Explainable Assessment Model for Digital Transformation Maturity

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Keywords: Digital Transformation, Maturity, Assessment, Machine Learning, Explainability, Organizations.

Abstract: Digital transformation has become a critical factor for organizational success in the modern business landscape. However, effectively and automatically assessing the maturity of this transformation remains a significant challenge. In this paper, we address the need for a unified and explainable digital maturity model to guide organizations in their transformation journey. Our primary research questions focus on the development of a core digital maturity model, the automatic validation of its effectiveness, and its explainability. To this end, we propose a core model composed of seven key dimensions (Technology, Strategy, Skills, Culture, Organization, Data, and Leadership) derived from an extensive literature review. Each dimension is assessed across five maturity levels (Basic, Discovery, Developed, Integrated, and Leadership). We then validate the proposed model by leveraging machine learning techniques to assess its applicability within organizations. Finally, we introduce an ensemble learning approach that combines unsupervised and supervised learning methods to enhance the explainability of the proposed digital maturity model. This approach aims not only to assess but also to elucidate the impact of different dimensions on digital maturity.

1 INTRODUCTION

In today's business world, digital transformation (DT) has become a key focus in both information systems research and business practice, with 84% of global companies considering it as critical to their survival in the next five years (Van Veldhoven and Vanthienen, 2022). Going digital is becoming a necessity as a study in 2011 done by MIT Center for Digital Business and Capgemini Consulting emphasized companies face common pressures from customers, competitors, and employees to initiate their DT (McAffee et al., 2011). According to the McKinsey research report in 2018, the current success rate for DT in enterprises is only 30 % (McKinsey and company, 2018). This is due to the fact that DT is a complex system engineering, which is affected by the interaction of many factors to jointly promote the success of such transformation. Thus, while navigating the complexities associated with the DT, managers find themselves overwhelmed by the range of possible dimensions to consider (Kiron, 2016).

Significant progress has been made in understanding DT, with growing research on its driving factors. Still, a structured perspective is essential to effectively guide DT efforts (Neff, 2014). As a result, organizations require tailored guidance to navigate their DT journeys and assess their current level of digital maturity (DM). Hence, the need for an effective management of the stages of DT requires that digital maturity models (DMMs) to be put into practice (Thordsen et al., 2020). DM provides an accurate projection of a company's DT progress; it assesses the impact of such transformation, making it essential to measure the company's current position. It evolves with the ever-changing digital landscape (Akdil, 2017). Therefore, firms must continuously assess their maturity to adapt effectively in this dynamic environment. Such assessments are crucial and depend on models that provide reference frameworks, incorporating evaluation criteria and indicators. In this context, the main research questions explored in this paper are:
(1) How to build a core DMM for an efficient and relevant DM assessment?
(2) How to automatically validate the core model?
(3) How can the core model be interpreted and made explainable?
The structure of the paper is as follows: first, we conduct a comprehensive literature review to explore the current state of knowledge, including key concepts and DMMs in the field. Second, we identify exist-

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Hlel, J., Ben Yahia, N., Ben Saoud and N. B.
Explainable Assessment Model for Digital Transformation Maturity.
DOI: 10.5220/0013459300003967
In *Proceedings of the 14th International Conference on Data Science, Technology and Applications (DATA 2025)*, pages 310-317
ISBN: 978-989-758-758-0; ISSN: 2184-285X

ing research gaps related to DT and DM. Next, we present our core model for DM assessment. In the following section, we use machine learning (ML) techniques to validate the proposed model. Finally, we combine supervised and unsupervised learning methods to enhance its explainability.

2 BACKGROUND AND RESEARCH GAP

DM refers to the scenario in which an organization has successfully undergone a transformation (Akdil, 2017). It is not a static concept due to the digital landscape change (Akdil, 2017). Thus, an organization needs to assess it over time. In this context, maturity models (MMs) are conceived as "frameworks that evaluate the maturity of an organization through the definition of a set of structured levels" (Battista and Schiraldi, 2013). By examining the aspects of different MMs, common characteristics were extracted. They consist of (a) maturity level, (b) descriptor for each maturity level, (c) a generic description of each level, (d) dimensions, (e) elements linked to corresponding dimensions, and (f) a description of each element for each level of maturity (Fraser et al., 2002).

Although numerous MMs have been proposed, several factors contribute to their limitations in effectively assess an organization's DT (Akdil, 2017). For instance, many studies focus on specific regions and sectors and rely on diverse but potentially insufficient sample sizes. Additionally, the complexity of validating these models often necessitates third-party assistance, such as consultants, which increases costs and extends the time required for evaluations. In fact, validation of these models is frequently based on literature reviews or expert interviews, with minimal empirical evidence provided to substantiate their effectiveness. Moreover, a critical limitation of existing models is their lack of explainability. While they may provide an assessment of DM, they do not articulate the reasoning behind their conclusions. This opacity makes it difficult for organizations to understand why certain results are obtained or to derive actionable insights from the evaluation. Without explainability, organizations face challenges in building trust in the assessment process and aligning the findings with strategic decision-making. In this paper, we address these issues to develop an effective and actionable model that can better support organizations in navigating their DT.

3 THE PROPOSED CORE MATURITY MODEL

The proposed MM (Figure 1) serves as a core model with the minimum and sufficient dimensions for a relevant and efficient DM assessment. This study first undertakes a deep and up-to-date literature review, to develop a core holistic DMM that unifies the previous ones and covers several aspects of an organization's DT. The model is also generic built from multiple models from different sectors.

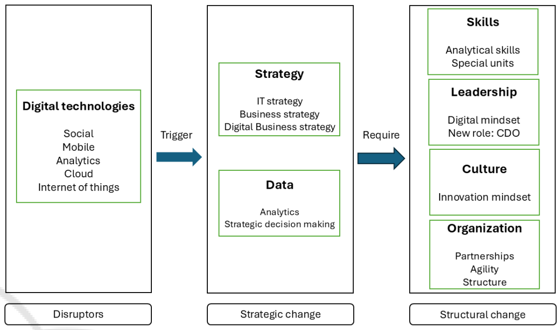

Figure 1: The proposed core DT maturity model.

3.1 The Dimensions of Proposed Maturity Model

As a basis for creating the core model, a review of the current literature on MMs was conducted. It involved a comparative analysis of several established models to assess the key dimensions crucial for achieving successful DT. The review led to the selection of seven core dimensions including technology, strategy, skills, leadership, culture, the organization, and data. Table 1 summarizes some of the existing models.

Table 1: Existing digital maturity models.

Dimension	Reference
Technology	(Foundation, 2023),(Tubis, 2023),(Khourshed et al., 2023), (Al-Ali and Marks, 2022), (van Tonder et al., 2024),(Kalender and Žilka, 2024)
Strategy	(Foundation, 2023), (Tubis, 2023), (Khourshed et al., 2023),(Al-Ali and Marks, 2022), (van Tonder et al., 2024),(Kalender and Žilka, 2024)
Skill	(Spaltini et al., 2022),(Khourshed et al., 2023), (Al-Ali and Marks, 2022), (van Tonder et al., 2024)
Culture	(Tubis, 2023),(Ávila Bohórquez and Gil Herrera, 2022), (van Tonder et al., 2024),(Kalender and Žilka, 2024)
Organization	(Foundation, 2023), (Khourshed et al., 2023),(van Tonder et al., 2024)
Data	(Foundation, 2023),(Tubis, 2023),(Ávila Bohórquez and Gil Herrera, 2022),(Khourshed et al., 2023)
Leadership	(Ávila Bohórquez and Gil Herrera, 2022), (Khourshed et al., 2023),(Al-Ali and Marks, 2022), (van Tonder et al., 2024),(Kalender and Žilka, 2024)

3.1.1 Digital Technologies

The emergence of digital technologies mentioned with the popular SMACIT have triggered DT as material antecedents (Vial, 2019). The literature describes digital technologies as inherent disrupters of the DT wave (Vial, 2019). They shape it due to their specific characteristics, referred to as digital properties. DT starts with the adoption of digital technologies, then evolving into an implicit holistic reshape of an organization, or deliberate pursuit of value creation (Vial, 2019).

3.1.2 Strategy

DT is depicted as a phenomenon that demands a rapid organizational response. Although the concept of strategy is often invoked to explain these responses, some researchers supported the traditional view which refers to the IT strategy as a subordinated functional-level strategy that must be aligned with the firm's business strategy. Others argue that strategic responses require two novel concepts in line with the DT: *digital business strategy*, which reflects a fusion between IT and business strategy, and *DT strategy* which is not part of any other strategy (Jimmy Bumann, 2019).

3.1.3 Skills

Prior research shows that human factors can significantly impact DT capacity (Kwon, 2017). Employee skills positively moderate the relationship between organizational capabilities and the success of DT. DT requires employees to depend more heavily on their analytical skills to solve increasingly complex business problems (Dremel, 2017). The survey done by MIT Center for Digital Business and Capgemini Consulting in 2011, reveals that some IT departments have established special units to track emerging technology skills and innovation centers to go with the digital disruption impact.

3.1.4 Leadership

In line with the DT, organizational leaders must ensure that their organizations develop a digital mindset to be capable of responding to the disruptions associated with the use of digital capabilities (Haffke, 2017). To that end, the literature highlights the creation of new leadership roles (Horlacher, 2016) as the *chief digital officer (CDO)*. The role of the CDO is to implement digital business strategy into a series of concrete actions.

3.1.5 Culture

Most of the firms that have initiated the DT often experience failures due to inert organizational cultures that resist change (Hartl, 2017). Yet, a suitable organizational culture is a key requirement for the successful transformation of businesses.

3.1.6 Organization

(Berghaus, 2017) considers partnerships and ecosystems an important element of this dimension. Hence, organizations must embrace a collaborative and partnership-driven approach by actively emerging and fusing organizational and IS strategy together to pursue respectful relationships with various stakeholders. While initially seen as competitors, partnerships should leverage each other's strengths to meet increasing customer needs. According to (Udovita, 2020), this dimension also encompasses the organization's agility, which refers to its ability to respond quickly to changes. Here, organizations should move away from traditional hierarchies and embrace leaner and flatter organizational structures (Vial, 2019).

3.1.7 Data

Data has a decisive role in the DT journey. The broad literature outlines that even strategic decision-making will be based on data-driven insights (Haffke, 2017). Furthermore, firms are engaging in analytics and combining with integrated data to gain a strategic advantage over competitors. As a consequence, organizations are compelled to enhance their proficiency in harnessing and leveraging data. Moreover, they can maximize the advantages of technologies by gathering data and using the derived insights to anticipate customer behavior.

3.2 Maturity Levels of Our Model

For the assessment of DM related to each dimension, we define a five-level maturity scale: 1—basic, level 2—discovery, level 3—developed, level 4—integrated, and level 5—leadership inspired from (Tubis, 2023). A detailed description of the assessment levels is presented in Table 4 in the appendix.

4 DATA-DRIVEN VALIDATION OF THE PROPOSED MM

In order to validate the proposed model, we rely on data-driven approaches. Thus, empirical evidence will be provided based on real data collected through an assessment survey. The process from data collection to the model validation is presented in Figure 2.

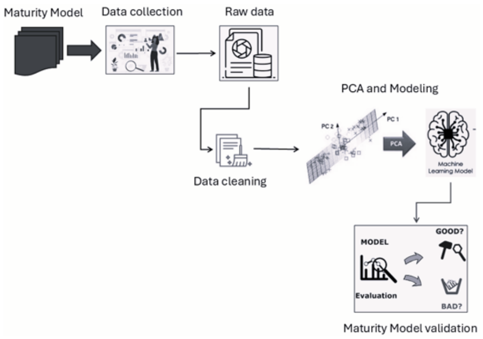

Figure 2: Model validation approach.

4.1 Data Acquisition and Interpretation

Our MM is structured around seven dimensions each is mapped to the criterion at each level according to the degree of maturity. Individual areas and sub-areas are assessed on five levels. The general characteristics of individual levels are presented in Table 2. This mapping is then used to produce a questionnaire filled out by employees at the management level, which is later carried out to assess organizational maturity level and collect the necessary data. After collecting 216 survey responses, the data was compiled into a structured tabular dataset. Our proposed scoring system uses Python-defined functions to compute DM scores for each dimension—stored as new features in the dataset—and calculates the overall maturity level as the average of these dimension scores based on organizational responses. Our final dataset features and their definition are shown in Table 2.

4.2 Principal Component Analysis

In our study, we rely on principal component analysis (PCA) to extract important insights from the collected data, to do so it is crucial to, first, determine how many principal components (PC) to select. The *elbow* test, is used to identify the best number of components (Abdi and Williams, 2010). It suggests using 7 PCs, which explain nearly 80% of the total variance.

In Figure 4 we plot the loading of each feature on every PC. PC1, dominated by features like Integration of Digital Skills (0.701), Training Sessions (0.416), and Mode of Analytics (0.270), represents organizational DM. PC2 captures a trade-off between skills integration (0.546) and factors like Culture of Digitization (-0.491) and AI Integration (-0.391), highlighting a tension between skill-building (0.546) and technological or cultural factors (-0.491). PC3 is influenced by Culture of Digitization (0.744), contrasting it with AI-driven strategies (-0.384), while PC4 emphasizes AI Integration (0.682). The later components, like PC5 to PC7, represent more specific patterns, such as partnerships, analytical capabilities, and strategic alignment (Digital Mindset).

Table 2: Dataset description.

Features	**Definition Domains in the survey**
Implementation of DT Plans	Yes, No
Budget for DT	Yes, No
Approach to Digitization Strategy	Business development is driven by the digitization strategy, implementing and optimizing its practices; Business development is driven by the digitization strategy
Openness to New Ideas	High, Low
Continuous Improvement Strategy	Yes, No
Culture of Digitization	Encourages advanced solutions, rewarding innovators; Promotes human-machine collaboration with transparent risk management
ICT Devices Usage	Yes, No
AI Integration	M2M (machine-to-machine) deployed; Cloud, IoT and AI; Cloud and IoT
Data Collection Strategies	Yes, No
Mode of Analytics	Descriptive; Descriptive, Predictive and Prescriptive; Descriptive and Predictive
Real Time Analytics	Yes, No
Digital Literacy Programs	Yes, No
Training Sessions	Planned, Random, Systematic
Integration of Digital Skills	Enhances operational efficiency and collaboration; Continuously improves knowledge sharing and skill development
Awareness of DT	Yes, No
Presence of CDO	Yes, No
Digital Mindset	Strongly Defined, Fully Embedded, Clearly Defined
Managing Key Partners	Yes, No
Managing Partnerships	Established partnerships contribute to operations; Fully integrated partnerships with real-time data exchange; Personalized partnerships with real-time data for decision-making
Overall Digital Maturity	1, 2, 3, 4, 5

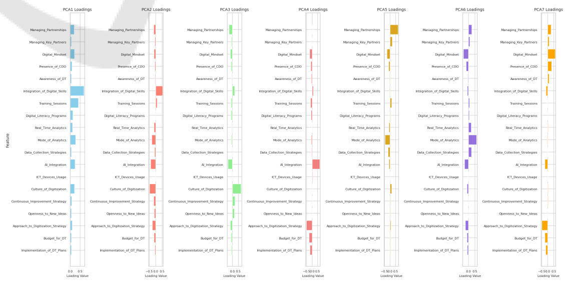

Figure 3: PCA loadings.

4.3 Machine and Deep Learning Algorithms for Model Validation

In our study, we explore machine and deep learning (DL) techniques for the validation of our model. The idea is to evaluate the effectiveness of the model in predicting actual outcomes. High prediction results suggest that the core model is valid and accurate for DM assessment. Since our dataset is structured, recommended ML algorithms were explored such as, K nearest neighbor (KNN), support vector machine (SVM), decision tree, ensemble of decision trees (random forest (RF) and extreme gradient boosting (XGBoost)), and multiple layer perceptron (MLP) (Yahia et al., 2021). In tabular data, relationships between features are often intricate and interdependent, requiring the model to capture both local and global patterns. Convolutional Neural Networks (CNNs) (Mziou-Sallami et al., 2023) are suited for this task. To effectively train them a large amount of data is required. Therefore, we used a data augmentation technique. This process expanded our dataset from 226 to 1000 records. Thus, we aim to validate the proposed model not only on a small dataset but also on a larger dataset to ensure its robustness and generalizability.

4.4 Results and Discussion

As mentioned above, we have applied KNN, SVM, decision tree, RF, XGBoost, and MLP for small real data, and CNN for augmented data. Table 3 shows the obtained results.

Table 3: Performance evaluation results.

Algorithm	Acc.	Prec.	Rec.	F1
KNN	0.80	0.83	0.78	0.78
SVM	0.95	0.93	0.97	0.95
Decision Tree	0.66	0.62	0.65	0.62
RF	0.79	0.81	0.81	0.81
XGBoost	0.78	0.76	0.87	0.78
MLP	0.83	0.81	0.84	0.82
CNN	0.73	0.75	0.73	0.72

Combined, these metrics imply that the model accurately captures underlying patterns in the data and generalizes well. This underscores that our proposed MM is accurate and can efficiently assess the DM.

In our study, we identified the minimal set of dimensions from the literature necessary for evaluating maturity and validated their sufficiency using ML and DL algorithms. By systematically excluding features representing specific dimensions, we observed a significant drop in model accuracy meaning that the evaluation of the digital maturity is no more optimal, demonstrating that this minimal set is both essential and optimal for assessing digital maturity without requiring additional dimensions thus the evaluation of the digital maturity is no more optimal.

5 EXPLAINABILITY OF THE PROPOSED MATURITY MODEL

Existing studies provide insights into the coverage of dimensions within MMs, but they fail to address how to explain their results. To bridge this gap, we suggest using a decision tree algorithm to identify rules derived from the outputs of a K-Means clustering algorithm. By doing so, our approach (illustrated in Figure 5) provides clear explanations for the clusters, maintaining the interpretability of results.

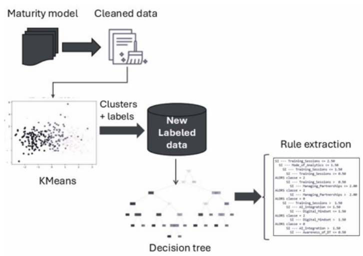

Figure 4: Cluster-based-classification for maturity model explainability.

Clustering offer a powerful tool for grouping organizations based on their maturity characteristics (Wani, 2024). Ensuring that derived decisions can be clearly understood is a fundamental requirement aiming at making clustering results transparent and meaningful. Thus, we enhanced our dataset with cluster labels generated by k-means and subsequently applied a decision tree classifier. By combining k-means' capability to detect patterns with the decision tree's explainability, we intend to make the assessment insightful. This approach was applied on both a small and augmented dataset, underscoring that our primary focus is not the validation of the data itself but the evaluation of the pipeline and the core MM.

5.1 A Cluster-Based-Classification Within Small Dataset

K-means require a predefined number of clusters (k), therefore, the elbow method is used. It involves calculating the WCSS for a range of k values and plotting WCSS against k. The optimal k is identified at the elbow point, where the rate of WCSS decrease levels off (Wani, 2024). Here, We got an "elbow" at $k=3$.

Then, having applied k-means, we assigned the resulting cluster labels to the data points, creating a newly labeled dataset. Below are the rules derived from the hybrid of the k-means and the decision tree algorithm. Each rule highlights the conditions under which a particular class (cluster) is predicted.

Rules extracted from the decision tree within the small dataset

1. **Rule 1:** If Training_Sessions $\leq$ 2.50 and Mode_of_Analytics $\leq$ 1.50, then:
   (a) If Training_Sessions $\leq$ 1.50, then:
      i. If Training_Sessions $\leq$ 0.50: **Class = 2**.
      ii. If Training_Sessions $>$ 0.50, then:
         A. If Managing_Partnerships $\leq$ 2.00: **Class = 2**.
         B. If Managing_Partnerships $>$ 2.00: **Class = 0**.
   (b) If Training_Sessions $>$ 1.50, then:
      i. If AI_Integration $\leq$ 1.50, then:
         A. If Digital_Mindset $\leq$ 1.50: **Class = 2**.
         B. If Digital_Mindset $>$ 1.50: **Class = 0**.
      ii. If AI_Integration $>$ 1.50, then:
         A. If Awareness_of_DT $\leq$ 0.50, then:
         B. If Approach_to_Digitization_Strategy $\leq$ 1.50: **Class = 2**.
         C. If Approach_to_Digitization_Strategy $>$ 1.50: **Class = 0**.
         D. If Awareness_of_DT $>$ 0.50: **Class = 0**.
2. **Rule 2:** If Training_Sessions $\leq$ 2.50 and Mode_of_Analytics $>$ 1.50, then:
   (a) If Approach_to_Digitization_Strategy $\leq$ 0.50, then:
      i. If Training_Sessions $\leq$ 1.50, then:
         A. If AI_Integration $\leq$ 3.50: **Class = 2**.
         B. If AI_Integration $>$ 3.50: **Class = 0**.
      ii. If Training_Sessions $>$ 1.50: **Class = 0**.
   (b) If Approach_to_Digitization_Strategy $>$ 0.50, then:
      i. If AI_Integration $\leq$ 1.50, then:
         A. If Culture_of_Digitization $\leq$ 0.50: **Class = 2**.
         B. If Culture_of_Digitization $>$ 0.50: **Class = 0**.
      ii. If AI_Integration $>$ 1.50: **Class = 0**.
3. **Rule 3:** If Training_Sessions $>$ 2.50: **Class = 1**.

5.2 A Cluster-Based-Classification Within Augmented Dataset

Even with augmented data, the elbow test remains robust, with k=3 .

Rules extracted from the decision tree within the augmented dataset

1. **Rule 1:** If Training_Sessions $\leq$ 2.50 and Mode_of_Analytics $\leq$ 1.50, then:
   (a) If Training_Sessions $\leq$ 1.50, then:
      i. If Digital_Literacy_Programs $\leq$ 0.50: **Class = 1**.
      ii. If Digital_Literacy_Programs $>$ 0.50, then:
         A. If Managing_Partnerships $\leq$ 1.50: **Class = 1**.
         B. If Managing_Partnerships $>$ 1.50, then:
         C. If Data_Collection_Strategies $\leq$ 0.50: **Class = 1**.
         D. If Data_Collection_Strategies $>$ 0.50: **Class = 2**.
   (b) If Training_Sessions $>$ 1.50, then:
      i. If AI_Integration $\leq$ 2.50, then:
         A. If Managing_Partnerships $\leq$ 2.50: **Class = 1**.
         B. If Managing_Partnerships $>$ 2.50: **Class = 2**.
      ii. If AI_Integration $>$ 2.50, then:
         A. If Approach_to_Digitization_Strategy $\leq$ 1.50, then:
         B. If Awareness_of_DT $\leq$ 0.50: **Class = 1**.
         C. If Awareness_of_DT $>$ 0.50: **Class = 2**.
         D. If Approach_to_Digitization_Strategy $>$ 1.50: **Class = 2**.
2. **Rule 2:** If Training_Sessions $\leq$ 2.50 and Mode_of_Analytics $>$ 1.50, then:
   (a) If Implementation_of_DT_Plans $\leq$ 0.50, then:
      i. If Training_Sessions $\leq$ 1.50, then:
         A. If AI_Integration $\leq$ 3.50, then:
         B. If Managing_Partnerships $\leq$ 2.50: **Class = 1**.
         C. If Managing_Partnerships $>$ 2.50: **Class = 2**.
         D. If AI_Integration $>$ 3.50, then:
         E. If Digital_Literacy_Programs $\leq$ 0.50: **Class = 2**.
         F. If Digital_Literacy_Programs $>$ 0.50: **Class = 1**.
      ii. If Training_Sessions $>$ 1.50: **Class = 2**.
   (b) If Implementation_of_DT_Plans $>$ 0.50, then:
      i. If ICT_Devices_Usage $\leq$ 0.50, then:
         A. If Continuous_Improvement_Strategy $\leq$ 0.50: **Class = 1**.
         B. If Continuous_Improvement_Strategy $>$ 0.50: **Class = 2**.
      ii. If ICT_Devices_Usage $>$ 0.50, then:
         A. If Managing_Key_Partners $\leq$ 0.50, then:
         B. If Mode_of_Analytics $\leq$ 2.50: **Class = 1**.
         C. If Mode_of_Analytics $>$ 2.50: **Class = 2**.
         D. If Managing_Key_Partners $>$ 0.50: **Class = 2**.
3. **Rule 3:** If Training_Sessions $>$ 2.50: **Class = 0**.

5.3 Findings Interpretation

The interpretation of the two generated rule bases reveal key insights into the DM. On the one hand, the rules exposes the importance of core features such as ”training sessions”, ”mode of analytics”, and ”AI integration” in determining classes/ clusters which validates the results obtained previously from the PCA. They, also, offer practical implications by guiding organizations to address gaps in areas like ”data collection” and ”partnership management” and emphasizing actionable steps that can enhance DM. On the other hand, findings emphasize the scalability of our MM, proving its adaptability to varying contexts. The consistency of interpretable rules across original and augmented datasets validates the framework’s robustness, illustrating its capability to generate meaningful assessments regardless of the dataset.

6 CONCLUSIONS

This paper presents a unified and explainable digital maturity model. By focusing on seven key dimensions, the model evaluates digital maturity across five levels. A data-driven validation approach based on machine learning has been used to validate the model. Then, an ensemble learning approach combining unsupervised and supervised methods is proposed to enhance the model’s effectiveness and explainability. As organizations evolve, the dynamic nature of digital maturity must be considered. Future work should focus on expanding the model to track organizational changes over time, providing a continuous feedback to optimize digital transformation efforts.

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APPENDIX

Table 4: Digital maturity assessment levels.

	Basic	Discovery	Developed	Integrated	Leadership
Strategy	The organization has prepared assumptions for the DT implementation or has implemented an initial plan with specific highlights.	The organization has an implemented strategy for digitization and assesses its effeciency through analyses. Managers and consultants notify the readiness for starting digital changes.	The organization has a devoted budget for DT. Employees at all levels of the organization are engaged in the DT processes.	Business development is drived by the digitization strategy. The organization conduted systematic risk assessment concerning DT.	The organization implements practices of digitization strategies and optimizes them.
Culture	Change management is supported by employees' openness and the assisstance of managers in implementing new ideas and innovations	The organization has adopted a continuous improvement strategy and a change management system. Employees are kept informed about the risks and changes associated with digitization.	Advanced solutions are fostered in the organization, and their owners are awarded. Employees benefit from a support in risk management related to digitization.	The organization worked with a culture open to digitization and use of new technologies. Employees agree with the coorporaton with active human-machine .	The organization applies optimal practices to cultivate a culture of collaborative human-machine interaction, arising from transparent risk management regarding digitization.
Technology	The organization uses information and communication technology for horizontal and vertical integration in the internal value chain. It also uses mobile devices for communication among employees.	The organization uses sensors for data collection and operation monitoring, in addition to cloud computing to save and share data.	The organization exploit the Internet of Things for device connection and data transfer among them.	The organization uses autonomous devices to help in decision making, and AI to optimize processes.	A machine-to-machine communication system (M2M) is deployed to allow devices to interact autonomously.
Data	The organization collected data periodically without a clear strategy. Basic standards are developed for data collection and share at least manually and insights are realised sporadically.	The organization implemented a data management strategy supported by advanced tools (data life cycle management and data quality). Basic descriptive analytics are used.	A clear data strategy has been established. The organization has automated data collection and distribution, including the automatic generation of reports sent to relevant managers. Descriptive and diagnostic analytics are used.	Data strategy is well -established and aligns closely with the strategic goals of the organization. The organization has deployed a data integration platform, to guarantee real-time data access. Predictive analytics are integrated into business processes	The organization completely integrates data as a core strategic asset into culture and operations. The organization use real-time and automated transfer of data between the existing systems. Prescriptive analytics are used to provide actionable recommendations for business outcomes enhancement.
Skills	The organization provides its employees with training sessions to enhance their digital skills (e.g., assistance for novel digital solutions, data analytics,...).	Employees imrpove their data analytical and analyses skills. A plan for acquiring and developing digital skills for employees and managers has also been in place.	The organization has implemented a systematic knowledge management and employee development strategy using analytical tools for its implementation.	The required skills related to DT and an cross-disciplinary mindset are ubiquitous which covers the whole levels of management.	The organization implements the best practices of knowledge management and employee development.
Leadership	There is little awareness or understanding of DT within leadership. There is no assigned leader in charge of riding digital initiatives.	Few leaders are starting to understand the necessity for a digital mindset.Initial steps are being taken to clarify the responsibilities of a CDO.	A digital mindset is clearly defined and articulated within the leadership team. A CDO is formally appointed with a clear mandate to drive and coordinate DT efforts.	Leadership shows a strong digital mindset, using data-driven decision making and a culture of innovation and continuous improvement. The CDO role is well-established and integrated into the executive leadership team.	The digital mindset is fully embedded within the leadership and organizational culture. The CDO role evolves into a central strategic function, driving DT.
Organization	Collaboration with partners is ad hoc and unstructured. There is minimal inetgration with business partners and information exchange is limited. Organization is rigid to change and its structure is hierarchical and siloed.	There is basic processes for managing relationships with key partners. Some processes have been adjusted to allow for quiker changes. Inititives to improve croos-functional communication and collaboration.	Key business partners are informationally integrated with some of the processes carried out as part of the organization. The organizational structure include clear roles and responsabilities.	The cooperation of the organization with business partners is individualized and managed based on analyses and infor -mation integration, as well as data available in real-time. There is a systematic approach to respond to changes and the organizational structure is flexible and supports dynamic reconfiguraton.	Partnerships are fully integraed, there is a continuous xchange of real-time data. The organization exhibits peak agility, with optimized processes for responsiveness and innovation optimized The organizational structure is highly fluid and adaptive