. The findings of the study indicate that technological, organizational, environmental, and socio-economic factors play a critical role in the transition to Industry 4.0. The results of the factor analysis have demonstrated that the scale possesses a reliable and valid structure, enabling a more systematic examination of the digital transformation processes of businesses in developing countries.

This research augments the existing literature in three significant ways. Firstly, it extends the previously fragmented and constrained conceptual understanding of Industry 4.0 adoption through the development of a holistic and integrated measurement scale. Secondly, by focusing on developing nations, this study addresses the current gap in research, which is predominantly oriented towards developed economies, and provides a tailored framework for these countries. Thirdly, the insights generated from this work offer actionable guidance for academic scholars, policymakers, and industry practitioners.

Limitations of The Study: Firstly, in the phase of literature, review only the research in form of arcticles included. For a boarder look into developing countries thesis and other academical reseach could be included. Secondly, during the literature review period academic databases are queried only once for each developing country. This may couse overlooking of some of the articles which is published in that period but after the exact query for that country. Lastly, in the phase of pilot study sample size is limited. Although sample size of 61 is above the trashold value mention in literature, it would have been statistically more powerful with a sample size of more than 100.

Recommendations for Policymakers: To accelerate the Industry 4.0 transformation in developing countries, policymakers should implement structural reforms that encourage technological adaptation. Primarily, financial support mechanisms such as tax reductions, subsidies, and low-interest loans should be established to incentivize businesses to adapt to digital transformation. Additionally, education curricula should be updated, and university-industry collaboration should be enhanced to cultivate a skilled workforce necessary for the adoption of Industry 4.0 technologies. Furthermore, regulatory frameworks should be developed in areas such as data security, cybersecurity, and intellectual property rights to ensure the safe and sustainable progression of the digital transformation process.

Recommendations for Businesses: Adapting to Industry 4.0 technologies is critical for businesses to gain a long-term competitive advantage. In this context, companies should develop digital transformation strategies and integrate technologies such as robotics, artificial intelligence, and big data analytics to optimize production processes. However, technological transformation should not be limited to infrastructural investments alone. Continuous training programs should be organized to enhance employees' digital skills, and awareness of digitalization should be raised within the business culture. In particular, SMEs should be encouraged to effectively utilize government support to overcome the financial and technical barriers they face during the digital transformation process.

Recommendations for Academicians and Researchers: While the findings of this study provide significant contributions to the understanding of the factors influencing Industry 4.0 adoption, they also offer various avenues for future research. Firstly, in-depth studies should be conducted to examine how Industry 4.0 is shaped by local and cultural dynamics. Additionally, the scale developed in this study should be applied across different sectors and regions to test its generalizability. Future research can focus on analyzing the long-term effects of Industry 4.0 investments on businesses' productivity, profitability, and employment structure.

In conclusion, this study not only contributes to academic literature by developing a systematic scale for the adoption of Industry 4.0 technologies in developing countries but also provides various practical recommendations for policymakers, businesses, and academicians. Effective management of the digital transformation process will only be possible through the collaboration of all stakeholders and will ensure the maximum utilization of the opportunities offered by Industry 4.0.

Author Contributions

Sayıl Saçak Düzgün: Literature review, Conceptualization, Methodology, Data Curation, Analysis, Writing-original draft *Üstün Özen*: Modelling, Writing-review and editing *Derya Fındık*: Modelling, Writing-review and editing

Conflict of Interest

No potential conflict of interest was declared by the authors.

Funding

This study is supported by the Scientific Research Projects Office of Atatürk University. The project number is SDK-2023-11763."

Compliance with Ethical Standards

For this study, the approval of the Ethics Committee of Atatürk University Social and Human Sciences was obtained with the decision dated 22.10.2024 and numbered 252.

Ethical Statement

It was declared by the authors that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

Atzori, L., Iera, A., Morabito, G. (2017). "Understanding the Internet of Things: Definition, Potentials, and Societal Role of A Fast Evolving Paradigm", *Ad Hoc Networks*, 56, 122-140. https://doi.org/10.1016/j.adhoc.2016.12.004

Ávila Bohórquez, J.H. and Gil Herrera, R. de J. (2022). "Proposal and Validation of An Industry 4.0 Maturity Model for SMEs", *Journal of Industrial Engineering and Management*, 15(3), 433-454. https://doi.org/10.3926/jiem.3673

Aygün, D. and Satı, Z.E. (2022). "Evaluation of Industry 4.0 Transformation Barriers for SMEs in Turkey", *Eskişehir Osmangazi Üniversitesi İktisadi ve İdari Bilimler Dergisi*, 17(1), 239-255. https://doi.org/10.17153/oguiibf.991213

Bag, S., Gupta, S. and Kumar, S. (2021). "Industry 4.0 Adoption and 10R Advance Manufacturing Capabilities for Sustainable Development", *International Journal of Production Economics*, 231, 107844. https://doi.org/10.1016/j.ijpe.2020.107844

Bag, S., Wood, L.C., Mangla, S.K. and Luthra, S. (2020). "Procurement 4.0 and Its Implications on Business Process Performance in A Circular Economy", *Resources, Conservation and Recycling*, 152, 104502. https://doi.org/10.1016/j.resconrec.2019.104502

Baio Junior, A.A., Carrer, M.J. (2022). "Adoption of Industry 4.0 technologies: an analysis of small and medium-sized companies in the state of São Paulo, Brazil", *Gestão & Produção*, 29, e122. https://doi.org/10.1590/1806-9649-2022v29e122

Banger, G. (2017). "Endüstri 4.0 Ekstra", Dorlion Yayınları, Eskişehir.

Basl, J. (2016). "The Pilot Survey of the Industry 4.0 Principles Penetration in the Selected Czech and Polish Companies", *Journal of Systems Integration*, 7(4), 3-8.

Baur, C., and Wee, D. (2015). Manufacturing's next act. McKinsey & Company. https://www.mckinsey.com/business-functions/operations/our-insights/manufacturings-next-act, (Accessed: 20.01.2025)

Becker, M., Mahr, D. and Odekerken-Schröder, G. (2023). "Customer Comfort During Service Robot Interactions", *Service Business*, 17(1), 137-165. https://doi.org/10.1007/s11628-022-00499-4

Belanche, D., Casaló, L.V. and Flavián, C. (2021). "Frontline Robots in Tourism and Hospitality: Service Enhancement or Cost Reduction?", *Electronic Markets*, 31(3), 477-492. https://doi.org/10.1007/s12525-020-00432-5

Boateng, G.O., Neilands, T.B., Frongillo, E.A., Melgar-Quiñonez, H.R. and Young, S.L. (2018). "Best Practices for Developing and Validating Scales for Health, Social, and Behavioral Research: A Primer", *Frontiers in Public Health*, 6, 149. https://doi.org/10.3389/fpubh.2018.00149

Bonekamp, L. and Sure, M. (2015). "Consequences of Industry 4.0 on Human Labour and Work Organization", *Journal of Business and Media Psychology*, 6(1), 33-40.

Brodny, J. and Tutak, M. (2023). "Assessing the Level of Digital Maturity in the Three Seas Initiative Countries", *Technological Forecasting and Social Change*, 190, 122462. https://doi.org/10.1016/j.techfore.2023.122462

Büchi, G., Cugno, M. and Castagnoli, R. (2020). "Smart Factory Performance and Industry 4.0", *Technological Forecasting and Social Change*, 150, 119790. https://doi.org/10.1016/j.techfore.2019.119790

Carpenter, S. (2018). "Ten Steps in Scale Development and Reporting: A Guide for Researchers", *Communication Methods and Measures*, 12(1), 25-44. https://doi.org/10.1080/19312458.2017.1396583

Cevik Onar, S., Ustundag, A. (2018). "Smart and Connected Product Business Models", *Industry 4.0: Managing The Digital Transformation,* Springer Series in Advanced Manufacturing. Springer, Cham. https://doi.org/10.1007/978-3-319-57870-5_2

Chahal, H., Gupta, M., Lonial, S. (2018). "Operational Flexibility in Hospitals: Scale Development and Validation", *Journal of the Operational Research Society*, 56 (10), 3733-3755. https://doi.org/10.1080/00207543.2018.1442941

Churchill, G.A. (1979). "A Paradigm for Developing Better Measures of Marketing Constructs", *Journal of Marketing Research*, 16 (1), 64-73.

Comrey, A.L. and Lee, H.B. (1992). "A First Course in Factor Analysis", Lawrence Erlbaum Associates, Hillsdale, NJ.

Dalenogare, L.S., Benitez, G.B., Ayala, N.F. and Frank, A.G. (2018). "The Expected Contribution of Industry 4.0 Technologies for Industrial Performance", *International Journal of Production Economics*, 204, 383-394. https://doi.org/10.1016/j.ijpe.2018.08.019

DeVellis, R.F. (2012). "Scale Development: Theory and Applications", 3rd Ed. Sage Publications, Thousand Oaks, CA, USA.

DeVellis, R.F. and Thorpe, C.T. (2021). "Scale Development: Theory and Applications", Sage Publications, Thousand Oaks, CA, USA.

Dey, N., Ashour, A.S., Shi, F., Fong, S.J. and Tavares, J.M.R.S. (2018). "Medical Cyber-Physical Systems: A Survey", *Journal of Medical Systems*, 42, 1-13. https://doi.org/10.1007/s10916-018-0921-x

Dhanvijay, M.M. and Patil, S.C. (2019). “Internet of Things: A Survey of Enabling Technologies in Healthcare and Its Applications”, *Computer Networks*, 153, 113-131. https://doi.org/10.1016/j.comnet.2019.03.006

Donnelly, C., Simmons, G., Armstrong, G. and Fearne, A. (2015). “Digital Loyalty Card ‘Big Data’ and Small Business Marketing: Formal versus Informal or Complementary?”, *International Small Business Journal*, 33(4), 422-442. https://doi.org/10.1177/0266242613502691

Dopico, M., Gómez, A., De la Fuente, D., García, N., Rosillo, R. and Puche, J. (2016). “A Vision of Industry 4.0 from An Artificial Intelligence Point of View”, *Proceedings on the International Conference on Artificial Intelligence (ICAI)*, 407.

Duman, M.C. and Akdemir, B. (2021). “A Study to Determine the Effects of Industry 4.0 Technology Components on Organizational Performance”, *Technological Forecasting and Social Change*, 167, 120615. https://doi.org/10.1016/j.techfore.2021.120615

Etikan, I., Musa, S.A. and Alkassim, R.S. (2016). “Comparison of Convenience Sampling and Purposive Sampling”, *American Journal of Theoretical and Applied Statistics*, 5(1), 1-4. https://doi.org/10.11648/j.ajtas.20160501.11

Field, A. (2013). “Discovering Statistics Using IBM SPSS Statistics”, Sage.

Flavián, C. and Casaló, L.V. (2021). “Artificial Intelligence in Services: Current Trends, Benefits and Challenges”, *The Service Industries Journal*, 41, 853-859. https://doi.org/10.1080/02642069.2021.1989177

Flavián, C., Ibáñez-Sánchez, S. and Orús, C. (2021). “Impacts of Technological Embodiment through Virtual Reality on Potential Guests’ Emotions and Engagement”, *Journal of Hospitality Marketing & Management*, 30, 1-20. https://doi.org/10.1080/19368623.2020.1770146

Frank, A.G., Dalenogare, L.S. and Ayala, N.F. (2019). “Industry 4.0 Technologies: Implementation Patterns in Manufacturing Companies”, *International Journal of Production Economics*, 210, 15-26. https://doi.org/10.1016/j.ijpe.2019.01.004

Ganjavi, N. and Fazlollahtabar, H. (2021). “Integrated Sustainable Production Value Measurement Model Based on Lean and Six Sigma in Industry 4.0 Context”, *IEEE Transactions on Engineering Management*, 70(6), 2320-2333. https://doi.org/10.1109/TEM.2021.3078169

Gholami, H., Lee, J.K.Y., Garza-Reyes, J.A. and Salameh, A.A. (2025). “Green Lean Six Sigma Practices: A Scale Development and Measurement Model from An Engineer’s Perspective”, *Journal of Manufacturing Technology Management*, 36(1), 179-202. https://doi.org/10.1108/JMTM-12-2023-0555

Ghosh, A.M., Halder, D. and Hossain, S.A. (2016). “Remote health monitoring system through IoT”, *5th International Conference on Informatics, Electronics and Vision (ICIEV)*. IEEE, 921-926.

Giger, M.L. (2018). “Machine Learning in Medical Imaging”, *Journal of the American College of Radiology*, 15, 512-520. https://doi.org/10.1038/s41746-022-00592-y

Görçün, Ö.F. (2017). “Dördüncü Sanayi Devrimi Endüstri 4.0”, Beta Yayıncılık, İstanbul.

Grabowska, M. (2018). “Przemysł 4.0 w Unii Europejskiej. Studia Europejskie”, *Studies in European Affairs*, 3, 257-279.

Greengard, S. (2017). “Internet of Things”, Optimist Yayınları, İstanbul.

Greer, S.A. (1989). “The Logic of Social Inquiry”, Transaction Publishers, Piscataway, NJ, USA.

Guadagnoli, E. and Velicer, W.F. (1988). “Relation of Sample Size to the Stability of Component Patterns”, *Psychological Bulletin*, 103(2), 265.

Hair, J.F., Black, W.C. and Babin, B.J. (2009). “Multivariate Data Analysis: A Global Perspective”, 7th Ed. Prentice Hall, Upper Saddle River.

Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2014). “Multivariate Data Analysis”, Pearson New International Edition, Pearson Education Limited.

Hays, W.L. (1973). “Statistics for the Social Sciences”, 2nd Ed. Holt, Rinehart and Winston, New York, NY, USA.

Hertzog, M.A. (2008). “Considerations in Determining Sample Size for Pilot Studies”, *Research in Nursing & Health*, 31(2), 180-191. https://doi.org/10.1002/nur.20247

Horváth, D. and Szabó, R.Z. (2019). “Driving Forces and Barriers of Industry 4.0: Do Multinational and Small and Medium-Sized Companies Have Equal Opportunities?”, *Technological Forecasting and Social Change*, 146, 119-132. https://doi.org/10.1016/j.techfore.2019.05.021

IMF. (2021). “The Future of Emerging Markets”, https://www.imf.org, (Accessed: February 22, 2024).

Isaac, S. and Michael, W.B. (1995). “Handbook in Research and Evaluation: A Collection of Principles, Methods, and Strategies Useful in the Planning, Design, and Evaluation of Studies in Education and the Behavioral Sciences”, 3. Ed., EdITS Publishers.

Jamwal, A., Agrawal, R. and Sharma, M. (2023). “Challenges and Opportunities for Manufacturing SMEs in Adopting Industry 4.0 Technologies for Achieving Sustainability: Empirical Evidence from An Emerging Economy”, *Operations Management Research*, 1-26. https://doi.org/10.1007/s12063-023-00428-2

Johanson, G.A. and Brooks, G.P. (2010). “Initial Scale Development: Sample Size for Pilot Studies”, *Educational and Psychological Measurement*, 70(3), 394-400. https://doi.org/10.1177/0013164409355692

Jovanovski, D.B., Seykova, D., Boshnyaku, A. and Fischer, D.C. (2019). "The Impact of Industry 4.0 on the Competitiveness", *International Scientific Journal ‘Industry* 4.0’, 5, 250-255.

Kang, H.S., Lee, J.Y., Choi, S., Kim, H., Park, J.H., Son, J.Y. and Noh, S.D. (2016). “Smart Manufacturing: Past Research, Present Findings, and Future Directions”, *International Journal of Precision Engineering and Manufacturing-Green Technology*, 3(1), 111-128. https://doi.org/10.1007/s40684-016-0015-5

Kannan, K.S.P. and Garad, A. (2020). “Competencies of Quality Professionals in the Era of Industry 4.0: A Case Study of Electronics Manufacturer from Malaysia”, *International Journal of Quality & Reliability Management*, 38(3), 839-871. https://doi.org/10.1108/IJQRM-04-2019-0124

Krägeloh, C.U., Bharatharaj, J., Sasthan Kutty, S.K., Nirmala, P.R. and Huang, L. (2019). “Questionnaires to Measure Acceptability of Social Robots: A Critical Review”, *Robotics*, 8(4), 88. https://doi.org/10.3390/robotics8040088

Lasi, H., Fettke, P., Kemper, H.G., Feld, T. and Hoffmann, M. (2014). “Industrie 4.0”, *Wirtschaftsinformatik*, 56(4), 261-264.

Lee, J. (2015). “Smart Factory Systems”, *Informatik-Spektrum*, 38(3), 230-235. https://doi.org/10.1007/s00287-015-0891-z

Leech, N.L., Barrett, K.C. and Morgan, G.A. (2005). “SPSS for Intermediate Statistics: Use and Interpretation”, 2nd Ed., Lawrence Erlbaum Associates.

Leichtmann, B., Hartung, J., Wilhelm, O. and Nitsch, V. (2023). “New Short Scale to Measure Workers’ Attitudes toward the Implementation of Cooperative Robots in Industrial Work Settings: Instrument Development and Exploration of Attitude Structure”, *International Journal of Social Robotics*, 15(6), 909-930. https://doi.org/10.1007/s12369-023-00996-0

Lu, Y. (2017). “Industry 4.0: A Survey on Technologies, Applications and Open Research Issues”, *Journal of Industrial Information Integration*, 6, 1-10. https://doi.org/10.1016/j.jii.2017.04.005

Metcalf, D., Milliard, S.T.J., Gomez, M. and Schwartz, M. (2016). “Wearables and the Internet of Things for Health: Wearable, Interconnected Devices Promise More Efficient and Comprehensive Health Care”, *IEEE Pulse*, 7, 35-https://doi.org/39. 10.1109/MPUL.2016.2592260

Mishra, R., Singh, R.K. and Gunasekaran, A. (2024). “Digitalization of Supply Chains in Industry 4.0 Environment of Manufacturing Organizations: Conceptualization, Scale Development & Validation”, *Production Planning & Control*, 35(11), 1278-1297. https://doi.org/10.1080/09537287.2023.2172622

Mourtzis, D., Siatras, V., Zogopoulos, V. (2020). “Augmented Reality Visualization of Production Scheduling and Monitoring”, *Procedia CIRP*, 88, 151-156. https://doi.org/10.1016/j.procir.2020.05.027

Nomura, T., Sugimoto, K., Syrdal, D.S. and Dautenhahn, K. (2012). “Social Acceptance of Humanoid Robots in Japan: A Survey for Development of the Frankenstein Syndorome Questionnaire”, *12th IEEE-RAS International Conference on Humanoid Robots (Humanoids 2012)*, 242-247. IEEE. https://doi.org/10.1109/HUMANOIDS.2012.6651527

Nunnally, J.C. (1978). “An Overview of Psychological Measurement.” *Clinical Diagnosis of Mental Disorders*, Editor: B.B. Wolman, 97-146. Springer.

Nunnally, J.C. and Bernstein, I.H. (1994). “Psychometric Theory”, McGraw-Hill.

Onday, O. (2017). “Dijital Dönüşüm”, Gazi Kitabevi, Ankara.

Özkanlısoy, Ö. and Bulutlar, F. (2022). “Measuring Using Disruptive Technology in the Supply Chain Context: Scale Development and Validation”, *Journal of Theoretical and Applied Electronic Commerce Research*, 17(4), 1336-1360. https://doi.org/10.3390/jtaer17040068

Pandya, D. and Kumar, G. (2023). “Applying Industry 4.0 Technologies for the Sustainability of Small Service Enterprises”, *Service Business*, 17(1), 37-59. https://doi.org/10.1007/s11628-022-00507-7

Pattanapairoj, S., Nitisiri, K. and Sethanan, K. (2021). “A Gap Study between Employers’ Expectations in Thailand and Current Competence of Master’s Degree Students in Industrial Engineering under Industry 4.0”, *Production Engineering Archives*, 27(1), 50-57. https://doi.org/10.30657/pea.2021.27.7

Patton, M.Q. (2002). “Qualitative Research & Evaluation Methods”, 3rd Ed., Sage Publications.

Pessl, E., Sorko, S.R. and Mayer, B. (2017). "Roadmap Industry 4.0 – Implementation Guideline for Enterprises" *Technology and Society*, 5(6), 10.

Pinto, A., Lemos, L., Carvalho, C., Santos, J., Menezes, P. and Nomura, T. (2025). "Translation, Adaptation, and Validation in Portuguese of an Acceptance Scale for Human–Robot Interaction in an Industrial Context", *Human Behavior and Emerging Technologies*, 2025(1), 8816379. https://doi.org/10.1155/hbe2/8816379

Popovich, A.A., Sufiiarov, V.S. and Grigoriev, A.V. (2017). "Additive Technologies-The Basis of Digital Custom Manufacturing", *Industry 4.0: Entrepreneurship and Structural Change in the New Digital Landscape*, 219-230.

Prinz, C., Morlock, F., Freith, S., Kreggenfeld, N., Kreimeier, D. and Kuhlenkotter, B. (2016). "Learning Factory Modules for Smart Factories in Industrie 4.0", *Procedia CIRP*, 54, 113-118. https://doi.org/10.1016/j.procir.2016.05.105

Raguseo, E. (2018). "Big Data Technologies: An Empirical Investigation on Their Adoption, Benefits and Risks for Companies", *International Journal of Information Management*, 38(1), 187-195. https://doi.org/10.1016/j.ijinfomgt.2017.07.008

Reischauer, G. (2018). "Industry 4.0 as Policy-Driven Discourse to Institutionalize Innovation Systems in Manufacturing", *Technological Forecasting and Social Change*, 132, 26-33. https://doi.org/10.1016/j.techfore.2018.02.012

Rha, J.S. and Lee, H.H. (2022). "Research Trends in Digital Transformation in the Service Sector: A Review Based on Network Text Analysis", *Service Business*, 16, 77-98. https://doi.org/10.1007/s11628-022-00481-0

Riazul Islam, S.M., Kwak, D., Humaun Kabir, M., Hossain, M. and Kwak, K-S. (2015). "The Internet of Things for Health Care: A Comprehensive Survey", *IEEE Access*, 3, 678–708. https://doi.org/10.1109/ACCESS.2015.2437951

Richert, A., Shehadeh, M., Müller, S., Schröder, S. and Jeschke, S. (2016). "Robotic Workmates: Hybrid Human-Robot-Teams in the Industry 4.0", T*he 11th International Conference on e-Learning-ICEL2016*, Kuala Lumpur.

Rikalovic, A., Suzic, N., Bajic, B. and Piuri, V. (2021). "Industry 4.0 Implementation Challenges and Opportunities: A Technological Perspective", *IEEE Systems Journal*, 16(2), 2797-2810. https://doi.org/10.1109/JSYST.2020.3023041

Rogers, E.M. (2003). "Diffusion of Innovations", Free Press.

Saçak Düzgün, S., Özen, Ü. and Fındık, D. (2024). "Endüstri 4.0 Teknolojilerinin Getirileri ve Önündeki Engeller Üzerine Kavramsal bir Çerçeve Önerisi", *AJIT-E: Academic Journal of Information Technology*, 15(3), 246-264. https://doi.org/10.5824/ajite.2024.03.004.x

Salkın, C., Oner, M., Ustundag, A. and Çevikcan, E. (2018). "A Conceptual Framework for Industry 4.0", *Industy 4.0: Managing the Dijital Transformation. Springer International Publishing*, Editors: A. Ustundag, E. Çevikcan, Switzerland.

Santos, M.Y., Oliveira Sá, J., Andrade, C., Lima, F.V., Costa, E., Costa, C., Martinho, B. and Galvão, J. (2017). "A Big Data System Supporting Bosch Braga Industry 4.0 Strategy", *International Journal of Information Management*, 37, 750-760. https://doi.org/10.1016/j.ijinfomgt.2017.07.012

Sarvari, P.A., Ustundag, A., Cevikcan, E., Kaya, I. and Cebi, S. (2018). "Technology Roadmap for Industry 4.0", *Industry 4.0: Managing the Digital Transformation. Springer International Publishing*, Editors: A. Ustundag, E. Çevikcan, 95-103.

Schaeffer, D.M. and Olson, P.C. (2014). "Big Data Options for Small and Medium Enterprises", *Review of Business Information Systems*, 18, 41-46. https://doi.org/10.19030/rbis.v18i1.8542

Schaffernak, H., Moesl, B., Vorraber, W., Koglbauer, I.V. (2020). "Potential Augmented Reality Application Areas for Pilot Education: An Exploratory Study", *Education Sciences*, 10, 86. https://doi.org/10.3390/educsci10040086

Schwab, K. (2016). "Die Vierte Industrielle Revolution", Pantheon Verlag.

Şimşek Demirbağ, K. (2021). "Endüstri 4.0 Dönüşümünün Türkiye Beyaz Eşya Sektöründeki Mevcut Durumu ve Mühendislik Işi Üzerindeki Etkisi", Doktora Tezi, İstanbul Teknik Üniversitesi Fen Bilimleri Enstitüsü, İstanbul.

Ślusarczyk, B., Nathan, R. J. and Pypłacz, P. (2021). "Employee Preparedness for Industry 4.0 in Logistic Sector: A Cross-National Study between Poland and Malaysia", *Social Sciences*, 10(7), 258. https://doi.org/10.3390/socsci10070258

Sözbilir, F. (2021). "Development and Validation of An Industry 4.0 Adaptation Potential Scale (4IRAPS)", *Technological and Economic Development of Economy*, 27(3), 704-721. https://doi.org/10.3846/tede.2021.14513

Stawiarska, E., Szwajca, D., Matusek, M. and Wolniak, R. (2021). "Diagnosis of the Maturity Level of Implementing Industry 4.0 Solutions in Selected Functional Areas of Management of Automotive Companies in Poland", *Sustainability*, 13(9), 4867. https://doi.org/10.3390/su13094867

Tabachnick, B.G. and Fidell, L.S. (2013). "Using Multivariate Statistics", 6th Ed., Pearson.

Thompson, B. (2004). "Exploratory and Confirmatory Analysis: Understanding Concepts and Applications", *American Psychological Association*, Washington, DC, USA.

Tortorella, G.L., Vergara, A.M.C., Garza-Reyes, J.A. and Sawhney, R. (2020). “Organizational Learning Paths Based upon Industry 4.0 Adoption: An Empirical Study with Brazilian Manufacturers”, *International Journal of Production Economics,* 219, 284-294. https://doi.org/10.1016/j.ijpe.2019.06.023

Vaidya, S., Ambad, P. and Bhosle, S. (2018). “Industry 4.0 - A Glimpse”, *Procedia Manufacturing*, 20, 233-238. https://doi.org/10.1016/j.promfg.2018.02.034

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003). “User Acceptance of Information Technology: Toward A Unified View”, *MIS Quarterly*, 27(3), 425-478.

Wang, L. and Wang, G. (2016). “Big Data in Cyber-Physical Systems, Digital Manufacturing and Industry 4.0”, *International Journal of Engineering and Manufacturing*, 4, 1-8.

Wang, S., Wan, J., Li, D. and Zhang, C. (2016). “Implementing Smart Factory of Industry 4.0: An Outlook”, *International Journal of Distributed Sensor Networks*, 12(1), 3159805. https://doi.org/10.1155/2016/315980

Wongchinsri, P. and Kuratach, W. (2016). “A Survey—Data Mining Frameworks in Credit Card Processing”, *13th International Conference on Electrical Engineering/Electronics*, *Computer, Telecommunications and Information Technology (ECTI-CON)*. IEEE, Chiang Mai, Thailand, 1-6.

Wu, M., Tam, H.P. and Jen, T.H. (2016). “Educational Measurement for Applied Researchers Theory into Practice”, Springer, Singapore.

Xu, L., He, W. and Li, S. (2014). “Internet of Things in Industries: A Survey”, *IEEE Transactions on Industrial Informatics*, 10(4), 2233-2243.

Yin, Y., Stecke, K.E. and Li, D. (2017). “The Evolution of Production Systems from Industry 2.0 through Industry 4.0”, *International Journal of Production Research*, 7543, 1-14. https://doi.org/10.1080/00207543.2017.1403664

Zezulka, F., Marcon, P., Vesely, I. and Sajdl, O. (2016). “Industry 4.0: An Introduction in the Phenomenon”, *IFAC-PapersOnLine*, 49(25), 8-12.

APPENDIX

Table A1. Turkish scale items from original questionnaire

1) E4.0'ın sanayide hedeflediği dijital dönüşüm, toplumu ve sanayiyi sürdürülebilirlik hedeflerine ulaşmada destekler.
2) Gelişmekte olan bir ülkede, E4.0 uygulamaları insanların sağlık, eğitim, gıda, su ve barınma gibi temel ihtiyaçlarının karşılanması gibi sosyal sürdürülebilirlik konularında fayda sağlar.
3) Gelişmekte olan bir ülkede, E4.0 uygulamaları ekonomide uzun vadeli bir bakış açısının sağlanması, finans endüstrisinin düzenlenmesi, ulusal borcun azaltılması vb. ekonomik sürdürülebilirlik konularında fayda sağlar.
4) Gelişmekte olan bir ülkede, E4.0 uygulamaları küresel ısınma, iklim değişikliği, vb. çevresel sürdürülebilirlik konularında fayda sağlar.
Döngüsel ekonominin sağlanması konusunda algılanan fayda
5) Gelişmekte olan ülkelerde E4.0 uygulamaları lineer ekonomiden döngüsel ekonomiye geçiş için faydalıdır.
6) Gelişmekte olan ülkelerde E4.0 teknolojileri döngüsel ekonomi uygulamalarının verimliliğini arttırır.
7) Gelişmekte olan ülkelerde E4.0, döngüsel ekonomiye geçişi destekler.
8) E4.0'ın benimsenmesi, operasyonel ve stratejik bilgiyi zamanında sağlayarak döngüsel ekonomiyi geliştirmeye yardımcı olur.
9) E4.0, tüm tedarik zincirinin daha akıllı olmasını sağlayarak, müşterilerin ihtiyaç duyduğu ürünlerin hızlı bir şekilde üretilmesini sağlar.
10) E4.0, yatay ve dikey entegrasyonlarla tedarik zincirlerinde dijital bilgi paylaşımını kolaylaştırır.
11) E4.0 uygulamaları, tedarik zinciri yönetiminde çeviklik ve esneklik sağlar.
12) Dijitalleştirilmiş çözümler kullanmak, firmaların iç ve dış değişikliklerle ve belirsizliklerle başa çıkmalarına ve rekabet ortamında başarılı olmalarına yardımcı olur.
19) E4.0'ın temel aldığı yapay zeka gibi yıkıcı teknolojiler işletmelere sundukları yenilik desteği ile işletmelere yeni iş fırsatları yaratma olanağı sunar.
20) E4.0'ın sağladığı teknolojiler, açık yenilik sürecinde temel zorluk olan karşılıklı güvenin tesis edilmesinde kritik bir rol oynar.
22) Dijitalleşme konusunda belirlenen seviyeye ulaşmak için öncelikle firmaların E4.0'ın getirdiği yeniliklerden ve bu olgunun sağladığı avantaj ve dezavantajlardan haberdar olması gerekir.
23) Firmalardaki E4.0 teknolojilerinin gereksinimleri ve etkisi konusundaki farkındalık eksikliği firmaların E4.0 ile bağlantılı fırsatları keşfetme şanslarını azaltmaktadır.
24) Bilgi eksikliği E4.0'a geçişte engelleyici faktörlerden biridir.
29) Gelişmekte olan ülkelerde eğitim sistemlerinin iş gücünü geleceğe yönelik olarak hazırlaması, E4.0'a geçişi etkiler.
30) Mesleki okullardaki ve üniversitelerdeki öğretmenlerin E4.0 konusundaki yetkinliklerinin artırılması, gelişmekte olan ülkelerin E4.0'a geçişini etkiler.
35) E4.0'a geçişte liderler, yıkıcı teknolojilere adapte olurken dijital dünyada gezinmelerini ve iletişim kurmalarını sağlayacak teknik ve dijital yeteneklere sahip olmalıdırlar.
36) Mevcut iş gücünün sahip olduğu yetkinlikler ile E4.0 ile ilişkilendirilen yetkinlikler arasındaki fark, gelişmekte olan ülkelerin ekonomik kalkınması için önemli bir engel teşkil etmektedir.
37) E4.0 gibi ilerlemelerin sürdürülebilmesi için kapsamlı bir sanayi politikası gereklidir.
38) Organizasyonların E4.0'ı başarıyla uygulayabilmesi için yenilikçi stratejilere ve hükümet politikalarına ihtiyaçları vardır.
39) E4.0'a geçişte gerekli teknolojinin gelişmesi için yenilik ve girişimcilik ekosistemleri için kolaylaştırıcı düzenlemeler yapılması gerekmektedir.
41) Gelişmekte olan ülkelerde E4.0 uygulamalarının benimsenmesi ülkelerin rekabet gücü, ekonomik büyümesi ve sanayide verimliliği arttırmak açısından önemlidir.