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ÖZGÜN ARAŞTIRMA / ORIGINAL ARTICLE

Sustainability Metrics for Assessing Technology Developments in Sustainable Operations Management Practices

Sürdürülebilir Operasyon Yönetimi Uygulamalarında Teknoloji Gelişmelerini Değerlendirmeye Yönelik Sürdürülebilirlik Ölçütleri

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Abstract

Aim: This study aims to identify and evaluate sustainability metrics that assess the environmental, economic, and social impacts of technological developments in operations management. It seeks to support sustainable decision-making in digital transformation processes.

Method: A literature review was conducted to identify relevant sustainability indicators. These metrics covering environmental (e.g., energy efficiency), social (e.g., employee safety, digital skills), and economic (e.g., cost-effectiveness) were further analyzed using the Fuzzy CRITIC method to assign objective weights and ensure a balanced, data-driven assessment.

Results: The Fuzzy CRITIC analysis revealed that Technology Payback Period, Digital Skills & Upskilling Rate, Return on Technology Investment, and Energy Efficiency Improvement were identified as the most critical metrics in evaluating the sustainability impact of digital technologies in operations management.

Conclusion: The proposed metrics offer a more holistic approach to assessing technological advancements in sustainable operations. This study provides practical insights for researchers, practitioners, and policymakers seeking to align innovation with sustainability goals in real-world settings.

Keywords

Sustainability, Operations Management, Digitalization, Performance, Decision Making Models

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Öz

Amaç: Bu çalışma, operasyon yönetiminde teknolojik gelişmelerin çevresel, ekonomik ve sosyal etkilerini değerlendiren sürdürülebilirlik metriklerini tanımlamayı ve analiz etmeyi amaçlamaktadır. Dijital dönüşüm süreçlerinde sürdürülebilir karar alma mekanizmalarını desteklemek hedeflenmiştir.

Yöntem: İlgili sürdürülebilirlik göstergelerini belirlemek için bir literatür taraması yapılmıştır. Çevresel (örn. enerji verimliliği), sosyal (örn. çalışan güvenliği, dijital beceriler) ve ekonomik (örn. maliyet etkinliği) boyutları kapsayan bu metrikler, nesnel ağırlıklar atamak ve dengeli, veri odaklı bir değerlendirme sağlamak amacıyla Fuzzy CRITIC yöntemi ile analiz edilmiştir.

Bulgular: Fuzzy CRITIC analizi, dijital teknolojilerin operasyon yönetiminde sürdürülebilirliğe etkisinin değerlendirilmesinde teknoloji geri ödeme süresi, dijital beceri ve yetkinlik geliştirme oranı, teknoloji yatırımlarının geri dönüşü ve enerji verimliliği iyileşmesi metriklerinin en kritik göstergeler olarak öne çıktığını ortaya koymuştur.

Sonuç: Önerilen metrikler, teknolojik gelişmelerin sürdürülebilir operasyonlar açısından daha bütüncül bir şekilde değerlendirilmesini sağlamaktadır. Bu çalışma, yeniliklerin sürdürülebilirlik hedefleriyle uyumlu hâle getirilmesini amaçlayan araştırmacılar, uygulayıcılar ve politika yapıcılar için pratik çıkarımlar sunmaktadır.

Anahtar Kelimeler

Sürdürülebilirlik, Operasyon Yönetimi, Dijitalleşme, Performans, Karar Verme Modelleri

Introduction

The increase of the importance of digital technologies in operations management has transformed the processes, proposing new operational dynamics (Angelopoulos et al., 2023). With this respect, technological developments are one of the critical factors that trigger alterations in the operations management field. Rapid developments through digitalization transform the landscapes of operations management; therefore, radical changes caused by disruptive technologies should be managed by organizations (Choi et al., 2022). However, sustainability is a great concern for organizations and it should be considered as an integral component in adapting to these technological shifts. Sustainable practices need to be embedded in every stage of digital transformation to ensure that environmental, social, and economic impacts are effectively managed and minimized (Lai et al., 2023). These changes also directly affect the metrics used to assess sustainable operations management practices. From a more traditional point of view, metrics deliver necessary links between strategy, execution, and value creation in processes (Melnyk et al., 2004). Hence, they are critical for overall efficiency and operational success. Therefore, changes in operational procedures should be applied to metrics, and organizations should adopt newer and up-to-date metrics.

Understanding how technological advancements contribute to sustainable operations management requires a shift from traditional, one-dimensional performance metrics to more integrated and meaningful indicators. While efficiency, cost reduction, and output rates remain important, they no longer suffice on their own in evaluating the broader impacts of emerging technologies in today's complex operational landscapes (Hariram et al., 2023). Recent studies have emphasized that sustainability across environmental, social, and economic domains has become central to this assessment, reflecting the growing demand for responsible and future-oriented management practices (Dichabeng et al., 2025). This necessitates a rethinking of how organizations align technological integration with sustainability objectives, rather than treating them as separate or sequential concerns.

By embedding sustainability into the core of operations, companies do not only minimize environmental harm but also foster social equity and ensure economic resilience. Accordingly, evaluating technology's role in promoting responsible resource use, ethical labor practices, and long-term profitability is no longer optional, it is a strategic necessity for modern operational excellence.

For any meaningful evaluation of technological solutions, it is now more important than ever to consider all three dimensions of sustainability environmental, social, and economic. As organizations navigate increasingly complex digital transformations, relying on traditional metrics alone is no longer sufficient. Instead, understanding and implementing modern sustainability indicators has become a key factor in maintaining competitiveness, achieving operational efficiency, and fulfilling broader sustainability commitments (Lai et al., 2023). Therefore, it is essential to take these aspects of sustainability into account when evaluating sustainable operations. From this perspective, this research seeks to recognize innovative sustainability metrics that have arisen due to technological developments in operations management, emphasizing environmental, social, and economic sustainability. It aims to provide recommendations for organizations looking to adopt these newer sustainability metrics in their operations management practices, ensuring that technological developments contribute positively to their sustainability goals.

This study is designed as follows: the second section will cover a detailed literature review that discusses the evolving structure of metrics in operations management by comparing traditional and newer metrics, with a particular focus on sustainability dimensions; environmental, social, and economic. The third section will present the framework of the chapter, where new metrics are introduced for sustainable operations management in the context of technology development. This section will include different sub-sections, proposing distinct metrics for each sustainability dimension, addressing how technological advancements contribute to sustainable operations. Section 4 covers outline the methodology used to assess and evaluate the proposed metrics. The Fuzzy CRITIC method will be introduced as the primary evaluation tool to measure and manage uncertainty and complexity in the metrics, particularly for assessing sustainability outcomes in operations management. The section will also describe the data collection process, model development, and any assumptions made. After that, Section 5 consist of implementation and results. Lastly, discussions and conclusions.

Literature Review: Evolution of Metrics in Operations Management

Operations management is a strategic area that encompasses the processes of effectively planning, executing and controlling the resources of organizations. Historically, metrics used to evaluate success in this area have focused mostly on classical performance indicators such as productivity, efficiency, cost control and delivery times (Neely et al., 1995). Especially with the development of process improvement methods, these metrics have become the basic tools for measuring organizational performance (Gunasekaran et al., 2001). According to literature review, there are lots of studies about metrics in operations management (Melnyk et al., 2004; Gunasekaran & Kobu, 2007).

However, globalization, increasing environmental pressures, societal expectations and the rapid development of digital technologies have transformed the scope of metrics used in operations management. While traditional metrics focused only on short-term financial outputs, today businesses must also consider multidimensional performance criteria such as long-term sustainability, environmental responsibility, social impact and technological adaptation (Elkington, 1998; Kleindorfer et al., 2005). Hence, sustainability becomes more important with the development of technology. Academic studies conducted in recent years clearly demonstrate that operational performance should be evaluated within the framework of sustainability. Ahi and Searcy (2013) state that the indicators used in the context of sustainable supply chain management are quite diverse and that a standard metric framework has not yet been established. Similarly, Chardine-Baumann and Botta-Genoulaz (2014) emphasized the importance of multi-criteria performance measurement, arguing that environmental, social and economic performance indicators should be considered together.

Besides sustainability, the role of technology has become increasingly central in this transformation process. Especially with the integration of Industry 4.0, IoT (Internet of Things), big data, artificial intelligence (AI) and automation systems into operations management, measuring the impact of technology on sustainability has become an important research area (Hwang et al., 2014; Frank et al., 2019). Choi et al. (2022) states that digital transformation causes radical organizational structural changes and that this transformation should be monitored with appropriate metrics. Moreover, Angelopoulos et al. (2023) emphasize that digital technologies not only increase efficiency in operational processes, but also positively affect environmental performance and social balance.

Recent studies further deepen this perspective by focusing specifically on artificial intelligence and platform-based operational structures. Martuscelli et al. (2026) provide a comprehensive systematic literature review on the use of artificial intelligence in operations management and propose a classification framework for achieving operational excellence in manufacturing. Their findings highlight that AI-driven metrics increasingly focus on real-time decision-making, predictive capabilities, and process adaptability rather than traditional static performance indicators. Similarly, Yandamuri (2026) emphasizes the role of AI-enabled workflow automation and predictive analytics in enhancing enterprise operations. The study shows that integrating predictive models into operational processes not only improves efficiency but also enables more proactive and data-driven performance measurement systems.

In addition, Fu et al. (2026) examine the evolution of supply chain ecosystems through platformization and propose a two-stage model explaining how digital platforms reshape operational structures. Their findings suggest that platform-based operations require new performance metrics that capture network effects, collaboration intensity, and ecosystem-level value creation rather than firm-level efficiency alone.

Therefore, in recent years, there is a need for consider sustainability and digital technologies together in operations management (Akbari et al., 2022). The number of studies on determining technology-focused sustainability metrics is increasing. For example, Machado et al. (2020) examined the potential of digital technologies to reduce the environmental footprint. Similarly, Yadav et al. (2020) analyzed the relationship between technological maturity level and sustainable operational performance and proposed new metrics in this context. Moreover, Dichabeng et al. (2025) comprehensively analyzes the role of digitalization in measuring sustainable performance by focusing on the development of sustainability indicators in the context of smart and connected digital production systems. Similarly, Duan et al. (2025) evaluates the impacts of digital technologies and environmental sustainability on circular supply chains using the fuzzy TOPSIS model and numerically bases the environmental benefits of technological integration. In addition, Opoku and Li (2025) empirically examine the impacts of sustainable management practices on operational and sustainable performance in developing economies, emphasizing the decisive power of managerial practices in shaping sustainability performance. In line with these studies, this research also reveals that digital transformation should be evaluated not only with its technological or economic dimensions, but also with social and environmental sustainability indicators.

Therefore, by considering the importance of the topic, this study aims to determine multidimensional and up-to-date sustainability metrics to measure the effects of technological developments on sustainable operations management, based on these developments in the existing literature. The developed metrics are expected to contribute to both the academic field and guide practical applications.

Development of New Metrics for Assessing Technological Advancements in Sustainable Operations Management

The rapid emergence of digitalization and advanced technologies has significantly reshaped operations management in recent years (Lai et al., 2023). From AI and the IoT to robotic process automation and data analytics, these innovations are redefining how businesses manage workflows, make decisions, and deliver value. While these tools offer clear gains in speed and efficiency (Demartini et al., 2019), they also bring forward an urgent need to realign operational strategies with sustainability goals (Jianing et al., 2024).

Sustainability today is no longer confined to environmental issues alone; it also encompasses economic stability and social responsibility (Hariram et al., 2023). Improving operational efficiency is valuable, but so is reducing ecological damage, ensuring ethical labor practices, and supporting long-term financial resilience (Jianing et al., 2024). To fully understand the role of technology in supporting these goals, there is a growing need for more comprehensive evaluation tools. Traditional metrics such as cost reduction, speed, or throughput offer only a partial view. They often overlook how technologies contribute to resource conservation, waste reduction, and social equity. Therefore, operations managers must begin to incorporate updated sustainability metrics that reflect the broader impact of digital technologies on people, profit, and the planet (Dichabeng et al., 2025).

In order to fill this gap, this study focuses on the development of new metrics that can evaluate the impacts of technological developments on sustainable operations management. These metrics are based on three main sustainability dimensions: environmental sustainability, social sustainability and economic sustainability. The metrics determined for each dimension measure how digital technologies have an impact on operational processes and how these impacts contribute to long-term sustainability goals (shown in Table 1).

Table 1. Sustainability Metrics

Sustainability Metrics	Explanation	Sustainability Dimension	Related Literature
Carbon Footprint Reduction	Reduction in greenhouse gas emissions thanks to technology	Environmental	Tabaku et al. (2025)
Energy Efficiency Improvement	Reduction in energy consumption per unit of output	Environmental	Cai et al. (2025)
Waste Reduction Rate	Reduction rate in waste production through digitalization	Environmental	Fatorachian & Pawar (2025)
Sustainable Resource Usage	More efficient use of resources such as water, raw materials, etc. with digital solutions	Environmental	Butturi et al. (2025)
Employee Health and Safety Index	Effect of technologies such as automation to reduce work accidents	Social	Ozobu et al. (2025)
Digital Skills & Upskilling Rate	Rate of development of digital skills of employees	Social	Molla et al. (2025)
Technology Inclusiveness Index	Access to technology and equal utilization of all employee groups	Social	Cen et al. (2025)
Return on Technology Investment	Financial return on technological investments	Economic	Ze & Loang (2025)
Cost Savings through Automation	Operational cost reduction achieved through digital technologies	Economic	Atieh et al. (2025)
Technology Payback Period	Investment payback period of new technologies	Economic	Gao et al. (2025)

In this study, a total of 10 metrics covering environmental, social and economic sustainability dimensions were determined in order to evaluate the effects of technological developments on sustainable operations management in a multidimensional manner. While traditional operations management metrics generally focus on direct operational outputs such as efficiency, production volume, cost reduction and delivery time; the metrics in this list aim to measure the effects of technological developments on environmental, social and economic sustainability. Especially with the spread of technologies such as digitalization, automation, AI and data analytics, indicators such as carbon footprint reduction, energy efficiency, digital skill development and return on technology investments have become important performance criteria of modern operations management. Therefore, these sustainability metrics were developed to evaluate not only internal business efficiency but also more responsible, inclusive and sustainable business models that create long-term value and are often defined as "new generation metrics" in the literature. These metrics aim to measure the effects of digitalization and technological transformation in today's operational processes both quantitatively and qualitatively. While environmental metrics measure direct environmental impacts such as energy efficiency and carbon footprint, social metrics focus on human-oriented indicators such as employee safety and increasing digital competencies. Economic metrics are aimed at evaluating the financial return and cost-effectiveness of technological investments. These determined metrics will be weighted with the Fuzzy CRITIC method in the continuation of the study, enabling an objective and holistic analysis of sustainability performance.

Methodology: Fuzzy CRITIC

Fuzzy Logic

The concept of fuzzy logic was first put forward in 1965 by Prof. Lotfi A. Zadeh. Zadeh's aim was to develop systems that could more closely mimic human thinking and decision-making processes (Saoud et al., 2025). Fuzzy logic is a logic system that can model situations that cannot be defined with clear boundaries, are uncertain or partially true (Hatefi et al., 2025). While the truth value of a proposition in classical binary logic can only be "true" (1) or "false" (0), in fuzzy logic a proposition can take any value between 0 and 1 (Dinçer et al., 2025). This approach is quite effective in modeling real-world uncertainties and "partially true" situations. One of the most important features of fuzzy logic is that it can use linguistic variables to describe real-life uncertainty. In classical mathematical systems, variables are usually defined with numerical (quantitative) expressions, but in fuzzy logic, these variables can be defined in verbal terms, that is, in expressions naturally used by people. Such expressions can be defined as "linguistic scales" or "linguistic terms". The advantage of linguistic scales is that they can better model human thinking (Gökalp & Eti, 2025). When making decisions, people usually think not with precise numbers, but with verbal expressions such as "a little fast", "very slow", "low risk", "medium effective". Thanks to fuzzy logic, these uncertain and relative expressions can be converted into mathematical operations. This approach is particularly effective in expert systems, AI applications, control systems, and user-oriented interfaces. For example, a washing machine can automatically set the appropriate wash time by recognizing linguistic scales such as "lightly soiled," "medium soiled," and "very soiled."

For example, while the expression "the weather is hot" cannot be clearly evaluated as true or false in classical logic, fuzzy logic makes a more flexible evaluation by assigning a truth value of 0.7 to this situation. Recently, fuzzy logic is effectively used in many areas such as automatic control systems, AI, robotics, air conditioning systems and medical diagnosis.

CRITIC & Fuzzy CRITIC Method

In intricate and unpredictable decision-making scenarios, accurately assessing the significance of criteria is a crucial factor that directly influences the quality of the decisions made. In this situation, the CRITIC (Criteria Importance Through Intercriteria Correlation) approach enables the identification of objective weights founded on the degrees of variation and connection among criteria, eliminating the necessity for subjective assessments from decision-makers (Diakoulaki et al., 1995). Nonetheless, when uncertainty and ambiguous data are present in the decision context, the traditional CRITIC approach might be inadequate (Haleem et al., 2021). The Fuzzy CRITIC method, designed for these scenarios, integrates fuzzy logic concepts with the CRITIC methodology and incorporates fuzzy information provided by decision-makers using linguistic terms (Haktanır & Kahraman, 2022). With this approach, ambiguous relationships among criteria can be represented more accurately, leading to more consistent weights. The literature suggests that the Fuzzy CRITIC method enhances decision-making quality and serves as a valuable tool for addressing multi-criteria issues, particularly in applications related to energy, sustainability, and industry 4.0 (Mukhametzyanov, 2021; Liu et al., 2023). In this regard, Fuzzy CRITIC emerges as a comprehensive decision support instrument that considers both uncertainty and inter-criteria relationships.

For implementation of fuzzy CRITIC;

Stage 1: Problem Definition and Criteria Determination

In the first step, the problem that is the subject of the decision-making process is clearly defined and the evaluation criteria are determined. These criteria are selected according to the opinions of the decision makers and the purpose of the study.

Stage 2: Determination of Linguistic Scale and Selection of Defuzzification Method of Fuzzy Numbers

In this study, a seven-stage verbal evaluation scale was preferred in order to express expert opinions linguistically in the decision-making process. Each linguistic expression was modeled with the corresponding trapezoidal fuzzy numbers. Trapezoidal fuzzy numbers provide wider definition ranges, especially compared to triangular structures, and enable more detailed and realistic modeling of uncertainty. In the stage of converting these data with fuzzy values into numerical form, a method developed by Wang et al. (2006), which is frequently referenced in the literature, was used. The method in question (Equation 1) calculates the average value by considering the four basic parameters of the trapezoidal number and thus provides a single numerical value that can be used in decision analyses.

$$A = \frac{1}{3}\left(x_1 + x_2 + x_3 + x_4 - \frac{x_3 x_4 - x_1 x_2}{x_3 + x_4 - x_1 - x_2}\right) \quad (1)$$

Linguistic Scale and the crisp values of the method is shown as following; Very Low (VL), Low (L), Medium Low (ML), Medium (M), Medium-High (MH), High (H), Very High (VH) and the crisp values are 0.067, 0.200, 0.350, 0.500, 0.65, 0.800, 0.933, respectively.

Stage 3: Decision Matrix Preparation

At this stage, a decision matrix is created that covers experts and metrics. Each decision maker's assessment of a particular metrics is located in a cell of the matrix and each value is symbolized by a_ir.

Stage 4: Normalization of the decision matrix

In this study, the criteria should be divided into two as beneficial and non-beneficial in nature.

For non-beneficial criteria, low values are preferred and, in this case, the normalization process is carried out with Equality (3).

For beneficial criteria high values are considered more advantageous and normalization is carried out using Equality (4).

In these equations;

x_{ij} presents the normalized matrix, a_i^- is the minimum value, and a_i^+ is the maximum value.

$$x_{ij} = \frac{a_{ij} - a_i^+}{a_i^- - a_i^+} \quad (3)$$

$$x_{ij} = \frac{a_{ij} - a_i^-}{a_i^+ - a_i^-} \quad (4)$$

Stage 5: Calculation of Correlation Coefficient Between Criteria

The correlation between attributes can be found using equation 5 ρ_{jk}

$\overline{x}_j$ and $\overline{x}_k$: mean values of *j*th and *k*th attributes.

$$\rho_{jk=} \sum_{i=1}^{m} (x_{ij} - \overline{x}_j) \left(x_{ik} - \overline{x}_k \right) / \sqrt{\sum_{i=1}^{m} (x_{ij} - \overline{x}_j)^2 \sum_{i=1}^{m} \left(x_{ik} - \overline{x}_k \right)^2} \quad (5)$$

Stage 6: Sample Standard Deviation Calculation

To obtain information about the distribution of each criterion and data spread, the sample standard deviation is calculated with Equation (6).

$$\sigma_j = \sqrt{1/\left(n-1\right) \sum_{j=1}^{n} \left(x_{ij} - \overline{x}_j\right)^2} \quad (6)$$

Stage 7: Determining index C.

The C index considers both the information content of the criteria and their relationship with other criteria. This value is found using Equation (7) and represents the discrimination of each criterion.

$$C_j = \sigma_j \sum_{k=1}^{n} (1 - \rho_{jk}) \quad (7)$$

Stage 8: Calculation Weights of the Criteria

In the last step, the relative importance of each criterion, that is, its weight, is obtained with the help of Equation (8). Weights are determined proportionally according to C indices. By comparing the weight values obtained, the criteria can be analysed according to their order of importance.

$$w_j = C_j / \sum_{j=1}^{n} C_j \quad (8)$$

Implementation and Results

In this study, new sustainability metrics were determined in order to evaluate the impact of technology developments on sustainable operations management. In this process, the weights of sustainability metrics were calculated using the Fuzzy CRITIC method. In the first step, 10 basic indicators based on environmental, social and economic sustainability dimensions reflecting sustainability metrics were determined and the weights of each metrics were calculated using the Fuzzy CRITIC method. A total of nine experts participated in the implementation of this method. The professional characteristics of the participants are presented in the Table 2.

Table 2. Professional Characteristics of Experts

Experts	Position	Profession
Expert 1	Sustainability Manager	Corporate Sustainability Strategy
Expert 2	Operations Manager	Process Optimization
Expert 3	Environmental Consultant	Sustainable Practices
Expert 4	Industrial Engineer	Technology in Sustainable Production
Expert 5	Data Analyst	Performance Analysis
Expert 6	Supply Chain Manager	Sustainable Supply Chains
Expert 7	Renewable Energy Specialist	Eco-friendly Technology
Expert 8	IT Specialist	Automation in Operations
Expert 9	Corporate Finance Expert	Cost-Benefit Analysis

The experts in this study are competent in the environmental, economic and social dimensions of sustainability, as well as the impact of technological developments on operations management. The experts have knowledge in areas such as sustainable production, green supply chain, data analysis, environmentally friendly energy technologies and financial sustainability. In addition, a multi-faceted approach has been adopted in which the use of technology is evaluated not only in terms of efficiency but also in terms of social benefit and social responsibility. In this way, sustainable operations management has been addressed from a holistic perspective.

Experts were asked to evaluate new sustainability metrics for technology developments in sustainable operations management for by using the linguistic variables presented in Table 4. Expert (E) evaluations for each metrics are presented in Table 3.

Table 3. Expert's Linguistic Evaluations

Sustainability Metrics (SM)		E1	E2	E3	E4	E5	E6	E7	E8	E9
S_M1	Carbon Footprint Reduction	L	ML	VL	VL	VL	VH	VL	L	VL
SM_2	Energy Efficiency Improvement	L	L	L	L	M	L	L	L	L
SM_3	Waste Reduction Rate	VL	ML	ML	ML	ML	VL	ML	ML	ML
SM_4	Sustainable Resource Usage	MH	MH	M	M	M	M	M	M	M
SM_5	Employee Health and Safety Index	MH	VL	MH	H	MH	H	MH	MH	VH
SM_6	Digital Skills & Upskilling Rate	H	M	H	H	H	H	H	H	H
SM_7	Technology Inclusiveness Index	H	VH	H	VH	VH	VH	VH	ML	VH
SM_8	Return on Technology Investment	VL	VL	L	L	L	L	L	M	L
SM_9	Cost Savings through Automation	H	ML	H	ML	VH	ML	ML	ML	VL
SM_{10}	Technology Payback Period	L	ML	VL	VL	VL	VH	VL	L	VL

In this study, the Fuzzy CRITIC method was applied through several systematic steps. First, linguistic evaluations obtained from experts were converted into triangular fuzzy numbers based on predefined scales. Then, these fuzzy numbers were defuzzied to obtain crisp values, which enabled the construction of the initial decision matrix. In the next step, the decision matrix was normalized by considering the type of criteria (benefit or cost). Subsequently, the standard deviation of each criterion was calculated to measure the contrast intensity, while the correlation coefficients between criteria were used to determine the degree of conflict among them. Finally, the amount of information for each criterion was computed, and the objective weights were derived accordingly.

The next stage involves representing each of the linguistic variables using crisp values, and a normalized matrix is derived using equation 3. In this section, the attributes should be defined as beneficial or non-beneficial. Since this study focuses on sustainability metrics, except "technology payback period", other attributes are categorized under beneficial attributes, and the aim is to maximize these. "Technology Payback Period" is a cost-type criterion and here it is preferred to be lower. In terms of sustainability, it is more advantageous to return the investment in a short time. The normalized matrix for this study is presented in Table 4.

Table 4. Normalized Matrix

	SM_1	**SM_2**	**SM_3**	**SM_4**	**SM_5**	**SM_6**	**SM_7**	**SM_8**	**SM_9**	**SM_{10}**
SM_1	0,182	0.327	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.846
SM_2	0.182	0.154	0.182	0.154	0.500	0.154	0.154	0.000	0.154	1.000
SM_3	0.000	0.327	0.386	0.327	0.327	0.000	0.327	0.250	0.327	0.500
SM_4	0.795	0.673	0.591	0.500	0.500	0.500	0.500	0.500	0.500	0.327
SM_5	0.795	0.000	0.795	0.846	0.673	0.846	0.673	0.750	1.000	0.000
SM_6	1.000	0.500	1.000	0.846	0.846	0.846	0.846	1.000	0.846	0.154
SM_7	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.250	1.000	0.000
SM_8	0.000	0.000	0.182	0.154	0.154	0.154	0.154	0.500	0.154	1.000
SM_9	1.000	0.327	1.000	0.327	1.000	0.327	0.327	0.250	0.000	1.000
SM_{10}	0.182	0.327	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.846

After that, correlation values are presented in Table 5.

Table 5. Correlation Values

	SM_1	**SM_2**	**SM_3**	**SM_4**	**SM_5**	**SM_6**	**SM_7**	**SM_8**	**SM_9**	**SM_{10}**
SM_1	1.000	0.544	0.918	0.768	0.873	0.563	0.776	0.475	0.593	-0.584
SM_2	0.544	1.000	0.479	0.479	0.469	0.435	0.611	-0.042	0.402	-0.497
SM_3	0.918	0.479	1.000	0.836	0.940	0.352	0.848	0.549	0.646	-0.616
SM_4	0.768	0.479	0.836	1.000	0.744	0.538	0.988	0.634	0.956	-0.913
SM_5	0.873	0.469	0.940	0.744	1.000	0.249	0.765	0.331	0.539	-0.460
SM_6	0.563	0.435	0.352	0.538	0.249	1.000	0.518	0.249	0.556	-0.594
SM_7	0.776	0.611	0.848	0.988	0.765	0.518	1.000	0.601	0.924	-0.886
SM_8	0.475	-0.042	0.549	0.634	0.331	0.249	0.601	1.000	0.643	-0.592
SM_9	0.593	0.402	0.646	0.956	0.539	0.556	0.924	0.643	1.000	-0.957
SM_{10}	-0.584	-0.497	-0.616	-0.913	-0.460	-0.594	-0.886	-0.592	-0.957	1.000

Each metric's standard deviation σ_j, index values C_j, and weights w_j are presented in Table 6.

Table 6. Standard deviation, index values, and weights

	σ_j	C_j	w_j
SM_1	0.4478	1.8236	0.0802
SM_2	0.3224	1.9733	0.0868
SM_3	0.3978	1.6105	0.0709
SM_4	0.3581	1.4216	0.0626

Table 6. Continue

	σ_j	C_j	w_j
SM_5	0.3574	1.6258	0.0715
SM_6	0.3949	2.4217	0.1066
SM_7	0.3390	1.3071	0.0575
SM_8	0.3333	2.0506	0.0902
SM_9	0.4122	1.9369	0.0852
SM_{10}	0.4341	6.5545	0.2884

As a result of the evaluation made according to weight values, the effect of the criteria on the decision process varies. The highest weight belongs to SM10 (0.2884); this reveals that SM10 is the most decisive criterion in the decision-making process. Criteria such as SM6 (0.1066), SM8 (0.0902) and SM2 (0.0868) also have relatively high weight and make a significant contribution to the process. In contrast, the lowest weight was observed in SM7 (0.0575); this shows that the effect of SM7 on the decision process is limited. Similarly, SM4 (0.0626) and SM3 (0.0709) are evaluated as lower priority criteria with low weight. In this context, SM10 is the prominent criterion, and criteria such as SM6 and SM2 are among the important elements that follow it.

Discussions and Conclusion

In this study, 10 performance criteria covering environmental, social and economic sustainability dimensions were determined in order to evaluate the effects of digital technologies on sustainable operations management and the weights of these criteria in decision processes were analyzed. According to the results, it was observed that there were significant differences between the priorities of decision makers.

The findings obtained in this study reveal that the impact of digital technologies on sustainability performance should be evaluated multidimensionally, not only at the operational but also at the managerial level. The digital transformation process should not be reduced to technology investments alone; strategic integration of this process with economic, social and environmental sustainability dimensions is of critical importance for managers.

In the existing literature, the impact of digital technologies on sustainability performance is generally addressed within the framework of operational efficiency, cost advantage and process optimization (Choi et al., 2022; Atieh et al., 2025). However, most of these studies do not examine the social and environmental sustainability dimensions in a sufficiently holistic manner. The findings of this study provide an original contribution to the literature in that they show that not only economic but also social and environmental metrics can be decisive in business decision processes. In contrast to prior studies that predominantly emphasize operational efficiency, the present findings suggest a more balanced decision structure in which social and environmental criteria also play a significant role. This indicates a shift from a purely efficiency-driven perspective toward a more integrated sustainability-oriented evaluation framework.

The highest weight in the analysis results belongs to the "technology payback period" (SM10) criterion. This finding reveals that managers primarily consider short-term financial returns in digital investments. Similarly, in the studies of Ze and Loang (2025) and Gao et al. (2025), it is stated that the payback period is an important factor in shaping investment decisions. However, it should be noted that decision structures that focus only on short-term economic benefits may undermine long-term sustainability goals. This finding is consistent with the dominant techno-economic perspective in the literature; however, unlike previous studies, the current results also demonstrate that such short-term financial prioritization coexists with increasing attention to non-economic criteria. This suggests that while traditional investment logic remains influential, it is no longer the sole determinant in decision-making.

One of the most striking aspects of the findings is that the "digital skills and upgrade rate" (SM6) criterion, one of the social sustainability indicators, was evaluated with the second highest weight.

These findings suggest that organizations increasingly recognize the strategic value of human resource competence within digital transformation efforts. Supporting this view, Molla et al. (2025) highlight that improving employees' digital skills directly enhances a company's ability to adapt to change and innovate effectively. Therefore, managers are encouraged to treat human capital investment not as an auxiliary measure but as a core component of digital transformation strategies, embedding training and upskilling programs into broader organizational planning. Compared to earlier studies that treat workforce capabilities as a supporting factor, the high ranking of this criterion in the present study indicates that human capital is increasingly positioned as a central driver of digital transformation success.

The third-highest ranked criterion is return on technology investment (SM8) reflects a strong managerial expectation that digital technologies will yield not only infrastructure improvements but also measurable contributions to profitability. This aligns closely with Atieh et al. (2025), who underline the economic rationale driving many digital transformation initiatives.

An equally important insight emerges in the area of environmental sustainability: the energy efficiency increases criterion (SM2) received a nearly equal weight to SM8. This challenges the assumptions of prior studies, such as Tabaku et al. (2025), where environmental metrics are often underemphasized in decision-making frameworks. In contrast, this study indicates that environmental indicators like energy efficiency can rise to strategic prominence when they clearly translate into cost savings. This underscores a practical shift manager are more likely to prioritize sustainability when it aligns with operational efficiency and financial logic.

Taken together, these insights reveal the growing need for a strategic mindset in digital transformation that acknowledges sustainability's multidimensional nature. Rather than chasing quick returns alone, leaders must strike a balance between short-term efficiencies and long-term value creation, ensuring that technological adoption supports resilience, responsibility, and competitiveness across all fronts. Although financial indicators such as payback period are decisive in decision-making processes, strategic sustainability criteria such as human resource development and energy efficiency should not be ignored beyond these indicators. Decision structures focusing on such long-term effects will enable institutions to achieve permanent and comprehensive success in digital transformation.

However, digital skill development stands out as a key determinant in the success of digitalization. The fact that this criterion has the second highest importance in the study clearly shows that human capital is a strategic resource as much as technology. Therefore, managers' investments in developing employees' digital competencies will increase institutional resilience, facilitate technological adaptation and strengthen transformation capacity.

On the other hand, the high weight given to environmental sustainability criteria such as energy efficiency shows that such metrics are not only a part of corporate social responsibility but also an important element of financial sustainability. Digital solutions that provide energy savings contribute to reducing environmental impacts and provide direct economic benefits to institutions by reducing costs. In this context, it is important for managers to integrate environmental metrics into their digital investment strategies in a holistic manner.

From a practical perspective, the findings of this study provide several actionable implications for managers and decision-makers. First, managers should not rely solely on short-term financial indicators such as payback period when evaluating digital investments; instead, they should adopt a balanced evaluation framework that incorporates social and environmental criteria. Second, organizations are advised to prioritize employee digital skill development by systematically investing in training and upskilling programs, as human capital has been identified as a critical success factor in digital transformation. Third, environmental performance metrics, particularly energy efficiency, should be explicitly integrated into investment decision models, as they contribute simultaneously to cost reduction and sustainability goals. Finally, decision-makers are encouraged to design integrated performance measurement systems that align digital transformation initiatives with long-term sustainability strategies.

As a result, the multi-dimensional sustainability approach has become not only a preference for managers in today's digital transformation processes, but also a strategic necessity that will create a competitive advantage. Digital investments should no longer be limited to economic output targets; they should be evaluated with a holistic perspective that includes areas such as social development, employee competence and environmental impact. This study clearly shows managers that sustainability should not be considered as a supporting element, but as a fundamental management priority that should be positioned at the center of digital transformation strategies. The long-term sustainability of corporate success will only be possible with the balanced and strategic integration of economic, social and environmental criteria.

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Özet

Bu çalışma, dijital teknolojilerin sürdürülebilir operasyon yönetimine etkilerini değerlendirmek amacıyla çevresel, sosyal ve ekonomik boyutları kapsayan çok boyutlu sürdürülebilirlik metriklerini belirlemeyi ve analiz etmeyi amaçlamaktadır. Dijital dönüşüm çağında, teknolojik gelişmelerin işletmeler üzerindeki etkileri yalnızca verimlilik veya maliyet avantajları ile sınırlı kalmamakta; çevresel etkiler, çalışanların dijital yetkinlikleri ve yatırımların ekonomik geri dönüşleri gibi birçok sürdürülebilirlik göstergesini de doğrudan etkilemektedir. Bu bağlamda çalışma, sürdürülebilirlik performansının ölçümünde kullanılabilecek güncel metriklerin belirlenmesi ve bu metriklerin karar verme süreçlerindeki ağırlıklarının analiz edilmesi üzerine odaklanmıştır.

Çalışmada ilk olarak literatür taraması ile toplam 10 sürdürülebilirlik metriği belirlenmiştir. Bu metrikler çevresel (karbon ayak izi azaltımı, enerji verimliliği, atık azaltımı, kaynak kullanımı), sosyal (çalışan güvenliği, dijital beceri gelişimi, teknolojiye erişim) ve ekonomik (yatırım geri dönüşü, otomasyonla maliyet tasarrufu, teknoloji geri ödeme süresi) sürdürülebilirlik boyutlarında sınıflandırılmıştır. Metriklerin karar süreçlerindeki önem düzeyleri, çok kriterli karar verme tekniklerinden Fuzzy CRITIC yöntemi kullanılarak belirlenmiştir. Bu yöntem, hem kriterler arasındaki ilişkiyi hem de veri belirsizliklerini dikkate alarak objektif ağırlık hesaplaması yapılmasına imkân tanımaktadır.

Çalışma kapsamında, farklı sektörlerden dokuz uzman değerlendiriciye söz konusu metrikler sunulmuş ve uzmanların dilsel ifadeleri sayısal değerlere dönüştürülerek analiz yapılmıştır. Analiz sonucunda, en yüksek ağırlığa sahip kriterin «teknoloji geri ödeme süresi» olduğu belirlenmiştir. Bu bulgu, yöneticilerin dijital yatırımlarda kısa vadeli finansal geri dönüşleri öncelikli olarak dikkate aldığını göstermektedir. Ancak bu yaklaşımın uzun vadeli sürdürülebilirlik hedeflerini gölgede bırakabileceği uyarısında bulunulmaktadır.

İkinci en yüksek ağırlık ise «dijital beceri ve yetkinlik geliştirme oranı» kriterine verilmiştir. Bu sonuç, sosyal sürdürülebilirlik boyutunun, özellikle dijital dönüşüm süreçlerinde insan sermayesinin geliştirilmesinin kurumsal başarıda stratejik bir rol oynadığını ortaya koymaktadır. Üçüncü en yüksek ağırlık ise «teknoloji yatırımlarının geri dönüşü» metriğinde gözlemlenmiştir. Bu bulgu, işletmelerin teknolojiyi yalnızca operasyonel iyileştirmeler için değil, aynı zamanda kârlılık amacıyla da stratejik olarak değerlendirdiğini göstermektedir.

Dikkat çekici bir diğer sonuç ise, çevresel sürdürülebilirlik göstergelerinden biri olan "enerji verimliliği iyileşmesi" metriğinin, ekonomik göstergelere yakın bir ağırlıkta değerlendirilmiş olmasıdır. Bu durum, çevresel kriterlerin karar süreçlerinde yalnızca sosyal sorumluluk bağlamında değil, aynı zamanda maliyet düşürücü ve verimlilik artırıcı etkileriyle de önemli bir yer tuttuğunu göstermektedir.

Elde edilen bulgular, dijital dönüşüm süreçlerinde sürdürülebilirlik değerlendirmesinin yalnızca operasyonel değil, aynı zamanda yönetsel düzeyde de bütüncül olarak ele alınması gerektiğini ortaya koymaktadır. Karar vericilerin sadece ekonomik kazanımları değil, aynı zamanda çalışan gelişimi ve çevresel etki gibi sosyal ve çevresel unsurları da dikkate alması, kurumların uzun vadeli başarısı için kritik önemdedir. Çalışma, ayrıca mevcut literatüre özgün bir katkı sunarak, dijital teknolojilerin sürdürülebilirlik performansı üzerindeki etkisini bütüncül ve çok boyutlu bir yaklaşımla analiz etmenin gerekliliğini vurgulamaktadır.

Sonuç olarak, bu çalışma dijital dönüşüm stratejilerinde sürdürülebilirliğin merkezî bir unsur olarak ele alınması gerektiğini, teknolojik yatırımların yalnızca kısa vadeli ekonomik getirilere değil, aynı zamanda sosyal gelişim ve çevresel sürdürülebilirliğe katkı sağlaması gerektiğini ortaya koymaktadır. Geliştirilen metrikler ve kullanılan yöntem, hem akademik çalışmalar hem de uygulayıcılar için stratejik karar alma süreçlerinde değerli bir araç sunmaktadır.