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DETERMINING SUBJECTIVE WEIGHTS IN DISCRETE EVENT SIMULATION (DES) IMPLEMENTATION CHALLENGES IN MANUFACTURING ENTERPRISES[1]

İMALAT İŞLETMELERİNDE AYRIK OLAY SİMÜLASYONU (DES) UYGULAMA ZORLUKLARININ ÖZNEL AĞIRLIKLARININ BELİRLENMESİ

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ABSTRACT

In the Industry 4.0 era, manufacturing enterprises need various digital optimization tools to adapt to digital transformation. This study aims to identify the subjective weights of the challenges faced by manufacturing enterprises when implementing Discrete Event Simulation (DES), one of the prominent optimization tools of the Industry 4.0 era. The challenges examined in this empirical research are derived from the existing literature. In this study, three experts responsible for DES implementation and production in their organizations were consulted. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) was used to reflect the subjective weights of the decision criteria and the cause-effect relationships between them. The DEMATEL method is a method used in the Multi-Criteria Decision Making (MCDM) literature to determine the subjective weights of decision criteria. As a result of the study, the importance ranking of the challenges faced by manufacturing enterprises in DES implementation was obtained and the causal relationship between these challenges was determined. Identifying the causal relationship between these challenges can provide decision makers with a competitive advantage in overcoming these challenges. Adoption of the findings of the study will facilitate the adoption of DES, resulting in reduced costs, increased customer satisfaction and competitive advantage for industry professionals.

ÖZET

Endüstri 4.0 döneminde, üretim işletmeleri dijital dönüşüme uyum sağlamak için çeşitli dijital optimizasyon araçlarına ihtiyaç duymaktadırlar. Bu çalışma, Endüstri 4.0 döneminin öne çıkan optimizasyon araçlarından biri olan Ayrık Olay Simülasyonunu (DES) uygularken üretim işletmelerinin karşılaştığı zorlukların öznel ağırlıklarını belirlemeyi amaçlamaktadır. Bu ampirik araştırmada incelenen zorluklar mevcut literatürden türetilmiştir. Bu çalışmada, işletmelerinde DES uygulaması ve üretiminden sorumlu üç uzmanın görüşlerine başvurulmuştur. Karar kriterlerinin öznel ağırlıklarını ve bunlar arasındaki neden-sonuç ilişkilerini yansıtmak için Karar Verme Deneme ve Değerlendirme Laboratuvarı (DEMATEL) kullanılmıştır. DEMATEL yöntemi, Çok Kriterli Karar Verme (ÇKKV) literatüründe karar kriterlerinin sübjektif ağırlıklarını belirlemek için kullanılan bir yöntemdir Çalışma sonucunda, imalat işletmelerinin DES uygulamasında karşılaştıkları zorlukların önem sıralaması elde edilmiş ve bu zorluklar arasındaki nedensellik ilişkisi belirlenmiştir. Bu zorluklar arasındaki nedensel ilişkinin belirlenmesi, karar vericilere bu zorlukların üstesinden gelmede rekabet avantajı sağlayabilir. Çalışmanın bulgularının benimsenmesi, DES'in benimsenmesini kolaylaştırarak endüstri profesyonelleri için maliyetlerin düşmesi, müşteri memnuniyetinin artması ve rekabet avantajı ile sonuçlanacaktır.

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Introduction

Industry 4.0 is leading to significant changes that concern manufacturing enterprises today. With the 4th industrial revolution, manufacturing enterprises have started to face a rapid digital transformation. The digital transformation brought by the industry 4.0 has affected all processes related to manufacturing enterprises. In this new transformation, business models and business processes have changed, product life cycles have shortened, the need for flexibility has increased and the orientation towards technological tools has intensified. To remain competitive, manufacturing enterprises need to be able to adapt to change and make data-driven decisions (Comuzzi, 2018). There are various optimization tools in the literature that manufacturing enterprises can use to increase their competitiveness in the industry 4.0 era. One of these tools is Discrete Event Simulation (DES). DES is an analytical method that increases the flexibility and adaptation capacities of manufacturing enterprises. By using DES, it is possible to create scenarios without making changes to physical systems. (Kshatra, 2019).

Industry 4.0 encompasses a multitude of digital technologies and optimization tools that impact manufacturing enterprises. Due to the role these tools play during digital transformation, they need to be analyzed from various perspectives that includes possible advantages and disadvantages. Implementations of DES offer numerous benefits in manufacturing enterprises. DES results in enhanced decision-making capacities, more efficiency and productivity, cost-effectiveness, improved system reliability, increased flexibility, and enhanced compatibility. (Khin & Kee, 2022; Sinha & Noble, 2008). Additionally, numerous challenges await manufacturing enterprises in the implementation of DES. To address the challenges associated with DES implementation, decision-makers must determine the subjective weights of the decision criteria influencing the implementation, thereby discerning their significance. (Xie & Verbraeck, 2018). To achieve this objective, the literature on Multiple Criteria Decision Making (MCDM) utilizes subjective weighting methods. These subjective weights signify the relative importance and priority assigned to various challenges influencing the implementation of DES in manufacturing enterprises. Through the allocation of these weights, decision-makers can strategically distribute resources to tackle the challenges. (Xie & Verbraeck, 2018; Jianlin et al., 2021; Schriber & Brunner, 2007).

In this empirical study, The Decision-Making Trial, and Evaluation Laboratory (DEMATEL), was chosen as the method in this study. DEMATEL method is a method used in the Multi-Criteria Decision Making (MCDM) literature to determine the subjective weights of decision criteria (Utama et al., 2021). The most important benefit of the method is that it is an effective method that examines the structure and relationships between the criteria (Li et al., 2020). The challenges analyzed in this empirical study were based on a literature review. The data source of the study consists of the opinions of 3 experts responsible for DES applications in their manufacturing enterprises. The aim of the study is to reveal the challenges faced by manufacturing enterprises during the implementation of DES. The findings of the study will help to decision and policy makers to understand the importance of these challenges and the relationships between them. Adopting the study's findings will result in reduced costs, improved customer satisfaction, and competitive advantage for industry professionals by facilitating the adoption of DES.

1. Conceptual Framework

The challenges examined in this empirical research were derived from existing literature. These challenges represent the most frequently encountered challenges in the context of DES implementation. These challenges are "Data Availability and Accessibility, Data Quality and Integrity, Data Integration and Interoperability, Data Granularity and Detail, Data Analysis and Interpretation, Data Privacy and Security, Model Complexity, Customization and Flexibility, Model Validation and Verification, Model Maintenance and Updates, Model Integration with Existing Systems, Model Integration with Other Systems, Resource and Expertise Requirements, Resistance to Change, Cost" (Xie & Verbraeck, 2018; Bokrantz et al., 2017; Ademujimi & Prabhu, 2022; Jacobson & Yücesan, 1999; Hill, 2007; Tiwari, 2011; Nutaro et al., 2008; Fernández et al., 2021; Flores-García et al., 2018)

Data Availability and Accessibility: Collecting data suitable for running simulation models is very difficult. Manufacturing enterprises usually do not have the data set suitable for running a simulation model. DES applications are open to challenges in data collection and storage, as they are based on both real-time and historical data. Apart from the applicability of the data, accessing these data is also considered a challenge. The collected data needs to be extracted from the database and processed in a way that is suitable for use.

Data Quality and Integrity: For DES applications to work correctly and efficiently, it is important that the data is of a quality suitable for processing. Problems in data quality prevent the DES from providing valid and reliable results. That also means that data quality problems can impact the accuracy and reliability of DES models. If the data is not of good quality at the time it is stored, the data cleansing to obtain data of the quality needed for DES models to work is a tedious task. In addition, the data must be integrated. Otherwise, the desired results cannot be obtained from the DES application. High-quality input data is essential for successful DES applications.

Data Integration and Interoperability: Combining data from different sources and systems is a challenge in DES applications. Manufacturing enterprises often use many different software and hardware. The fact that the data obtained from these different types of software and recorded by these different types of hardware are in different formats makes it difficult to implement DES.

Data Granularity and Detail: The main purpose of simulation applications is to optimize the real world by mimicking it. This challenge arises from the need for highly accurate and detailed data to both parameterize and validate the model. The excessive detail and complexity of the collected data makes it difficult to implement DES applications. This granularity and detail requirement can be time-consuming and resource-intensive, especially for complex processes with inherent variability, limiting accessibility for manufacturing enterprises. In such cases, DES requires longer processing times and increased computational effort. For the simulation to provide results that are appropriate for the real-world problem, a balance must be struck between the level of detail and the level of data processing required.

Data Analysis and Interpretation: The analysis and interpretation of data challenge stems from the vast amount of data generated by the simulation. Analyzing and interpreting the collected data is not easy due to its complexity. Extracting meaningful patterns from the analysis, diagnosing, making informed decisions, and implementing them is one of the most difficult phases of DES implementation. Without proper analysis correct interpretations cannot be made. In the absence of correct interpretations, it is not possible to have a successful DES implementation.

Data Privacy and Security: Data privacy and security are often among the challenges discussed in any business where data use is involved. The challenge of "Data Privacy and Security" in DES applications for manufacturing enterprises is related to the protection of sensitive information. For manufacturing enterprises, information that also has financial value is highly sensitive. The fact that this data contains information on how the production is done means that it is also considered in the known-how status. For this reason, manufacturing enterprises want to protect this data. It is critical to ensure that the data needed during DES applications remains secure against unauthorized access, breaches, and cyber threats. Manufacturing organizations need to fulfill legal requirements regarding data privacy.

Model Complexity: The implementation of DES models poses a significant challenge due to the complexity involved in representing complex systems. Simulation models contain a large number of variables. There are also many causal relationships between these variables. When handling complex models simultaneously, the simulations can become stiff because of the computations of dynamic equations.

Customization and Flexibility: Manufacturing systems are unique. This uniqueness causes each product item in manufacturing systems to consist of different processes. Accordingly, there is a need for customized DES applications.. As the complexity of the model increases, its flexibility decreases and it becomes difficult to model new components integrated into the system.

Model Validation and Verification: DES involves ensuring that the simulation model accurately represents the real-world system it intends to mimic. Validation refers to the process of confirming that the model behaves in accordance with the actual system, while verification focuses on verifying the correctness of the model's implementation. This challenge arises because manufacturing processes are complex and dynamic, making it difficult to capture all the intricacies in the simulation model. Validating and verifying the model requires careful comparison of simulation outputs with real-world data, conducting sensitivity analyses, and involving domain experts to assess the model's accuracy. Overcoming this challenge is crucial to ensure that the simulation results can be trusted and used to make informed decisions in manufacturing enterprises.

Model Maintenance and Updates: The complexity of maintaining and updating simulation models, especially in the context of multicomponent maintenance systems, requires considering various dependencies, such as stochastic, structural, economic, and resource dependencies Additionally, the state-of-the-art in simulation-based optimization for maintenance systems highlights the need for systematic classification of literature and outlining main trends in modeling and optimizing maintenance systems.

Model Integration with Other Systems: Applications of Discrete Event Simulation (DES) in manufacturing organizations are anticipated to operate cohesively and in conjunction with other systems. Nonetheless, these systems might receive data that is formatted variably. Due to incompatible data formats, different system architectures and the need for real-time synchronization, integrating DES applications with other systems is a challenging task.

Model Integration with Existing Systems: There are also challenges in integrating DES applications into existing systems. Due to the wide variety of data architecture and hardware structure, there are some challenges from obtaining the data needed to integrating the application. The software and hardware changes required for integration are challenging, but these costs must be incurred for a smooth integration.

Resource and Expertise Requirements: As with all applications that depend on the use of technology, DES applications require a high level of expertise. Experts are needed at all stages of DES modeling, from the beginning of data collection to implementation and evaluation. The expert involved in these processes should not only know the software to be used, but also have a certain level of expertise in the system being modeled. In addition to these areas of expertise, knowledge of statistics is also needed. Expertise is also required for interpretation and updates.

Resistance to Change: Resistance to change refers to discontent and resistance to change in existing systems. This resistance could make it difficult to implement DES practices. To overcome this challenge, it is important to involve employees in the simulation process and communicate the benefits of simulation. By doing so, this can give employees a sense of ownership and lead to a successful application.

Cost: Although DES implementations are cost-effective compared to modifying real systems, their long-term implementation imposes a financial burden on organizations. The need for an expert to implement DES, the software and hardware used in the DES implementation, all add up to a certain cost.

2. DEMATEL (The Decision-Making Trial and Evaluation Laboratory)

Decisions are inherently subjective. The need to reflect the inherent subjectivity in decisions arises from the role of decision makers in decision processes. Multi-Criteria Decision Making (MCDM) methods are used in where decisions are made based on more than one criterion. Some of the MCDM methods are aimed at determining the level of importance of the decision criteria. In cases where the importance levels should be determined by reflecting the subjective opinion of the decision maker, subjective weighting methods are used. The purpose of subjective weighting is to provide a framework in which the decision maker's opinions are integrated into the decision problem. These approaches acknowledge that various criteria in a decision-making context may hold different levels of importance or significance, which might not always be determined using objective methods. These methods refer to the quality of decisions that cannot be solely based on objective, quantifiable data. Rather, these methods recognize the essential part played by decision maker’s judgment, preferences, and values in shaping decisions. That also mean that these methods not only enhance transparency in the decision-making process but also guarantees that the final decisions are in line with the objectives and subjective opinions of the decision makers.

DEMATEL (Decision-Making Trial and Evaluation Laboratory) is a method used to find criteria weights by taking into account the interactions between criteria (Hwang & Lin, 2012) DEMATEL was developed to improve the understanding of specific problems and to identify feasible solutions to complex problem sets in a hierarchical structure. The method identifies “dispatcher criteria” as those with greater impact and higher priority, while “receiver criteria” are those with lower impact and lower priority among all the criteria. (Kobryn, 2017). DEMATEL allows decision makers to solve problems by categorizing impact factors into cause and effect groups to better understand the causal relationship (Li &Tzeng, 2009). DEMATEL method consists of six consecutive steps (Tsai & Chou., 2009; Keleş et al., 2023):

Step 1: Creating the direct relationship matrix (A)**.** The expert group is asked to answer the question "at what level do the criteria influence each other?" according to the influence levels determined in Table 1. As seen in the example, the direct relationship matrix (X) is of size nxn. At this stage, it is determined to what extent which criterion influences which criterion.

Table 1. Scale of Impact Levels

Numeric Value / Definition	
0	No Influence
1	Low Influence
2	Moderate Influence
3	High Influence
4	Very High Influence

Table 2. Direct Relationship Matrix (X)

	Criterion 1	Criterion 2	Criterion 3
Criterion 1	0	3	1
Criterion 2	1	0	1
Criterion 3	2	1	0

Table 2 presents the direct relationship matrix (X), which shows the relationship between criteria in an nxn dimension. Each decision maker is asked to fill in the direct relationship matrix by answering questions. The aim at this stage is to determine the relationship between the criteria in the model. Therefore, the answers given by the decision maker should be based on their own needs and expectations, which will shape the model specifically for them. In other words, by filling in the direct relationship matrix, decision makers reflect their subjective opinions and judgments in the model.

$$X = \begin{bmatrix} 0 & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & 0 \end{bmatrix}$$

The average direct relationship matrix (A) is obtained by taking the arithmetic mean of the X direct relationship matrices using the following equation. This new matrix reflects the group decision.

$$a_{ij} = \frac{1}{H} \sum x_{ij}$$

$$A = \begin{bmatrix} 0 & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & 0 \end{bmatrix}$$

Step 2: Constructing the normalized direct-relationship matrix (M). Using the average direct-relationship matrix (A), the normalized direct-relationship matrix (M) is found. In matrix M, the diagonal values should be 0 and the other values should lie between 0 and 1. The following formula gives the normalized relationship matrix.

$$S = \max\left(max \sum_{j=1}^{n} a_{ij} \,, max \sum_{i=1}^{n} a_{ij} \right)$$

$$M = \frac{A}{S}$$

Step 3: Determining the total relationship matrix (T). Once the normalized direct-relationship matrix (M) is obtained, the total relationship matrix (T) is derived using the following formula (Tsai et al., 2009).

$$T = M^1 + M^2 + M^3 + \cdots = \sum_{i=1}^{\infty} M^i$$

$$T = M\,(M - I)^{-1}$$

Step 4: Determine the row sum D and column sum R of the total direct relationship matrix (T).

$$D_i = \sum_{j=1}^{n} t_{ij}$$

$$R_j = \sum_{j=1}^{n} t_{ij}$$

The D+R value indicates the positive or negative relationship between each criterion and the other criterion, and the D-R value indicates the net effect of the criteria on the model. The group with a negative D-R value is referred to as the “receiver” criteria, while the group with a positive D-R value is referred to as the “dispatcher” criteria. The D and R values represent the row and column sum of the total relationship matrix, respectively.

Step 5: The threshold value is calculated by averaging the sum of all cells in the total relationship matrix. Direct influence graph is drawn with D-R value on the horizontal axis and D+R value on the vertical axis.

Step 6: In the final stage, criterion weights are calculated as follows.

$$w_i = \sqrt{[D_i + R_i]^2 . [D_i - R_i]^2}.$$

$$w_i = \frac{w_i}{\sum_{j=1}^{n} W_i}$$

3. Data Analysis

In the Industry 4.0 era, when manufacturing enterprises need various digital optimization tools to adapt to the digital transformation, it is important to examine the possible challenges to be encountered during the implementation of these tools. For this purpose, this study aims to determine the subjective weights of the challenges faced by manufacturing enterprises in the implementation of Discrete Event Simulation (DES), which is one of the prominent optimization tools of the industry 4.0 era. The results of the study are important in terms of determining the importance ranking of the challenges to be faced by manufacturing enterprises in DES applications. In addition, the identification of the causal relationship between these challenges and the identification of the challenges in the influencing position will provide a competitive advantage to decision makers in dealing with all these challenges. Policy makers will be able to deal with the challenges encountered during the implementation of the DES tool, which stands out during digital transformation, by considering the results obtained. In this study, for this purpose, the opinions of 3 experts who are responsible for DES implementation and manufacturing in their enterprises were consulted. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) was used to reflect the subjective weights of the decision criteria as well as the cause-and-effect relationships between the decision criteria. As the data of the study, the decision matrices filled in by the three experts were not shared separately, but the decision matrix showing the group decision was included.

Table 3. Direct Relationship Matrix (Group Decision)

	Data Availability and Accessibility	Data Quality and Integrity:	Data Integration and Interoperability	Data Granularity and Detail	Data Analysis and Interpretation	Data Privacy and Security	Model Complexity	Customization and Flexibility:	Model Validation and Verification	Model Maintenance and Updates	Model Integration with Other Systems	Model Integration with Existing Systems	Resource and Expertise Requirements	Resistance to Change	Cost
Data Availability and Accessibility	0,00	0,00	3,00	0,00	3,00	1,33	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	1,67
Data Quality and Integrity:	4,00	0,00	4,00	3,00	4,00	4,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	2,00
Data Integration and Interoperability	3,00	3,00	0,00	3,00	3,67	3,00	2,00	4,00	2,00	1,67	2,00	2,00	1,67	2,00	2,00
Data Granularity and Detail	4,00	4,00	3,00	0,00	4,00	3,00	3,00	2,67	2,00	2,00	2,00	2,00	2,00	2,00	2,00
Data Analysis and Interpretation	0,00	0,00	0,00	0,00	0,00	0,00	3,67	4,00	4,00	4,00	4,00	4,00	3,00	2,67	3,00
Data Privacy and Security	4,00	2,00	1,67	4,00	0,00	0,00	0,00	2,00	0,00	2,67	3,00	3,00	0,00	0,00	3,00
Model Complexity	0,00	0,00	0,00	0,00	0,00	0,00	0,00	4,00	4,00	4,00	4,00	4,00	4,00	2,00	4,00
Customization and Flexibility:	0,00	0,00	0,00	0,00	0,00	0,00	4,00	0,00	4,00	4,00	4,00	4,00	4,00	0,00	1,67
Model Validation and Verification	0,00	0,00	0,00	0,00	3,00	0,00	4,00	4,00	0,00	4,00	4,00	4,00	1,67	0,00	2,00
Model Maintenance and Updates	0,00	0,00	0,00	0,00	0,00	0,00	2,00	4,00	2,00	0,00	4,00	4,00	4,00	2,00	3,00
Model Integration with Other Systems	0,00	0,00	0,00	0,00	0,00	0,00	2,00	2,00	2,00	2,00	0,00	3,00	4,00	2,00	4,00
Model Integration with Existing Systems	0,00	0,00	0,00	0,00	0,00	0,00	0,00	2,00	0,00	2,00	3,00	0,00	4,00	4,00	0,00
Resource and Expertise Requirements	1,67	3,00	3,00	4,00	4,00	4,00	0,00	2,00	4,00	3,67	3,00	3,00	0,00	4,00	4,00
Resistance to Change	2,67	3,00	3,00	3,00	3,00	3,00	0,00	2,00	0,00	2,00	1,67	1,67	4,00	0,00	4,00
Cost	2,00	2,00	2,00	1,67	2,00	3,00	0,00	0,00	0,00	1,67	3,00	3,00	4,00	2,00	0,00

The row and column sums of the direct relationship matrix showing the group decision were taken and the normalized direct relationship matrix (M) was created by using the maximum value of 43.3 among these sums.

Table 4. Normalized Direct Relationship Matrix (M)

	Data Availability and Accessibility	Data Quality and Integrity:	Data Integration and Interoperability	Data Granularity and Detail	Data Analysis and Interpretation	Data Privacy and Security	Model Complexity	Customization and Flexibility:	Model Validation and Verification	Model Maintenance and Updates	Model Integration with Other Systems	Model Integration with Existing Systems	Resource and Expertise Requirements	Resistance to Change	Cost
Data Availability and Accessibility	0,00	0,00	0,07	0,00	0,07	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,04
Data Quality and Integrity:	0,09	0,00	0,09	0,07	0,09	0,09	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,05
Data Integration and Interoperability	0,07	0,07	0,00	0,07	0,08	0,07	0,05	0,09	0,05	0,04	0,05	0,05	0,04	0,05	0,05
Data Granularity and Detail	0,09	0,09	0,07	0,00	0,09	0,07	0,07	0,06	0,05	0,05	0,05	0,05	0,05	0,05	0,05
Data Analysis and Interpretation	0,00	0,00	0,00	0,00	0,00	0,00	0,08	0,09	0,09	0,09	0,09	0,09	0,07	0,06	0,07
Data Privacy and Security	0,09	0,05	0,04	0,09	0,00	0,00	0,00	0,05	0,00	0,06	0,07	0,07	0,00	0,00	0,07
Model Complexity	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,09	0,09	0,09	0,09	0,09	0,09	0,05	0,09
Customization and Flexibility:	0,00	0,00	0,00	0,00	0,00	0,00	0,09	0,00	0,09	0,09	0,09	0,09	0,09	0,00	0,04
Model Validation and Verification	0,00	0,00	0,00	0,00	0,07	0,00	0,09	0,09	0,00	0,09	0,09	0,09	0,04	0,00	0,05
Model Maintenance and Updates	0,00	0,00	0,00	0,00	0,00	0,00	0,05	0,09	0,05	0,00	0,09	0,09	0,09	0,05	0,07
Model Integration with Other Systems	0,00	0,00	0,00	0,00	0,00	0,00	0,05	0,05	0,05	0,05	0,00	0,07	0,09	0,05	0,09
Model Integration with Existing Systems	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,05	0,00	0,05	0,07	0,00	0,09	0,09	0,00
Resource and Expertise Requirements	0,04	0,07	0,07	0,09	0,09	0,09	0,00	0,05	0,09	0,08	0,07	0,07	0,00	0,09	0,09
Resistance to Change	0,06	0,07	0,07	0,07	0,07	0,07	0,00	0,05	0,00	0,05	0,04	0,04	0,09	0,00	0,09
Cost	0,05	0,05	0,05	0,04	0,05	0,07	0,00	0,00	0,00	0,04	0,07	0,07	0,09	0,05	0,00

The total relationship matrix (T) was obtained by using Step 3. By averaging the cell values in the 15x15 dimensional total relationship matrix, the threshold value was calculated as 0,11. Values above 0,11 are marked to indicate the difficulty affected by the challenge in the row.

Table 5. Total Relationship Matrix (T)

	Data Availability and Accessibility	Data Quality and Integrity:	Data Integration and Interoperability	Data Granularity and Detail	Data Analysis and Interpretation	Data Privacy and Security	Model Complexity	Customization and Flexibility:	Model Validation and Verification	Model Maintenance and Updates	Model Integration with Other Systems	Model Integration with Existing Systems	Resource and Expertise Requirements	Resistance to Change	Cost
Data Availability and Accessibility	0,02	0,02	0,08	0,02	0,09	0,05	0,02	0,03	0,02	0,03	0,04	0,04	0,04	0,02	0,07
Data Quality and Integrity:	0,14	0,04	0,13	0,11	0,14	0,13	0,04	0,06	0,05	0,06	0,07	0,07	0,07	0,05	0,11
Data Integration and Interoperability	0,13	0,12	0,06	0,12	0,16	0,13	0,12	0,19	0,13	0,15	0,17	0,17	0,16	0,12	0,16
Data Granularity and Detail	0,16	0,14	0,13	0,06	0,18	0,14	0,14	0,17	0,13	0,16	0,18	0,18	0,18	0,13	0,17
Data Analysis and Interpretation	0,04	0,04	0,04	0,05	0,06	0,05	0,15	0,19	0,17	0,20	0,22	0,22	0,21	0,14	0,18
Data Privacy and Security	0,13	0,08	0,08	0,13	0,06	0,05	0,04	0,11	0,05	0,13	0,15	0,15	0,09	0,06	0,14
Model Complexity	0,04	0,04	0,04	0,05	0,06	0,05	0,06	0,18	0,16	0,19	0,21	0,21	0,21	0,12	0,19
Customization and Flexibility:	0,03	0,03	0,03	0,04	0,05	0,04	0,14	0,09	0,16	0,18	0,19	0,19	0,20	0,07	0,13
Model Validation and Verification	0,03	0,03	0,03	0,03	0,11	0,04	0,15	0,18	0,07	0,18	0,20	0,20	0,15	0,07	0,14
Model Maintenance and Updates	0,04	0,04	0,04	0,04	0,05	0,05	0,09	0,16	0,11	0,09	0,19	0,19	0,20	0,11	0,16
Model Integration with Other Systems	0,03	0,04	0,04	0,04	0,05	0,04	0,08	0,11	0,10	0,12	0,09	0,15	0,18	0,10	0,16
Model Integration with Existing Systems	0,03	0,03	0,03	0,03	0,04	0,04	0,03	0,09	0,04	0,10	0,13	0,06	0,16	0,13	0,06
Resource and Expertise Requirements	0,12	0,14	0,14	0,16	0,19	0,17	0,09	0,18	0,18	0,22	0,23	0,23	0,16	0,19	0,23
Resistance to Change	0,13	0,13	0,13	0,13	0,15	0,14	0,06	0,14	0,08	0,15	0,16	0,16	0,21	0,08	0,20
Cost	0,10	0,09	0,10	0,09	0,11	0,12	0,05	0,08	0,06	0,12	0,16	0,16	0,18	0,11	0,09

As shown in step 4, D values were determined by taking row sums and R values were determined by taking column sums. D-R values were identified as dispatcher challenges and negative ones as receiver challenges. Dispatcher challenges are marked in the table. D+R values indicate the importance of the challenge for the model. Accordingly, the most and least important challenges to be included in the model are also shown in the table. The graph in step 5 is not drawn because it does not provide an effective and understandable visual when drawn for a 15x15 matrix.

Table 6. Identification of Dispatcher and Receiver Criteria

	D	R	D-R	D+R
Data Availability and Accessibility	0,60	1,17	-0,57	1,76
Data Quality and Integrity:	1,28	1,00	0,28	2,28
Data Integration and Interoperability	2,10	1,12	0,98	3,23
Data Granularity and Detail	2,24	1,10	1,14	3,34
Data Analysis and Interpretation	1,98	1,52	0,46	3,50
Data Privacy and Security	1,43	1,25	0,18	2,68
Model Complexity	1,84	1,26	0,57	3,10
Customization and Flexibility:	1,58	1,97	-0,40	3,55
Model Validation and Verification	1,61	1,52	0,08	3,13
Model Maintenance and Updates	1,55	2,10	-0,55	3,65
Model Integration with Other Systems	1,35	2,37	-1,03	3,72
Model Integration with Existing Systems	1,02	2,37	-1,36	3,39
Resource and Expertise Requirements	2,63	2,37	0,26	5,01
Resistance to Change	2,05	1,52	0,53	3,58
Cost	1,63	2,21	-0,58	3,84

Following the equation in Step 6, the subjective criteria weights of the challenges were determined as follows. The most and least important criteria are marked in the table.

Table 7. Identification of Subjective Criteria Weights

Data Availability and Accessibility	0,04
Data Quality and Integrity:	0,05
Data Integration and Interoperability	0,07
Data Granularity and Detail	0,07
Data Analysis and Interpretation	0,07
Data Privacy and Security	0,05
Model Complexity	0,06
Customization and Flexibility:	0,07
Model Validation and Verification	0,06
Model Maintenance and Updates	0,07
Model Integration with Other Systems	0,08
Model Integration with Existing Systems	0,07
Resource and Expertise Requirements	0,10
Resistance to Change	0,07
Cost	0,08

Conclusions and Recommendations

According to the D-R value in Table 6, the dispatcher challenges are "Data Quality and Integrity, Data Integration and Interoperability, Data Granularity and Detail, Data Analysis and Interpretation, Data Privacy and Security, Model Complexity, Model Verification and Validation, Model Integration with Existing Systems, Resource and Expertise Requirements". By focusing on these challenges, decision makers and policy makers can also address the other challenges that these challenges influence. When the D+R values are analyzed, it is seen that the values are close to each other. Accordingly, it is understood that the challenges in the model are selected in a mutually inclusive manner. According to D-R value the challenge that contributes the least to the model is the "Data Availability and Accessibility" challenge. The challenge that contributes the most is "Resource and Expertise Requirements".

When the challenges that are affected by the challenge in the row by being above the threshold value calculated according to the total relationship matrix in Table 5 are examined; it is seen that data-based challenges affect model-based challenges. "Model Complexity, Customization and Flexibility, Model Validation and Verification, Model Maintenance and Updates, Model Integration with Other Systems, Model Integration with Existing Systems" challenges are heavily affected by data-driven challenges. In other words, challenges such as insufficient quality of data, too much detail, problems in data interpretation and data security make the model more complex, rigid, difficult to update and troublesome to integrate. In addition, data-related challenges make it difficult to find resources and experts, affect resistance to change and increase costs.

There is no challenge affected by the "Data Availability and Accessibility" challenge, which is one of the data-based challenges. When the total relationship matrix is examined, it is seen that the reason why the data is not available and accessible is because the data does not have the desired quality, detail and security. Data is kept intensively in manufacturing enterprises. However, the main problem is that this stored data does not have the qualities that will enable DES applications.

The "Model Complexity, Customization and Flexibility, Model Validation and Verification, Model Maintenance and Updates, Model Integration with Other Systems, Model Integration with Existing Systems" challenges related to the model are mostly affected by the challenges in themselves. Model-driven challenges rarely affect data-driven challenges.

The "Resource and Expertise Requirements" challenge appears to affect all challenges except "Model Complexity". Accordingly, it is understood that to overcome the problems experienced in DES applications, it is necessary to first train experts and allocate resources to DES applications.

The cost-related difficulty is mostly in the receiver position. The challenges affected by "Cost" are "Data Analysis and Interpretation" and "Data Privacy and Security". Accordingly, it can be interpreted that other challenges experienced increase costs, causing "Cost" to be perceived as a challenge.

When the subjective weights in Table 7 are examined, it is seen that the "Data Availability and Accessibility" challenge has the lowest weight with 4%, and the "Resource and Expertise Requirements" challenge has the highest weight with 10%. The weight of other challenges has taken similar values. In this case, the interpretation that can be made is that the most important of the challenges encountered is "Resource and Expertise Requirements", and the least important is "Data Availability and Accessibility". Since other challenges receive similar weights, instead of prioritizing them, the dispatcher ""Data Quality and Integrity, Data Integration and Interoperability, Data Granularity and Detail, Data Analysis and Interpretation, Data Privacy and Security, Model Complexity, Model Verification and Validation, Model Integration with Existing Systems, Resource and Expertise Requirements" challenges should be addressed and other challenges in the receiving position should also be resolved.

Based on the fact that the importance weights obtained from the model are very close to each other, it is suggested that the study be repeated under the general headings of "data-driven", "model-driven", "human resource-driven" and "cost-driven". In this way, clearer relationships between these criteria can be revealed. With this more generalized classification of criteria, it may be possible to obtain more generalized criteria weights with clearer differences between criteria.

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