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Global Institute for Agri-Tech Economics (GIATE)
Food, Land & Agribusiness Management Department
Harper Adams University
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Smart Agriculture Technology Evaluation: A Linguistic-based MCDM Methodology

Deniz Uztürk[A] and Gülçin Büyüközkan[B*]

[A] *Department of Management, Business Research Center, Galatasaray University, Istanbul, Beşiktaş, Turkey*
[B] *Department of Industrial Engineering Galatasaray University, Istanbul, Beşiktaş, Turkey*

Abstract

Agricultural operations have been highly affected by all the industrial revolutions. From ancient times to today, agrarian systems have evolved parallel to technological developments. For a decade, we have been facing a new industrial revolution, Industry 4.0. It is for sure that the existing agrarian systems will be affected by this digital transformation. Since agricultural systems are critical production networks for civilizations, their change should be addressed carefully. For that purpose, this paper focuses on the technology evaluation for Smart Agriculture (SA). The SA area is chosen thanks to its importance for sustainable development and production systems. Thus, the expectations from SA are derived from the SA advantages stated in the academic and industrial literature. Afterward, the technologies are assessed according to their ability to meet these expectations. To obtain the most powerful technology, the expectations are first weighted via the 2-Tuple Linguistic (2-TL) DEMATEL technique, then 2-TL-MARCOS is used to calculate the technology prioritization. To overcome the ambiguity about a newly emerged subject as SA, using linguistic variables via the 2-TL approach is one of the essential contributions of this paper. Moreover, this paper suggests a multi-criteria decision-making (MCDM) approach to create a comprehensive understanding of digital technologies and their use and benefits in agricultural systems. A real case study is presented with a sensitivity analysis to test the proposed methodology's applicability and replicability.

Keywords

2-Tuple Linguistic Model, DEMATEL, Digital technologies, Industry 4.0, MARCOS, Smart Agriculture

Presenter Profile

Deniz Uztürk is a Ph.D. student in industrial engineering and a research assistant in the Management Department on Numerical Methods area at Galatasaray University, Turkey. She holds her Master of Science in Industrial Engineering, where she worked on sustainable building design. Her research areas include smart technologies, multi-criteria decision making, fuzzy logic, and applications.

* Corresponding Author: Gülçin Büyüközkan, Galatasaray University, Istanbul, Turkey, 34349, email: gbuyukozkan@gsu.edu.tr

Introduction

From ancient times until the end of the 19th century, conventional farming techniques depended on human power. Specified tools such as hoes, sickles, and pitchforks were necessary to farm (Cugno et al., 2021). Because of the massive reliability of human labor, productivity was low in such conventional techniques. By the beginning of the 20th century, developments in faster and more efficient production approach extended into the agrarian field. The 20th century was the plunge point to mechanized food production (De Clercq et al., 2018). With agricultural machinery, agrarian operations gradually transformed into a process that relied on less human power. The second revolution in the agricultural area also occurred in the 20th century with Industry 2.0 (the Second Industrial Revolution).

The third industrial revolution, Industry 3.0, introduced new software and communication technologies that upgraded the automation capacity in the production lines. After assigning oil as the primary energy source, Industry 3.0 helped to explore new and renewable energies such as hydroelectricity and wind power. By exploring new energy sources and technologies, Industry 3.0 paved the way for precision agriculture (Carrer et al., 2022).

In short, agricultural operations were highly affected by the three previous industrial revolutions. The change in the production lines was reflected in the farming activities. Currently, we are talking about the new industrial revolution called Industry 4.0. Fluctuating market conditions in a globally connected world challenge companies to continuously adapt and embrace digital transformation across all functions, including procurement, logistics, manufacturing, asset management, and factory operations (Deloitte, 2020).

Agriculture has a critical importance for civilization, with an importance that constantly increases with the depletion of natural resources. Agricultural digitalization is a agricultural industrialization’s serious constituent that focuses on agricultural research, infrastructural improvements, and data services. Consequently, in this paper, the primary aim is to evaluate the digital technologies resulting in more efficient agricultural transformation. Technology transfer is crucial to transforming existing conventional systems. Therefore, this paper suggests a roadmap to follow while choosing the right and efficient technology to reach Smart Agriculture (SA).

SA is the restoration of existing farming methods with efficient, rapid, and sustainable ones (with technological integration) (Collado et al., 2019). As a topic that has emerged recently, our and experts' knowledge on this subject is fuzzy. To overcome this ambiguity, using linguistic variables in evaluations is accepted as an advantageous approach in literature (Zadeh, 1965). Hence, this paper suggests a multi-criteria decision-making (MCDM) based approach integrated with the 2-TL Linguistic (2-TL) Model (Herrera and Martínez, 2000). The MCDM approach enables a holistic analysis of the digital transformation in agriculture and its expectations based on the technologies. The use of linguistic variables is chosen to create a flexible environment for decision-making closer to the human cognitive process.

The main contributions of this paper can be summarized as follows:

- Providing a linguistic-based framework for technology assessment in an emerging field such as SA,
- Generating a deeper understanding of technology use and benefits in SA.
- Using the 2-TL-DEMATEL-MARCOS framework for the first time in the SA area.
- Investigating expectations for SA and their interrelations.

The paper's organization is as follows: Next section will provide the literature review. The following section will present the details of the suggested MCDM-based methodology. Afterward, a case study will be presented followingly its results and discussions. Finally, conclusions will be provided at the end.

Literature Review

The literature review is the critical component of the suggested methodology. Based on the academic and industrial literature, expectations from SA and related digital technologies are defined. Figure 1 indicates the mutual occurrences of digital technologies in the recent (2020-2021 and 2022) academic literature. The thickness of the lines indicates the power of mutual use, and the nodes' size indicates the number of occurrences in the recent literature. As seen from the network visualization obtained by VosViewer[8], the digital technologies are highly stated in the SA area. The network visualization also defined two different clusters for the technologies.

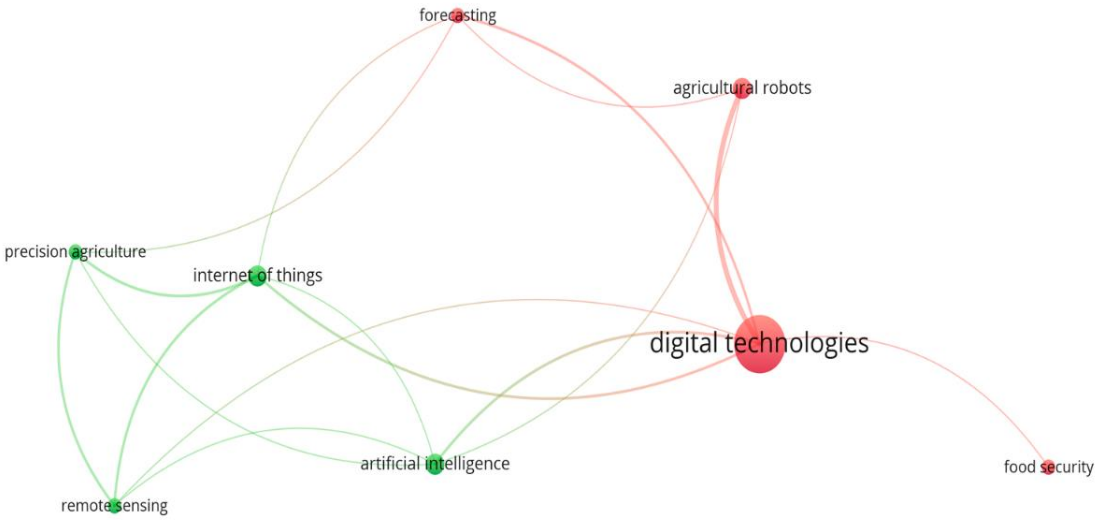


Figure 1: Network visualization of keyword occurrences of digital technologies in SA.

The green group is concentrated chiefly on precision agriculture, which emphasizes the use of information technologies (IT) for more efficient crop production (Agrawal et al., 2020; Carrer et al., 2022; Dhillon et al., 2020; Ivanovski et al., 2020; Maffezzoli et al., 2021). IoT, remote sensing technologies, and their integration with artificial intelligence (AI) are critical for that purpose. Under the AI technologies, we can also count Machine Learning (ML) and Deep Learning (DL) (Costa et al., 2021). Their integration is crucial for reaching "precision" or "smart" agriculture.

The other group, the red one, primarily emphasizes automation in agriculture using robotic technologies (Cubero et al., 2020; Dharmasena et al., 2019; Gorlov et al., 2020; Singh and Kaur, 2021). At this part, with automation, the control over agricultural production is increased. Consequently, food security can be handled by integrating Blockchain technology and forecasting technologies based on AI/DL/ML and Big Data. As the "digital technologies" node is the biggest one, it can be concluded that their use in SA is critically vital for agricultural

[8] https://www.vosviewer.com

transformation. Based on their critical importance in agricultural transformation, this paper focuses on assessing and choosing the most appropriate technology to ensure the expectations from SA.

The expectations from the SA are also generated from the academic and industrial literature. The expectations' foundations are based on the advantages stated in the SA literature. They will be used as evaluation criteria to define the technologies' ability to meet expectations for the technology evaluation process. The following table gives the detected five main expectations from SA.

Table 1: Expectations from SA (Abioye et al., 2020; Ait Issad et al., 2019; "Building partnerships for sustainable agriculture and food security," n.d.; Collado et al., 2019; Deloitte, 2020; McKinsey and Co., 2020)

E#	Expectations from SA
E1	Efficient strategy generation
E2	Risk Management
E3	Trustable, on-time data
E4	Resource optimization
E5	Food security

The following section will provide more information about the suggested model for tech ology evaluation and the details of the proposer integrated MCDM techniques.

Methods

This section gives the preliminaries of the recommended methodology. The first section provides basic concepts of the 2-TL model and its benefits. Then the standard DEMATEL method is explained briefly with the group decision-making (GDM) technique. The technique used for technology evaluation, 2-TL MARCOS, is presented in detail at the end.

Figure 2 summarizes the general concept of the suggested model. Here expectations are the evaluation criteria and the technologies approach as alternatives in the 2-TL-MARCOS methodology. As seen from the figure, an assessment matrix is formed to assess the technologies based on their ability to meet the criteria.

During the evaluations, linguistic variables are essential to creating an unbiased, flexible environment for decision-makers (DMs). Using the 2-TL model enables computation and analysis closer to human cognitive processes. The model contains two stages:

1) The weighting of criteria (expectations) via 2-TL DEMATEL
2) Prioritization of technologies via 2-TL MARCOS.

In both stages, the GDM approach is integrated with 2-TL DEMATEL and MARCOS to create an unbiased decision-making environment. Plus, the Delphi approach is followed during collecting assessments from DMs.

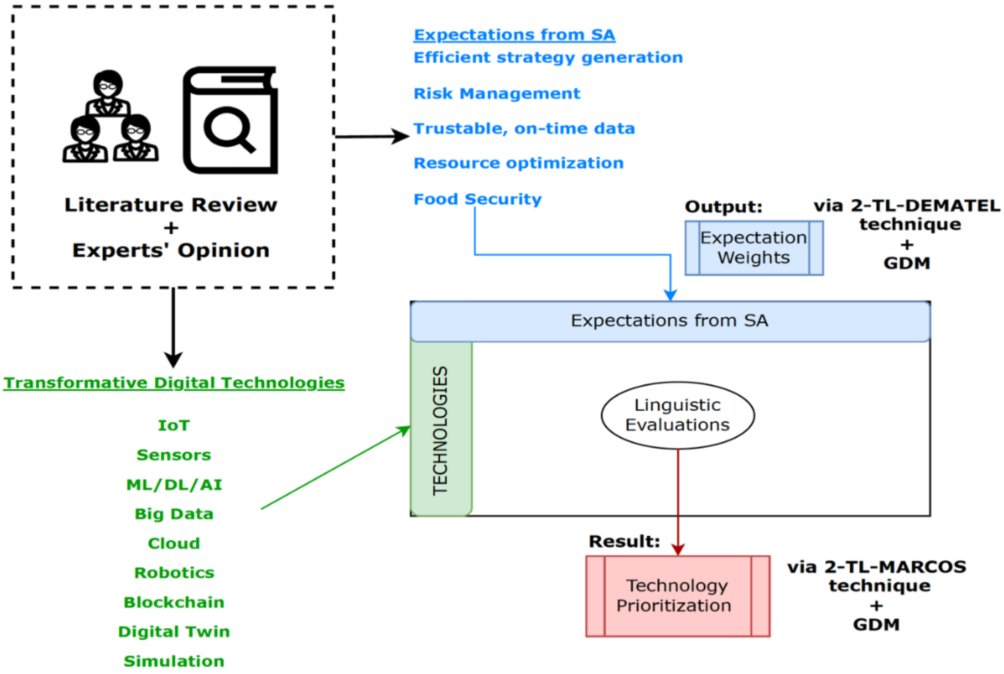


Figure 2: Suggested model for technology assessment for SA.

2-TL Linguistic Model

The 2-TL linguistic approach is first unveiled by (Herrera and Martínez, 2000). This model helps to work with heterogeneous information. Besides, it can handle multi-granular information. It is suitable for GDM, where group members have different experiences about the same subject. The 2-TL linguistic model is generally used with various MCDM models to emphasize their ability to deal with linguistic data and diminish data loss during the translation phase (Buyukozkan and Uzturk, 2017; Geng et al., 2017; Karsak and Dursun, 2015).

The 2-TL fuzzy linguistic representation model represents the linguistic information using a 2-TL *(S, α)* here; *S* is a linguistic label, and *α* is a numerical value representing the value of the symbolic translation. The function is defined as:

$$\Delta_s : [0, g] \rightarrow \overline{S}$$

$$\Delta_s(\beta) = (S_i, \alpha), with \begin{cases} i = round(\beta) \\ \alpha = \beta - i \end{cases}$$

The linguistic term set *S* could be converted into 2-TL form by adding zero value as in the

$$S_i \in S \Rightarrow (S_i, 0)$$

following relation:

The 2-TL linguistic model, a linguistic, symbolic computational model, modifies the fuzzy linguistic approach by including a parameter to the linguistic representation to increase the accuracy and the interpretability of the results (Martínez et al., 2015). The 2-TL linguistic model enables us to deal with variables closer to the human beings' cognitive processes and augment the computations' accuracy. For further details about the 2-TL model, readers can refer to (Martínez et al., 2015).

DEMATEL

DEMATEL (Gabus and Fontela, 1972) is an accurate MCDM tool that depicts the importance of related criteria. It also makes it possible to determine the causal relationships between evaluation criteria (Büyüközkan and Öztürkcan, 2010; Quader et al., 2016) and is suggested for the criteria weighting process. It is utilized in this study's framework because of its ability to check the interdependence among the proposed criteria and extract their interrelationships. Evaluating these relationships can help practitioners or policymakers to increase the evaluation processes' efficiency.

Group Decision Making

MCDM aims to discover the most appropriate alternative by conceiving multiple criteria concurrently. GDM may be adequate to reach an objective solution in this procedure. GDM involves various DMs having different backgrounds or points of view and handling the decision process distinctive from others. However, each DM has shared awareness of cooperating with each other to achieve a collective decision. While having haziness and uncertainty, reaching a consensus for a decision in a group with different opinions turns out to be more critical. Generally, GDM problems are solved using classic approaches, such as the majority rule, minority rule, or total agreement. Yet, these techniques do not assure an acceptable solution for all DMs (Büyüközkan and Güleryüz, 2015).

In this paper, a consensus-reaching process is followed by the Delphi approach. Delphi is a communication instrument that facilitates group decision-making. The Delphi process is very efficient for supporting a group of individuals to handle complicated problems as a group. The method is based on expert knowledge, and the group is principally formed with knowledgeable and expert contributors (Büyüközkan et al., 2004).

The assessment made by DMs depends on their judgment and is subjective. Accordingly, instead of crisp numbers, the linguistic variables are given to the DMs to represent their data's uncertain and subjective nature.

MARCOS Method

The MARCOS method is based on defining the relationship between alternatives and reference values (ideal and anti-ideal alternatives). Based on the determined relationships, the utility functions of options are determined, and compromise ranking is made concerning ideal and anti-ideal solutions. Utility functions represent the position of an alternative concerning an ideal and anti-ideal solution. Decision preferences are defined based on utility functions. The best option is the one closest to the ideal and, at the same time, furthest from the anti-ideal reference point.

The advantages of the MARCOS method are (Stević et al., 2020):

- the consideration of an anti-ideal and ideal solution at the very beginning of the formation of an initial matrix,
- closer determination of utility degree concerning both solutions,
- the proposal of a new way to determine utility functions and their aggregation,

- the possibility to consider a large set of criteria and alternatives while maintaining the method's stability.

MARCOS method is used for various MCDM problems in literature. Even if it is a newly introduced technique, it has been used for multiple sectors and areas (Du et al., 2022; Gamal et al., 2022; Khosravi et al., 2022; Rakhmangulov et al., 2022).

The MARCOS method is like the TOPSIS method; it covers seven uncomplicated steps to reach an optimum solution closer to the compromise solution (Stević et al., 2020). Also, the extension of the MARCOS method with the 2-TL linguistic model augments its flexibility and the interpretability of the results for complicated and ambiguous application areas.

To the best of our knowledge, the MARCOS method has not been used in SA. Besides, the 2-TL extension of MARCOS have not been applied in MCDM literature. Accordingly, to emphasize the MARCOS method's accuracy with linguistic variables and augment the objectiveness in decision-making, this paper provides a 2-TL MARCOS framework for smart agriculture technology evaluation.

2-TL MARCOS Method

The 2-TL MARCOS method is performed through the following steps:

Step 1: Forming the initial decision-making matrix.

Matrix D is the aggregated assessments of *l* DMs where $d_{ij} = \{d_{ij}^1, d_{ij}^2, d_{ij}^3 \dots, d_{ij}^l\}$ contains the relative importance of criterion *i* in relation to alternative *j* and $d_{ij} = (s_1, \alpha_1)$ includes the 2-TL linguistic values assigned by DMs.

$$D = [d_{ij}] = \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} \begin{bmatrix} d_{11} & \cdots & d_{1n} \\ \vdots & \ddots & \vdots \\ d_{m1} & \cdots & d_{mn} \end{bmatrix} \quad (1)$$

By applying 2-TL aggregation operators such as 2-TL arithmetic mean, 2-TL weighted average, L2TOWA operator etc. In this 2-TL MARCOS model, we suggest using the 2-TL weighted average operator as in Eq. (2):

$$\bar{x}^w\big((s_1, \alpha_1), (s_2, \alpha_2), \dots, (s_l, \alpha_l)\big) = \Delta\left(\frac{\sum_{i=1}^{l} \Delta^{-1}(s_i, \alpha_i).w_i}{\sum_{i=1}^{l} w_i}\right) = \Delta\left(\frac{\sum_{i=1}^{l} \beta_i.w_i}{\sum_{i=1}^{l} w_i}\right) \quad (2)$$

where, *l* is the number of DMs, $\{(s_1, \alpha_1), (s_2, \alpha_2), \dots, (s_l, \alpha_l)\}$ is a set of 2-TL linguistic values and $W = \{w_1, w_2, \dots, w_l\}$ is their associated wights.

Step 2: Forming the extended initial matrix.

This step is to define the ideal *(AI)* and anti-ideal *(AAI)* solutions. Depending on the nature of the criteria, *AI* and *AAI* values are obtained with the following equations

$$\begin{aligned} AAI &= \min_i d_{ij} \ if \ j \in beneficial \ criteria \ and \ \max_i d_{ij} \ if \ j \in cost \ criteria \\ AI &= \max_i d_{ij} \ if \ j \in beneficial \ criteria \ and \ \min_i d_{ij} \ if \ j \in cost \ criteria \end{aligned} \quad (3)$$

Step 3: Normalizing the extended initial matrix to obtain the normalized matrix *(N).* The following equations give the elements of the matrix *N*.

$$n_{ij} = (n_{ij}, \alpha_{ij}) = \Delta\left(\frac{\Delta^{-1}(d_{ai})}{\Delta^{-1}(d_{ij})}\right) \; if\ j\ is\ cost\ criteria$$

$$n_{ij} = (n_{ij}, \alpha_{ij}) = \Delta\left(\frac{\Delta^{-1}(d_{ij})}{\Delta^{-1}(d_{ai})}\right) \; if\ j\ is\ benefit\ criteria \tag{4}$$

Step 4: Obtaining the weighted matrix.

The weighted matrix *V* is obtained by multiplying the normalized matrix *N* with the weight coefficients.

$$(v_{ij}, \alpha_{ij}) = \Delta\left(\Delta^{-1}(n_{ij}, \alpha_{ij}) \otimes \Delta^{-1}(w_{ij}, \alpha_{ij})\right) \tag{5}$$

Step 5: Calculating the utility degree of alternatives *(K_i).*

$$(K_i^-, \alpha_i) = \Delta\left(\frac{\Delta^{-1}(s_i, \alpha_i)}{\Delta^{-1}(s_{aai}, \alpha_{aai})}\right)$$

$$(K_i^+, \alpha_i) = \Delta\left(\frac{\Delta^{-1}(s_i, \alpha_i)}{\Delta^{-1}(s_{ai}, \alpha_{ai})}\right) \tag{6}$$

where (s_i, α_i) presents the sum of the elements in the weighted matrix *V.* It can be obtained by the following equation:

$$(s_i, \alpha_i) = \sum_{i=1}^{n} (v_{ij}, \alpha_{ij}) \tag{7}$$

Step 6: Obtaining the utility function (*f(K_i))* of alternatives with the following equation:

$$(f(Ki), \alpha_i) = \Delta\left(\frac{\Delta^{-1}(K_i^+, \alpha_i) + \Delta^{-1}(K_i^-, \alpha_i)}{1 + \frac{1 - \Delta^{-1}(f(Ki^+), \alpha_i))}{\Delta^{-1}(f(Ki^+), \alpha_i)} + \frac{1 - \Delta^{-1}(f(Ki^-), \alpha_i))}{\Delta^{-1}(f(Ki^-), \alpha_i)}}\right) \tag{8}$$

where $(f(Ki^-), \alpha_i)$ is the utility function in relation to the anti-ideal solution and $(f(Ki^+), \alpha_i)$ represents the utility function in relation to the ideal solution. They can be obtained by the following equations:

$$(f(Ki^-), \alpha_i) = \Delta\left(\frac{\Delta^{-1}(K_i^+, \alpha_i)}{\Delta^{-1}((K_i^+, \alpha_i) + \Delta^{-1}((K_i^-, \alpha_i)}\right)$$

$$(f(Ki^+), \alpha_i) = \Delta\left(\frac{\Delta^{-1}(K_i^-, \alpha_i)}{\Delta^{-1}((K_i^+, \alpha_i) + \Delta^{-1}((K_i^-, \alpha_i)}\right) \tag{9}$$

Step 7: Alternative prioritization.

The alternatives' prioritization is based on the final values of utility functions. The most appropriate option is the one with the highest score.

Case Study

In this section, a case study is suggested to test the plausibility of our suggested framework. The model has two stages; a decision-making group is formed from three different experts for both stages. What we expect from the experts is first to determine the relations between expectations for 2-TL-DEMATEL and then determine the ability of technologies to meet the expectations for 2-TL-MARCOS.

Different sets are offered mainly to make DMs comfortable during their assessments and provide them a flexible environment to express their opinions about the subjects. The three experts have diverse backgrounds in digital technologies and SA. Accordingly, two different linguistic sets are provided to them for their assessments. Here Table 2 gives the details of linguistic sets.

Table 2: Linguistic sets provided to DMs.

2-TL sets	
S^5	*None (N)-Low(L)- Medium (M)- High(H)-Perfect(P)*
S^9	*None (N)-Low (L)-Medium Low (ML)-Almost Medium (AM)- Medium (M)-Almost High (AH)-High(H)- Very High (VH)-Perfect(P)*

Stage 1: Calculating the expectation weights and their interrelations.

The assessments for pairwise comparisons are obtained from the decision-making group. We have worked with three experts; two of them are highly experienced in digital technologies and the SA area. The third expert is only experienced in digital technologies and is less experienced in SA. Accordingly, we have provided S^9 for two experts more experienced in SA*;* S^5 *for* the third. Table 3 provides the linguistic assessments of DM1 as an example, and followingly, Table 4 presents the aggregated initial decision matrix.

After applying 2-TL-DEMATEL steps, the weights of the expectations are obtained followingly: *Efficient strategy generation, (M, 0.29*); *Risk management, (M,0.11)*; *Trustable, on-time data, (M, -0.15)*; *Resource optimization, (AM, 0.02*); *Food security, (M, -0.11)*. Further analysis will be given in the Results and Discussions section.

Table 3: Assessments for DM1.

Smart Agriculture Expectations	**Efficient strategy generation**	**Risk Management**	**Trustable on-time data**	**Resource optimization**	**Food Security**
Efficient strategy generation	0.00	P	L	AH	H
Risk management	VH	0.00	L	M	VH
Trustable, on-time data	H	H	0.00	VH	AH
Resource optimization	ML	ML	L	0.00	AM
Food Security	M	ML	ML	L	0.00

Table 4: Aggregated initial decision matrix.

Smart Agriculture Expectations	Efficient strategy generation	Risk Management	Trustable on-time data	Resource optimization	Food Security
Efficient strategy generation	0.00	(AM, -0.20)	(L, -0.45)	(ML, -0.05)	(ML, -0.38)
Risk management	(AM, -0.47)	0.00	(L, 0.43)	(L, 0.40)	(AM, -0.35)
Trustable, on-time data	(ML, 0.10)	(ML, 0.10)	0.00	(ML, -0.48)	(ML, -0.12)
Resource optimization	(L, -0.25)	(L, -0.02)	(L, -0.45)	0.00	(L, 0.13)
Food Security	(L,0.28)	(L, -0.18)	(L, -0.42)	(VL,0.43)	0.00

Stage 2: Technology prioritization according to the expectations.

This stage is to assess the technologies according to their ability to meet the expectations of SA. Based on this target, each DM evaluated technologies according to the expectations in the previous stage. Plus, the expectation weights will be used as criteria wight at this stage. The aggregated evaluation matrix is given in Table 5.

After obtaining Table 5, the 2-TL-MARCOS steps provided in the previous section are applied. According to the results, a ranking of technologies according to their ability to meet the expectations is obtained. The detail of the results and a sensitivity analysis will be given in the next section.

Table 5: Aggregated evaluation matrix for 2-TL-MARCOS.

	Efficient strategy generation	**Risk Management**	**Trustable on-time data**	**Resource optimization**	**Food Security**
IoT	(L, 0.2)	(ML, -0.17)	(AM, -0.35)	(AM,0.20)	(ML, -0.17)
Sensors	(L,0.25)	(ML, 0.10)	(ML,0.37)	(ML,0.37)	(L,0.40)
ML/DL/AI	(AM, -0.35)	(ML, 0.48)	(L, -0.15)	(ML, -0.05)	(ML, 0.10)
Big Data	(ML, -0.05)	(ML, -0.05)	(AM,0.20)	(ML,0.48)	(ML, -0.05)
Cloud	(ML, -0.37)	(L,0.40)	(ML, 0.10)	(L,0.13)	(L, -0.42)
Robotics	(L, -0.42)	(ML, -0.05)	(L, -0.45)	(AM, -0.47)	(L,0.40)
Blockchain	(L,0.33)	(ML, -0.17)	(ML, 0.10)	(ML, 0.10)	(AM,0.20)
Digital Twin	(AM,0.20)	(AM,0.20)	(L, -0.45)	(AM, -0.35)	(AM, -0.35)
Simulation	(ML, -0.38)	(AM, -0.35)	(L, -0.30)	(ML, 0.10)	(ML, -0.05)
AI	**(AM,0.20)**	**(AM,0.20)**	**(AM,0.20)**	**(AM,0.20)**	**(AM,0.20)**
AAI	**(L, -0.42)**	**(L,0.40)**	**(L, -0.45)**	**(L,0.13)**	**(L, -0.42)**

Results and Discussions

The 2-TL-DEMATEL-MARCOS methodology is applied for the technology prioritization for SA. In the first stage, the expectation weights are obtained via the 2-TL-DEMATEL technique. The weights are presented in the linguistic form in the previous section, but their percentage weights are given in Figure 3 to better show their distribution for SA. As it can be seen from the figure, their importance is close. According to the numbers, it is easy to assume that

“Efficient strategy generation” seems to be the most critical expectation for SA. However, when the (D-R) values for each expectation are examined, cause-effect relations are obtained for expectations. If *(D-R)>0,* it means that the degree of affecting others is more substantial than the degree of being affected. Therefore, “Efficient strategy generation” is affected by two expectations: “Resource optimization” and “Food Security.” “Food security” is the third important expectation; yet concentrating on this expectation may provide a deeper impact on the transformation of agricultural systems. The (D+R) and (D-R) values are given in Figure 4. Accordingly, expectations 1,2,3 are influenced by other criteria.

(D+R) values stated in Figure 4 also state their importance. Accordingly, parallel to 2-TL-DEMATEL results, (D+R) values also show a similar ranking for expectation importance.

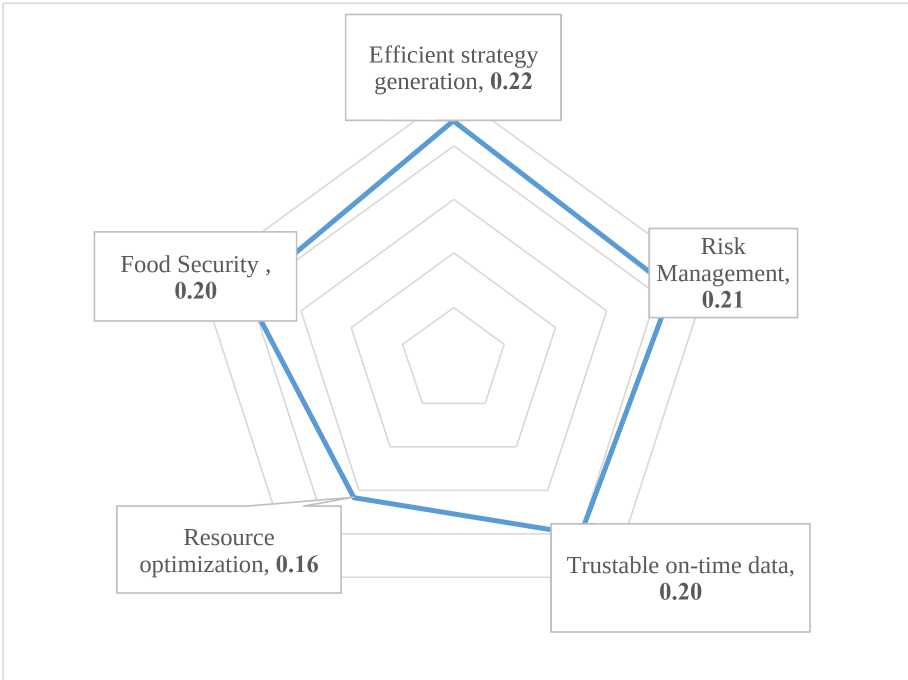


Figure 3: Expectation weighs on the radar chart.

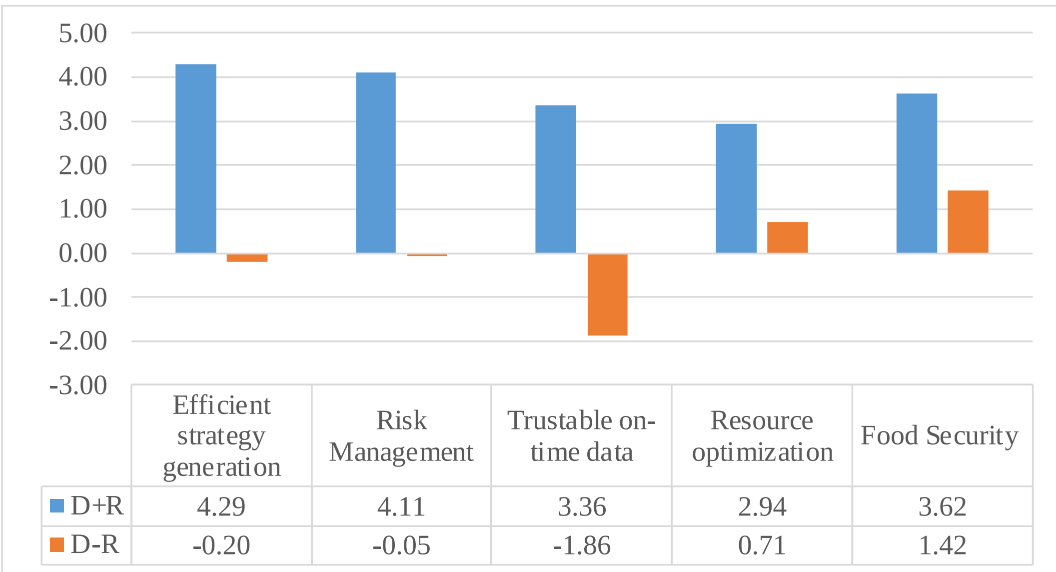
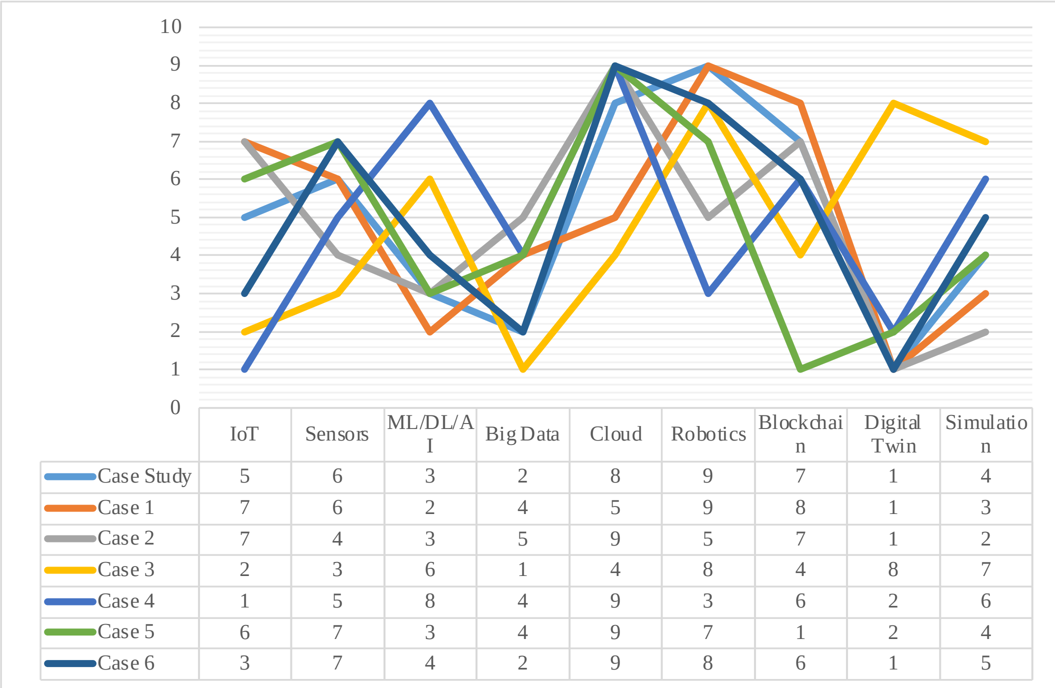


Figure 4: (D+R) and (D-R) values for expectations

Moreover, a sensitivity analysis to test the applicability under changing conditions. As stated in Figure 5, six different scenarios are generated, each emphasizing one expectation and last with equal weights. According to our case study, the most effective and moving technology for SA is selected as *Digital Twin*. When the different cases are compared, *Digital Twin* is still the one technology that is mostly ranked the first under different circumstances.

A *Digital Twin* is a digital equal of an actual entity that reflects its performances and states over its lifetime in a virtual space (Verdouw et al., 2021). Using Digital Twins as a management tool for farms allows aggregation of physical flows from its planning and control. Since the *Digital Twin* technology contains programming and AI/ML/DL together, maybe we can assume that the integration of ML/DL/AI together with programming may be the most powerful transforming milestone for conventional farming.



	IoT	Sensors	ML/DL/AI	Big Data	Cloud	Robotics	Blockchain	Digital Twin	Simulation
Case Study	5	6	3	2	8	9	7	1	4
Case 1	7	6	2	4	5	9	8	1	3
Case 2	7	4	3	5	9	5	7	1	2
Case 3	2	3	6	1	4	8	4	8	7
Case 4	1	5	8	4	9	3	6	2	6
Case 5	6	7	3	4	9	7	1	2	4
Case 6	3	7	4	2	9	8	6	1	5

Figure 5: Sensitivity analysis and case study results.

Conclusions

This paper suggests a linguistic-based MCDM methodology for the technology evaluations in SA. The SA area is chosen thanks to its importance for sustainable development. Also, with Industry 4.0, we face new production systems approaches. Since agriculture is civilization's most critical production network, its digital transformation should be addressed carefully. Therefore, the expectations from SA are derived from the SA advantages stated in the academic and industrial literature. Afterward, the technologies are assessed according to their ability to meet these expectations. To obtain the most powerful technology, first, the expectations are weighted via the 2-TL-DEMATEL technique, and then 2-TL-MARCOS is used to calculate the ranking.

According to the case study, the most prominent technology to meet the expectations is chosen as a *Digital Twin*. Yet, by analyzing these results, underlining the importance of AI/DL/ML technologies is necessary. For future studies, more analysis may be applied for further analysis of technologies and their dependencies. The 2-TL-MARCOS technique can be compared to other 2-TL-based methodologies. Moreover, by updating the expectation criteria, the same methodology can be applied to other sectors such as supply chain and construction.

In this study, the main limitation is the number of DMs used in the case. The number of DMs can be augmented to reach a more objective solution. Also, for future studies, a large group decision-making model can be applied to the same problem to cover more end-users and obtain real stakeholder opinion for expectation weighting.

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