An Interpretable Deep Learning Framework for Measuring Organizational Digital Transformation Readiness

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***Abstract*—The accelerating pace of digital transformation (DT) across industries demands accurate, transparent, and adaptable maturity evaluation frameworks capable of capturing complex organizational behaviors. Conventional fuzzy logic and decision tree-based maturity models cannot effectively represent the nonlinear dependencies among DT indicators and often produce inconsistent, opaque assessments. To overcome these limitations, this study proposes the TUMI (Transformer TabNet Unified Maturity Intelligence) framework, a novel hybrid deep learning architecture specifically designed for DT maturity assessment. The framework uniquely integrates FT-Transformer and TabNet, enabling simultaneous modeling of global feature dependencies through attention mechanisms and localized sparse feature selection aligned with DT maturity metrics. This domain-tailored hybridization goes beyond existing hybrid or ensemble approaches by supporting real-time readiness estimation, accommodating heterogeneous organizational indicators, and offering structured interpretability based on complementary attention weights and feature selection masks. The proposed model was trained using a multi-dimensional DT maturity dataset implemented in Python (PyTorch). Experimental results demonstrate strong predictive performance, with 97.0% accuracy, 96.0% precision, 95.0% recall, and an AUC of 98.2%, representing an 8.5% improvement over traditional fuzzy and decision tree models. The interpretability provided by the combined mechanisms offers clearer insight into the organizational determinants influencing maturity progression. Overall, TUMI enhances transparency, diagnostic capability, and scalability, providing an evidence-based, explainable, and cross-industry applicable solution for supporting organizations in evaluating and improving their digital transformation maturity.**

Keywords*—*Digital transformation; FT-Transformer; TabNet; maturity intelligence; deep learning

I. Introduction

DT has emerged as an important component of firm competitiveness due to its fundamental change in the way organizations have used technology to enhance operations, governance, and risk management [1]. In the case of publicly traded companies, digital maturity is positively correlated with the size of the market capitalization, investor trust, and sustainability by the market [2]. The latest progress in artificial intelligence (AI), cloud computing, and big data has increased the adoption pace - companies can create new business models and take strategic risks [3]. Nevertheless, evaluating the maturity of the process of DT, is one of the most challenging tasks of businesses that are subject to the control of financial indicators [4] The conventional models of maturity are basically the use of static checklists, expert views or qualitative surveys -all of which simplify the digital developments or are investment based but fail to encapsulate what [5]. Lastly, conventional approaches have a low propensity in considering uncertainty and linear relationships in organizational data [6]. The outcome is that more complex intelligent frameworks are required to take into account qualitative and quantitative cues, and give simpler, resilient, readable, and operational maturity analysis [7].

The most recent breakthroughs in artificial intelligence, particularly machine learning and deep learning, indicate potential for higher fidelity in organizational maturity assessments [8]. Ensemble techniques such as Random Forests and boosting methods are regarded as highly effective when working with structured datasets [9]. Challenges arise, though, as these techniques struggle to capture higher-order dependencies of features across environmental conditions [10]. Similarly, marker-based supervised classification deep learning methods, such as multilayer perceptrons, have the potential for predictive accuracy; however, they tend not to be explainable, and so create decreased buy-in in decision-making scenarios. Thus, a research gap exists where an advanced method improves performance while also providing explainability. To this end, researchers have begun to validate domain-specific models for structured, tabular datasets. FT-Transformer employs an attention mechanism to uncover complex feature interaction, whereas TabNet provides accuracy as well as interpretability using feature selection masks. While both FT-Transformer and TabNet are effective when used alone, they may not achieve their full potential. In order to address these limitations, the study proposes a new hybrid architecture that is vastly different as compared to the prior models of maturity assessment. The current deep learning, fuzzy-rule-based, and decision-tree methods fail to describe global aspects of feature dependencies and local sparse selection, as well as offer decision-tree specific interpretability in line with organizational indicators. FT-Transformer, combined with the TabNet TUMI framework, is the first to integrate both FT-Transformer and TabNet in domain-specific ways to support nonlinear maturity development, real-time evaluation needs, and multimodal enterprise information integration. This stance brings out the uniqueness of innovation and the methodological change that this study brings to the literature on maturity modeling. This research direction is also associated with a social impact, where the objectivity of an assessment of maturity can be provided by information, and will allow the digital transformation to be more fairly adopted by small and medium-sized businesses. The framework helps to enhance the access and equitableness of organizational readiness evaluation by reducing the reliance on specialized assessors and offering evidence-based information in an automated manner. In order to clearly define the objective of this work and fill in the existing research gap, the following research question is set:

How can a hybrid deep learning framework integrating FT-Transformer and TabNet enhance the accuracy and interpretability of digital transformation maturity assessment?

A. Problem Statement

The concept of DT maturity models is gaining traction in both academic and practitioner contexts; however, the majority of existing literature remains limited in significant ways. Most existing maturity models remain among the more traditional, qualitative frameworks, relying on descriptive scales and subjective expert evaluations, which limits their objectivity and industrial comparability [11]. Even when statistical or machine learning techniques have been utilized, the methods generally remain confined to more conventional, and often less-than-efficient, classifiers to standardize complexity, while also overlooking the nonlinear relationships or interactions among multiple organizational factors (e.g., culture, leadership, tech investments, and innovation capability) that shape the experience of the organization. Moreover, the deep learning models are not interpretable. Deep learning may be more precise, though such models do not give much insight into decisions to be made by decision-makers. Moreover, the existing literature usually follows up on maturity at a certain point in time, neglecting the dynamic and changing process of DT [12]. These shortcomings address the fact that they require flexible, open and legitimate instruments that can offer a holistic view of organizational maturity. Thus, it is evident that there are gaps in the literature to develop hybrid deep learning systems that can enhance predictive performance and offer useful information to practitioners. It is significant that organizations should address these gaps to evaluate their progress in DT and establish evidence-based plans to continue working and stay competitive.

B. Research Motivation

This research is motivated by the immediate need to develop objective and intelligible models in the evaluation of maturity in DT. The current methods lack sufficient variance (predictive ability) or fail to report results on Dunner (decisions) with respect to evenly relevant features. This study aims to create a hybrid structure that makes use of the advantages of FT-Transformer in its capability to model complicated interactions between features and the understandable features of TabNet, since the overall model accuracy and clarity will allow organizations to make data-driven and strategic choices to transform themselves.

C. Research Significance

This research is important in the sense that it creates a field of digital maturity measurement, which relies on the current state-of-the-art deep learning models. The hybrid system of FT-Transformer and TabNet is beneficial to the academies and the industry, since it balances the war between performance and explainability that has been long held. The findings will enable organizations to be more accurate at determining transformation readiness and, furthermore, identify what contributes to or is associated with maturity. Overall, the study introduces a findable, clarifiable, and solid instrument to the DT agenda in industries.

D. Key Contributions

- Proposed a novel hybrid deep learning framework (TUMI) that integrates FT-Transformer and TabNet to effectively capture both global feature dependencies and localized feature importance for DT maturity assessment.
- Introduced an attention-directed fusion scheme that interposes dense embeddings across the two branches, which better improves interpretability and model generalization across a wide range of organizational indicators.
- Introduces a domain-tailored hybrid deep learning architecture that uniquely combines attention-driven global feature interaction modeling with sparse, stepwise feature selection for DT maturity evaluation.
- Provides a two-level interpretability mechanism through Transformer attention maps and TabNet feature masks, offering more transparent maturity insights than current explainable AI methods in the DT domain.
- Development of a scalable and open-source maturity assessment tool, deployed in Python, based on Python, PyTorch framework, to support data-driven, real-time decision-making in organizations that have embarked on digital transformation.

The remainder of the study is organized as follows: Section II provides an extensive review of the related works that discusses the existing digital maturity models and their limitations. Section III elaborate on the proposed approach. Section IV present the experimental results and interpretation. The conclusion and future research directions, limitations, and recommendations are discussed in Section V.

II. Related Works

Marín Díaz & Galdón Salvador [13] improve group decision-making within organizations undergoing DT by suggesting a new methodology that calculates the Digital Maturity Level (DML) through fuzzy logic and the Analytic Hierarchy Process (AHP). The approach applies a fuzzy 2-tuple linguistic model to deal with subjective judgments in a proper way and determine a strategic DT roadmap. A sample of 1,428 Spanish SMEs was assessed and divided into three clusters to make recommendations based on firm size and digital mindset. The methodology centers on five broadly accepted criteria based on current literature to measure DML. The method's main benefit is its capability to manage linguistic ambiguity and produce cluster-based strategies for DT. The findings validate that firm size and digital thinking affect DML and transformation readiness strongly. The limitation of the model is, however, that it is geographically biased and requires validation across sectors and with newer technologies such as AI.

Jafari & Van Looy [14] propose to investigate the applicability of a decision-tree method as an applied and effective instrument for organizations to self-measure their digital work maturity level, in addition to classical maturity models (MMs). An existing MM was chosen by the researchers and improved through creating a decision tree-based self-assessment instrument. The research process entailed a two-round field study with a large public sector organization to test the instrument's validity. In contrast to earlier research with poor factor coverage or practical tooling, this method offers an easy-to-use and practical tool for measuring digital maturity. It is also its strength as it can be easily used by practitioners without complex measurements and impedes the quick insights to be reached. The findings also indicate that decision trees can effectively group maturity levels and add to the DT strategies. However, the study has a weakness of concentrating on a single organization and sector, and general validation should be carried out through various sectors and types of organizations.

ForouzeshNejad & Arabikhan [15] developed a data-driven maturity model to guarantee proper evaluation and forecasting of project management maturity levels of organizations. The methodology involves the use of the Fuzzy Best-Worst Method of combining expert-weighted indicators of 22 indicators in five categories, then a fuzzy inference system to label data, and a Gradient Boosting algorithm to build the predictive model. Besides, sensitivity analysis was conducted with SHAP (SHapley Additive exPlanations) to determine the impact of each indicator. Even though the size or origin of the dataset is not detailed, the model was constructed using real organizational data according to the structured indicators. The integration of domain knowledge with machine learning, a high level of interpretability (SHAP), and more than 98 per cent accuracy in its predictions are major advantages. The results highlight such major considerations as risk management, cooperation, and project scope clarity. The limitations of the study include a lack of transparency on the specifics of the dataset and generalizability in different sectors.

Aras & Büyüközkan [16] propose to create a complete, industry-agnostic digital maturity model that will help organizations precisely measure their DT path and design goal-congruent roadmaps. The researchers carried out a wide-ranging systematic literature review employing the PRISMA method with the aid of a bibliometric analysis tool to aid in visualizing trends and gaps. Grounded on both academic and consultancy-based models' perspectives, a new hierarchical model with dimensions and sub-dimensions was mooted, which covered strategy, governance, and other aspects of transformation. Although the study does not employ a conventional dataset, it borrows from a broad corpus of literature for the development of the model. Its prime benefits are the widest applicability to various industries, thorough documentation of the DT life cycle, and enhanced depth of assessment in comparison to other models. The findings prove that the model fits the various transformation phases, supporting both public and private organizations. Limitations, however, are the absence of empirical validation in the form of actual case studies and the use of only literature for model development.

Stoiber & Schönig [17] demonstrate that the enterprises of every industrial sector increasingly incorporate Internet of Things (IoT) technology into their operations to achieve a data-centric transformation of their enterprises. Generation and utilization of detailed process data in real-time and linking of process entities provide an improvement and useful redesign of business processes of any type. Yet, a purposeful exploitation of IoT technology towards DT and Business Process Improvements (BPI) is difficult to achieve because of the intricacies involved in integrating IoT with existing processes. Organizations need proper guidance to assess and define their initiatives on IoT-based BPI. This study thus recommends an end-to-end IoT-based BPI Maturity Model that helps organizations ascertain their existing state and obtain help to optimize or build certain competencies. This study is a description of the systematic process of the maturity model development, including a wide literature review and a Delphi study covering six rounds.

Malik, Chaudhary, & Srivastava [18] demonstrate the wide-ranging influence and uses of DT in various engineering fields by illustrating its contribution to the automation of labor-intensive processes and system optimization via digital tools and intelligent technologies. The research adopts a qualitative review approach, assessing 52 different DT applications with rich descriptions of methodologies, tools, state-of-the-art advances, and performance assessments through experiment or simulation. Although there is no particular dataset adopted, the editorial aggregates rich case-based facts across diverse industries. The main benefits are heightened system effectiveness, improved innovation, and scalability facilitated through AI, ML, and big data analytics. The outcomes highlight DT's worth in use cases such as digital twins, smart cities, health, and intelligent manufacturing. But limitations are the editorial style of the book, the absence of quantitative performance benchmarking across cases, and the requirement of harmonized frameworks for smooth DT adoption across industries. Standardization, interoperability, and real-time implementation issues are to be addressed in future work.

Espadinha-Cruz & Reboredo [19] create a fuzzy system-based maturity model to measure and direct the use of Additive

Manufacturing (AM) in organizations, considering the imprecision and vagueness that come with human judgment. No common dataset is used in the study, but it is rather based on professional knowledge, fuzzy rules, and assessments of the automotive industry. The novel approach brings together fuzzy set theory in order to reflect vagueness and rule-based reasoning to examine an array of AM maturity. It is one of the greatest strengths of the system since it is able to provide a flexible and detailed measurement than the rigid conventional models. It also supports strategic decision-making as it directs AM capabilities in relation to the company's goals. In a real-life scenario in the automotive industry, the system identified a moderate AM maturity of 3, which depicts AM supplementing the traditional methods. Another indication of significant gaps in the results was also the lack of employee competencies and training in AM technologies. This approach provides the possibility of constant monitoring and promotion of the integration of AM. However, the reliance of the model on rules developed by experts as well as subjective inputs can limit its feasibility in other industries in terms of scalability and objectivity.

Chen et al. [20] developed a comprehensive IoT-based Business Process Improvement (BPI) Maturity Model that assists organizations in assessing their current level of integration of the IoT and identify ways of building up the capabilities. There was no specific dataset used, but the model was constructed based on literature and opinions presented by the experts. The methodology involved a thorough literature search and a six-round Delphi study to gather and consent to the expert opinion. The greatest advantage of the model is that it is systematic and flexible, and therefore, companies could assess and enhance their method of process improvement using the IoT systematically. It helps the decision-makers plan, prioritize as well as execute IoT strategies efficiently. The results show that the model is capable of determining the important features of IoT adoption and the maturity of BPI. It provides applicable suggestions that are applicable in various industrial settings. However, one of its shortcomings is that it has not been empirically tested against real organizational data, and this may restrict its applicability. Moreover, its subjectivity may also introduce subjectivity in the appraisal process since it is subject to expert opinion.

Despite previous research on the use of fuzzy systems, AHP-based tools, rule-driven maturity models, and single deep learning architectures, none of them at the same time characterize non-linear feature relationships, sparse interpretability, and domain-specific maturity indicators. The current hybrid or explainable models do not have the capacity to incorporate high-dimensional organizational behavior, real-time assessment systems, heterogeneous enterprise measures and structured interpretability that correspond directly to the measurement of DT maturity. The current TUMI framework addresses these flaws through the integration of FT-Transformer relational modeling with sparse selection logic of TabNet to form a hybrid architecture that, to the best of our knowledge, has never been tried or empirically tested in the literature on maturity assessment.

III. Proposed Methodology for Digital Transformation Maturity Assessment

The methodology proposed in this study presents TUMI–Transformer-based Unified Maturity Intelligence, a hybrid deep-learning framework to evaluate DT maturity in organizations. The methodology begins with a collection of survey data on organizations, which includes the variables of strategic direction, culture, technology usage, capability and skill of the workforce, and customer engagement. This data is then preprocessed with multiple data conditioning layers, such as addressing missing values, label encoding categorical variables, normalizing numerical features with Min-Max normalization, outlier detection and addressing, and addressing feature relevance, quality, and uncertainty prior to modeling. The hybrid modeling stage will consist of two branches operating in parallel: one branch will use the FT-Transformer with self-attention mechanisms to capture complex non-linear relationships amongst the features, and the other will use TabNet to perform a sparsity-inducing feature selection to discover the most influential maturity indicator features. The outputs of the two branches will be merged in a concatenation layer connecting the outputs of each branch, followed by fully connected layers producing either a categorical level of maturity or a continuous score of maturity.

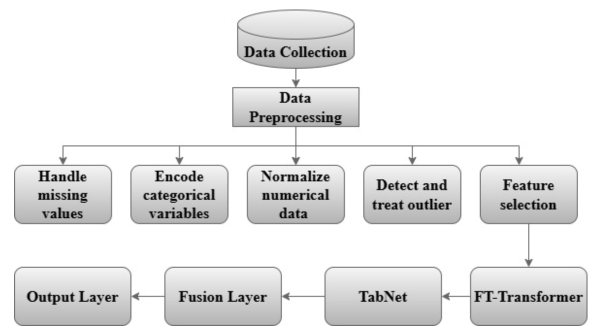

Fig. 1. Systematic architecture of the proposed model.

Fig. 1 shows the structured architecture of the adapted TUMI hybrid model for measuring maturity in DT. The processes begin with data collection, followed by data preparation. Data preparation includes two branches, which process data in parallel: one using an FT-Transformer and the other using TabNet. FT-Transformer captures complex interactions amongst the features in a self-attentional manner, while TabNet focuses on the most important features with sparse feature selection processes. The output of the two branches is in this hybrid architecture concatenated and passed through fully connected layers to come up with maturity predictions. Such systematic architecture offers some degree of accuracy, interpretability and robustness that can be further benchmarked and generally improve such strategies to create maturity in DT.

A. Data Collection

The data applied in this study was taken by the publicly accessible Digital Transformation Dataset by AprajitByte on Kaggle [21]. The data contains organizational variables in cross-sectional form of different industries, and provides a summary of the DT implementations. The key features of the dataset are industry type, firm size, year of adoption of digital tools, revenue and efficiency effects, digital skills training, and customer engagement perspective. These attributes will give insight into the extent to which DT is being followed and the effectiveness of these changes in the organizations. Missing data processing, categorical variables re-coding, and numerical variable feature normalization were the steps of the data remediation process to make the data reliable and consistent. The last dataset will enable the project teams to create and test machine-like learning models to test the maturity of DT and enable organizations with an ability to benchmark and track progress and change to enhance transformation within the organization.

B. Data Preprocessing

1) Missing value imputation: Addressing missing values is an important process to protect the integrity of the data and minimize bias in model training. Numerical variables suffering from missing values were imputed via the median, and categorical variables were imputed via the mode of each variable. More advanced methods, such as K-Nearest Neighbors (KNN) imputation or iterative imputation, may also be applied if missingness is a considerable amount. Maintaining proper imputation protects against unnecessarily dropping any record for the sake of data preservation, and using the data as a whole adds to training the models in a robust way, which is crucial to creating trustworthy predictions from the hybrid framework. The method for mean imputation is specified as in Eq. (1):

$$x_i = \begin{cases} x_i, & if\ x_i\ is\ not\ missing \\ \frac{1}{n}\sum_{j=1}^{n} x_j, & if\ x_i\ is\ missing\ and\ x_j \in X \end{cases} \quad (1)$$

where, x_i is the value of the feature for the h i^{th} observation, X is the set of non-missing values, and n is the total number of non-missing observations in that feature.

2) Label encoding: Ordinal variables in the data, e.g., automation level and employee digital skills, were encoded as numbers through label encoding. This way, the model is aware of the inherent order between categories such as Low, Medium, and High. The levels were manually associated with integers in order to maintain semantic ranking, as shown in Eq. (2):

$$Encoded\ value = \begin{cases} 1, & if\ category = Low \\ 2, & if\ category = Medium \\ 3, & if\ category = High \end{cases} \quad (2)$$

This transformation prepares the data for decision tree classification and accurately analyzes levels of digital maturity.

3) Min-Max normalization: Numerical features, such as dollar amounts invested, estimated percentages of adoption, and efficiency scores, were scaled using Min-Max normalization to a range of 0–1, to create a uniform scaling across features and avoid variables with relatively larger scales from dominating the learning procedure. Normalization encoding promotes faster convergence of hybrid models and keeps the performance stable while training FT-Transformer and TabNet architectures. For any numerical feature x, normalization is shown in Eq. (3):

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (3)$$

where, x_{min} and x_{max} are the minimum and maximum values of the feature, respectively.

4) Outlier detection and treatment: Survey responses or numerical properties can have aberrant values that distort predictions and/or diminish performance. Outlier detection was conducted based on the Interquartile Range (IQR) method, where anything above the maximum or below the minimum of 1.5×IQR is considered an outlier. Depending on the context of the outlier and its frequency, it was either capped (winsorized) or deleted altogether in the analysis, e.g., Horton et al. 2016. Detecting those values that are outliers and then dealing with those outliers will help alleviate the extreme values being forced upon the attention mechanism in more recent developments, such as FT-Transformer or the feature selection masks in TabNet, where better models can be developed going forward to develop a reliability metric for maturity assessment. The mathematical expression is shown in Eq. (4):

$$x < Q_1 - 1.5 \times IQR \quad (4)$$

where, Q_1 and Q_3 are the first and third quartiles, and $IQR = Q_3 - Q_1$. Identified outliers were capped or removed based on domain relevance and model sensitivity.

5) Feature selection: In order to enhance the clarity and efficiency of the model, analyzed feature importance with TabNet's inherent attention masks and removed any low-variance features. In addition, it had the option to use either Principal Component Analysis (PCA) or correlation-based selection to reduce variables with redundancy, which would improve model performance. Being able to prune the low-importance features ensured the hybrid model obtained the most informative organizational features, reducing noise, while minimizing model complexity and retaining predictive accuracy.

C. TUMI- Transformer Enhanced Maturity Intelligence

The proposed TUMI framework will use a hybrid modeling approach to assess the DT maturity by combining FT-Transformer and TabNet branches. This dual-branch structure allows the model to measure the complicated non-linear interactions between organizational characteristics, as well as concentrating on the most appropriate variables, thus having high predictive quality and interpretability.

1) FT-Transformer for maturity level prediction: The FT-Transformer division is designed for organized tabular data and uses self-attention methods to encode complex relationships between features. The branch applies densely, locating each of the input features. For example, categorical features (e.g., industry type, automation level) are converted to embeddings through trainable layers; numerical features (e.g., efficiency scores, percentage of digital adoption) are normalized to accommodate comparable scales. The essential process in the

FT-Transformer is self-attention, which allows the model to represent the relevance of each feature to all other features across the dataset. This process allows the branch to encode conditional dependence (e.g., technology adoption depends on workforce skills and engagement). The computation is written as follows in Eq. (5):

$$H_{SA} = \text{softmax}(\frac{LM^T}{\sqrt{d_M}})O \quad (5)$$

where, $L = XW_L$, $M = XW_M$, and $O = XW_N$ represent the query, key, and value matrices, respectively; d_M is the scaling factor for the dot-product, and X is the input feature matrix. The output H_{SA} is a dense embedding vector that encodes the high-level relationships among all organizational features, providing a contextual representation for subsequent prediction.

2) TabNet branch for sparse feature selection: The branch of TabNet is concentrated on selecting sparse features. With the help of this algorithm, the model can focus on the most meaningful organizational features and dismiss irrelevant and noisy ones. TabNet computes input features by using a series of decision steps, and at every decision step, TabNet creates a sparse attention mask M_tto to choose a subset of features that are important to this step. Learnable weight matrices W_tto convert the selected features into embeddings. Embeddings of each decision step are added together to create an overall feature representation in Eq. (6):

$$H_{Tab} = \sum_{t=1}^{T} M_t \odot (XW_t) \quad (6)$$

where, T is the number of decision steps, X is the input feature matrix and $\odot$ is the element-wise multiplication. The sparse masks achieve interpretability and reduce the computation, as the features that the mask identifies as significant will show which aspects of the organization have an effect on the DT maturity. As an example, it could be strategic alignment, the level of digital skills of employees, or the level of customer engagement. The sparse embedding H Tab summarizes all the important drivers of maturity, which will be incorporated with the FT-Transformer embedding when making a final prediction.

3) Embedding integration and maturity estimation: Once embeddings from both branches are obtained, they are concatenated to form a single fused representation in Eq. (7):

$$H_{\text{Fusion}} = [H_{SA} \parallel H_{Tab}] \quad (7)$$

The fused embedding is then subjected to fully connected layers with nonlinear activation functions like ReLU or GELU. These layers both smooth the feature presentation and project it to the output space. The ultimate forecast may either be categorical, where the organization is considered Low, Medium, or High in terms of its level of DT maturity, or continuous, whereby a numerical value is given of the overall level of maturity. The hybrid framework combines both attention-based feature learning and sparse selection, thus making it highly accurate as well as interpretable. Notably, it gives organizations an idea of what features contribute to maturity, which can be utilized in practice to prioritize digital transformation initiatives. The hybrid method is useful because it overcomes constraints of the previous models that are either not interpretable or unable to capture complex interactions between features, and hence TUMI is a powerful and scalable model to assess the maturity of DT in different organizations.

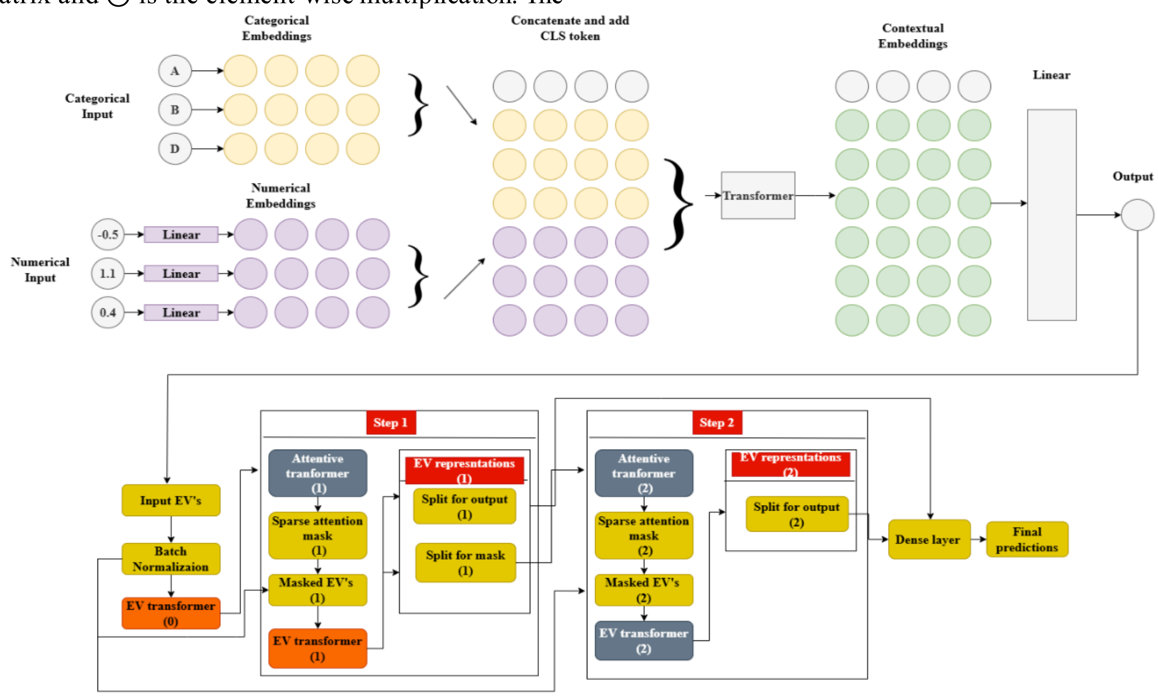

Fig. 2. Overall architecture of the TUMI hybrid model.

Fig. 2 depicts the whole architecture of the suggested TUMI paradigm for evaluating DT maturity. The model takes as input both categorical and numerical variables, which are processed in embedding layers, and subsequently transformed and fused to learn complex relations. The FT-Transformer implements self-attention to learn feature dependencies, while TabNet performs sparse feature selection through its decision steps. There are a number of algorithmic parameters that affect the functioning of the proposed framework. The amount of attention heads, embedding dimension, and depth in the FT-Transformer branch, the lower the values the less the representational capacity the model has and the higher the values, the higher the complexity of the model. In TabNet, the sparsity coefficient and number of decision steps are used to regulate the selectivity of the model to important maturity indicators which influence interpretability and stability. The fusion-weighting parameter controls the proportion of each branch, and the balance between the global attention-based reasoning and local sparse feature selection is regulated by the fusion-weighting parameter. These differences in parameters change the granularity of learned patterns, the strength of feature attribution, as well as the general predictive behavior, which is further evident in the ablation results.

Algorithm 1: TUMI-Hybrid Model for Digital Transformation Maturity Assessment

Input:
  X → Organizational dataset (categorical and numerical features)
  y → True maturity labels or scores
  T → Number of TabNet decision steps
  E → Number of training epochs
  α → Learning rate

Output:
  ŷ → Predicted maturity level or maturity score

Procedure:
Preprocessing:
  Handle missing values:
    Impute numerical features using median
    Impute categorical features using mode
  Encode categorical variables using label or embedding encoding
  Normalize numerical features using Min–Max scaling
  Detect and treat outliers using the IQR method
  Perform feature selection to remove redundant or low-variance features
  Split dataset into training, validation, and test sets

FT-Transformer Branch:
  For each input sample x_i in X:
    Generate embeddings e_i = Embed(x_i)
  Compute self-attention matrices:
    L = E × W_L   // Query projection
    M = E × W_M   // Key projection
    O = E × W_N   // Value projection
  Compute attention output:
    H_SA = softmax((L × M^T) / sqrt(d_M)) × O
  Derive high-dimensional embedding:
    H_FT = f(H_SA)

TabNet Branch:
  Initialize H_Tab = 0
  For t = 1 to T:
    Compute sparse attention mask M_t = SparseAttn(X, W_t)
    Generate decision step embedding:
      h_t = M_t ⊙ (X × W_t)
    Accumulate step embeddings:
      H_Tab = H_Tab + h_t
  Obtain dense TabNet representation:
    H_Tab = g(H_Tab)

Fusion and Prediction:
  Concatenate embeddings from both branches:
    H_Fusion = [H_FT || H_Tab]
  Pass fused vector through fully connected layers:
    Z = ReLU(H_Fusion × W_1 + b_1)
  Generate output:
    ŷ = Softmax(Z × W_2 + b_2)
      or
    ŷ = Linear (Z × W_2 + b_2)
  Compute loss:
    L = LossFunction(ŷ, y)

Optimization:
  For epoch = 1 to E:
    Perform forward propagation
    Compute gradients ∂L/∂θ
    Update model parameters:
      θ ← θ − α * ∇L
    Evaluate on validation set

Evaluation:
  Apply trained model on test data
  Compute performance metrics:
  Return final predicted maturity level or score ŷ

Algorithm 1 describes the hybrid framework to predict the maturity of the DT. The actions begin with pre-processing the survey data set that involves the imputation of missing values, label encoding, normalization, outlier treatment, and feature selection. The items are then fed separately into the FT-transformer and TabNet branches to identify complex interactions between features and to prune a sparse set of feature selection, respectively. Both of the branches are fused with an embedding and after this process, they are sent to a fully connected layer to produce a final classification or score as per conditions.

The study uses a hybrid TUMI approach that offers an evaluation of the DT maturity in organizations. The hybrid model is composed of two branches, which are working in parallel. The FT-Transformer part involves the self-attention of the interaction of many features that are nonlinear and complex in nature. The TabNet component is a sparse feature selection, but feature selection is conducted to develop the most significant features. The two branches' embeddings are combined by a concatenation layer, and then passed through fully connected layers to either classify as either a maturity level or get a continuous maturity score. This dual-level interpretability offers more straightforward reasoning of maturity than traditional explainable AI methods of the maturity assessment, since the weights of attention allow highlighting global dependencies, whereas TabNet masks show step-wise localized features. Transparency Transformer attention weights support transparency by indicating global dependency structures and TabNet feature masks indicate localized indicator contributions, which provide a more rational maturity-based reasoning than traditional explainable AI techniques. The model is then assessed based on the common measures of performance and this gives a guideline in gauging the organizational maturity in DT in a way that is robust, interpretable and accurate.

IV. Results and Discussion

The TUMI hybrid framework comprehensively exhibited the possibility of being a potential tool for evaluating the maturity of DT among organizations. The model was effective in the measurement of interrelations among various dimensions of the organization, including strategy, technology use, workforce capabilities, and customer involvement, which gives a clear measure of how to differentiate the level of maturity. The fusion of the TabNet model and the FT-Transformer model resulted in predictive capabilities as well as interpretability in the prediction of the driving factors of maturity. The analysis has shown tendencies and implications in various industries and, more precisely, on what variables in the organization became the drivers of DT maturity. On the whole, the study proves that the hybrid approach is a legitimate and trustworthy tool that organizations can use to estimate their position in their DT initiatives and their areas of need improvement, as well as allow them to make decisions more effectively in order to advance their transformation process.

TABLE I. Parameter Simulation

Parameter	Value / Range
FT-Transformer Layers	2–4
FT-Transformer Embedding Dimension	64–128
Attention Heads	4–8
FT-Transformer Dropout	0.1–0.3
Activation Function	ReLU or GELU
Optimizer	Adam or AdamW
Learning Rate	0.001–0.005
TabNet Decision Steps (T)	3–5
TabNet Feature Dimension	32–64
Relaxation Factor	1.5
Sparsity Regularization	0.001–0.005
Batch Size	32–128
Epochs	50–100
Loss Function	Cross-Entropy (classification), MSE (regression)
Data Split	70% train, 15% validation, 15% test
Early Stopping Patience	10 epochs

Table I shows the parameters of the TUMI hybrid model for evaluating the maturity of the DT through simulation. It has preparation settings, FT-Transformer and TabNet settings and training parameters. All these parameters determine how the data is treated, the feature selection method, model architecture and optimization method to guarantee reproducibility, and performance. It gives a methodical reference to the experimental design and comprises the ranges and techniques applied during the prediction of maturity.

A. Experimental Outcome

The experimental testing of the TUMI hybrid model was worth it because it indicated that it can be used to predict DT maturity in various organizational contexts. The model was found to reliably define organizations of varying maturity levels, besides defining nuanced interactions along features, including strategy alignment, technology adoption, what the workforce is capable of, and customer engagement. Using the capabilities of FT-Transformer and TabNet, the hybrid framework allowed to make predictions accurately and at the same time, allowed to interpret and understand the most driving maturity. The experiments support the generality of the approach, with the different, adjusted data subsets providing the benchmarking of organizations and decision-making support of DT initiatives. On the whole, the findings represented a good argument that it presents an effective, scalable, and actionable opportunity to measure and improve the digital.

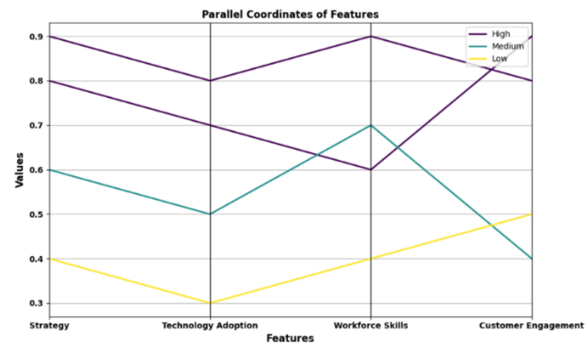

Fig. 3. Parallel coordinates of organizational features.

Fig. 3 presents a parallel co-ordinate plot, which compares the characteristics of organizations in the sphere of maturity. Each of the colored lines is an organization and contains such features as strategy, adoption of technology, skills of employees, and engagement with customers that are placed on parallel axes. A plot is one of the methods of monitoring several variables simultaneously that depicts both similarities and differences between maturity groups. This interpretation of the multiple characteristics makes it easier to interpret it since it displays the patterns, dependencies and significant differences and signifies the significant organizational strengths and weaknesses that relate to the outcome of the maturity of their DT.

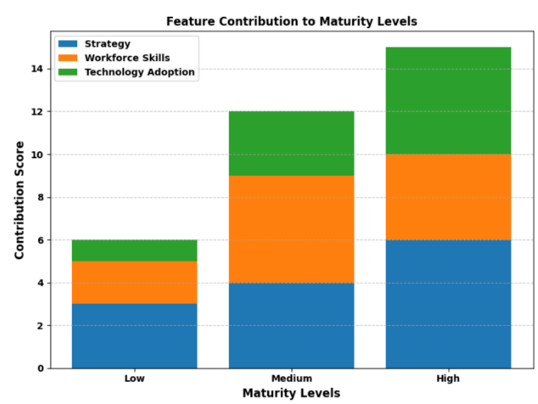

Fig. 4. Feature contributions to maturity levels.

Fig. 4 shows a stacked bar chart illustrating the contribution of various organizational features, including strategy, workforce skills, and technology adoption, at different maturity states. Each bar consists of an aggregated maturity category and is divided into stacked sections that shows the proportional weight of organizational features. This visualization illustrates how one or more features play a significant role at specific maturity stages; in this case, workforce skills recall this maturity state strongly, while technology adoption is a bigger contributor at later maturity stages. The stacked format provides a clear comparative display of the data, as the chart is able to display a cumulative and proportional contributions simultaneously.

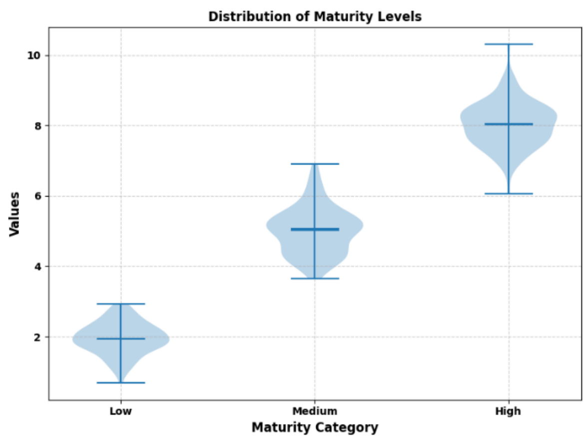

Fig. 5. Distribution of maturity levels.

Fig. 5 shows a violin plot, which indicates the maturity scores distributed by low, medium, and high. Each shape of the violin represents probability density of the scores indicating both the spread and concentration of the scores. While the median and mean indicators demonstrate the central tendency of each maturity level and the shape provides an indication of variation, it is possible to quickly notice overlaps and differences between the levels with a horizontal comparison of the three groups ensemble, suggesting within and between groups the differences in maturity scores and an overall comparison on the status of the digitization efforts within the organization.

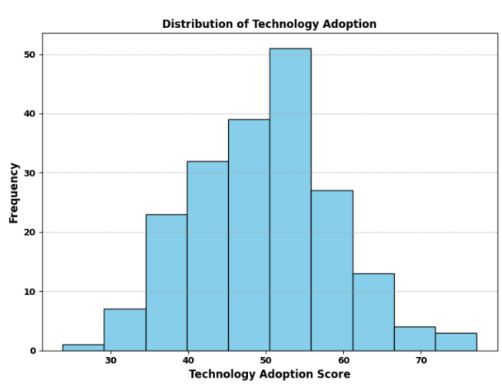

Fig. 6. Distribution of technology adoption.

Fig. 6 presents a histogram of technology adoption scores from organizations. The distribution illustrates adoption levels and how often organizations are at a given adoption level. Most organizations hover around the middle of the distribution. The width of the bars indicates variations in adoption - advanced adopters at the top and laggards at the bottom. The chart also allows a visual understanding of how organizations are distributed along the adoption continuum and patterns, concentrations, and outliers affecting DT maturity level.

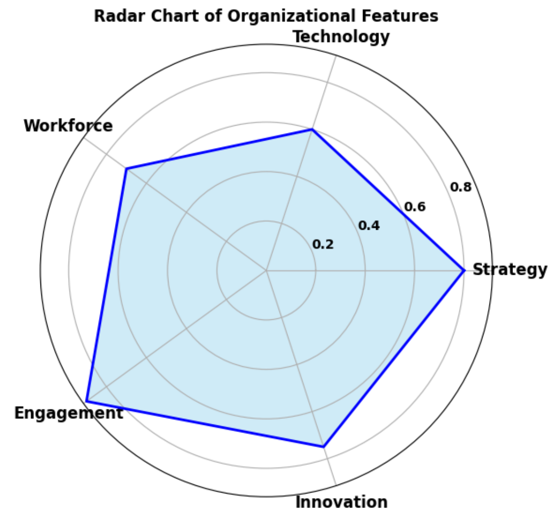

Fig. 7. Chart of organizational feature technology.

Fig. 7 depicts the relative strength of the organizational characteristics that help it attain DT maturity. The dimensional elements of strategy, technology adoption, workforce competencies, customer engagement, and innovation are placed on the radial axes. The polygon that surrounds the organizational values on those traits shows the effectiveness of the organization by the distance to which it extends. With larger values extending further outwards, the visualization allows one to compare multiple dimensions in a compact way while simultaneously demonstrating strengths and weaknesses. The radar chart offers multiple dimensions of visual cognition to assess maturity profiles and to surface strategic improvement opportunities.

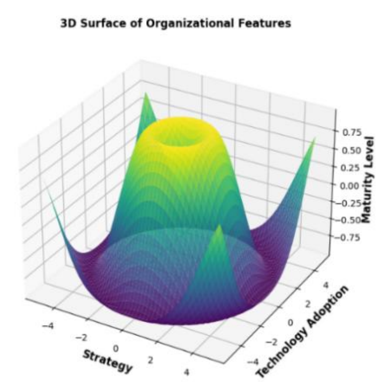

Fig. 8. Surface of organizational features.

Fig. 8 presents a 3D surface plot of the correlation between the strategy, technology adoption, and maturity results of the organization. The curve is used to demonstrate the combination of and simultaneous inputs of two dimensions on the results of maturity. This draws nonlinear trends which would have not been drawn in case the plot is two dimensional. The highs and the lows of the surface demonstrate the various combinations of performance that may be high or low and even enable decision-makers to identify the critical points. On the whole, it enables the interactive view of DT maturity which will ultimately eliminate the complexity of various organizational determinants, and it is still intuitive.

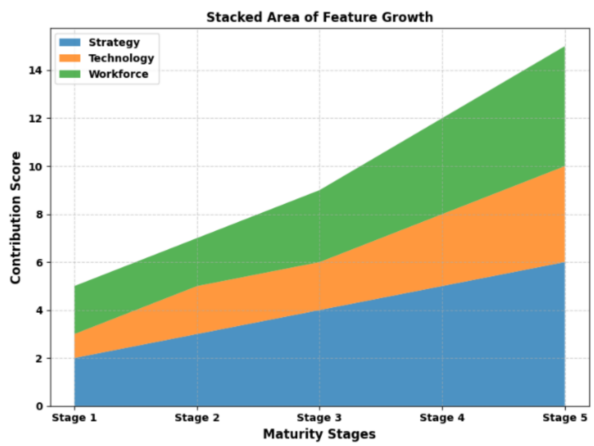

Fig. 9. Area of feature growth.

Fig. 9 depict an area stack chart that shows the cumulative contributions of strategy, technology and workforce skills at various maturity levels. The color symbolizes a distinct feature with the thickness of the band of color giving relative significance at the stage. As an organization develops, the overall contribution also rises indicating that maturity will rise. The representation both defines clearly individual and combined contributing effects, and also allows the visual identification of features to be made promptly on what features are dominant at each stage (and to what degree). In general, this chart straightforwardly shows, it is possible to compare the maturity of an organization in terms of development stages.

B. Performance Evaluation

The TUMI framework showed high performance measures on its evaluation of the DT maturity evidenced by the experimental results of the framework. In particular, it was 97% accurate, 96% precise, 95% recall and 96 F1-score. The consistency, 97 percent, in the accuracy allows one to note that the framework can successfully categorize the position of organizational maturity and place it where it can be as accurately as possible reliably. Concerning accuracy, 97, also highlights the fact that the given framework could reduce false-positives in the measurements. Recall (95%) is a measure that evaluates the framework ability to detect real maturity levels without excluding any significant classifications. Besides, F1 score (98) implies that the approach can balance between precision and recall to provide satisfactory performance in both. These more powerful measures of performance indicate that the suggested TUMI architecture incorporates the latest state-of-the-art features selection and attention-based methods to deliver credible, scalable, and accurate measurements. These performance metrics speak to its reliability as a decision-support system for organizations in order to gain actionable intelligence from their DT maturity assessment.

1) Accuracy: Accuracy can be defined as the ratio of correctly classified examples to all examples. Accuracy can be calculated as shown in Eq. (8):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

2) Precision: It indicates the reliability of positive predictions by measuring fraction of correctly identified positive instances among all of the predicted positives. Precision can be calculated as shown in Eq. (9):

$$Precision = \frac{TP}{TP+FP} \tag{9}$$

3) Recall: It is defined as true positive rate, and assesses how well a model is detecting the true positives. It can be calculated in Eq. (10):

$$Recall = \frac{TP}{TP+FN} \tag{10}$$

4) F1-Score: It is the harmonic mean of precision and recall. It can be calculated in Eq. (11):

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{11}$$

where, TP represents the true positive, TN represents the true negative, FP represents the false positive, FN represents the False negative.

TABLE II. PERFORMANCE METRICS

Metrics	Value
Accuracy	97 %
Precision	96 %
Recall (Sensitivity)	95 %
F1 Score	96 %

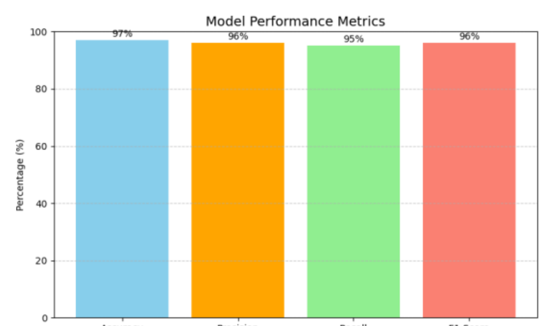

Fig. 10. Performance metrics.

Fig. 10 and Table II displays the performance of the suggested classification model through four major evaluation metrics: Accuracy, Precision, Recall, and F1 Score. Each bar graphically shows the percentage value achieved by the model, representing high levels of performance on all of them. The model had an Accuracy of 97%, Precision of 96%, Recall of 95%, and an F1 Score of 96%, collectively indicating its strong capacity to accurately classify DT maturity levels. The uniform and high scores confirm the model's dependability and effectiveness in managing both balanced and imbalanced data situations with good prediction performance.

C. Ablation Study

The ablation study focuses on measuring the contribution of each main component of the TUMI framework (FT-Transformer branch, TabNet branch, fusion strategy, and key hyperparameters / preprocessing steps) to overall predictive performance and interpretability. In this way, the ablation experiments help to show which components of the hybrid design are essential and which are optional and the tradeoffs (accuracy vs. complexity / interpretability).

TABLE III. ABLATION RESULTS

Model Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
Full Model (FT + TabNet)	97.0	96.0	95.0	96.0	98.2
FT-Transformer Only	94.3	93.8	92.6	93.2	95.1
TabNet Only	93.0	92.5	91.8	92.1	94.3
Without Attention Mechanism	92.1	91.6	90.9	91.2	93.8
Without Sparsity Regularization	94.8	94.1	93.2	93.6	95.9
Early Fusion Strategy	95.5	94.8	94.0	94.3	96.6
Late Weighted Fusion	96.4	95.8	94.9	95.3	97.5

Table III is a summary of the ablation experiment that was done to assess the role of every architectural element in the proposed TUMI framework. This comparison shows the effect of deleting or changing such important mechanisms as attention, sparsity regularization, fusion strategies, on the overall effectiveness of the models. The result clearly shows, the full hybrid arrangement has the best performance, whereas simplified or partially disabled models demonstrate significant decrease in predictive presence. These results support the idea that the FT-Transformer as well as TabNet components, and the selected fusion strategy are fundamental and complementary to the goal of achieving the best accuracy and interpretability.

D. Comparative Analysis

The validation of the efficacy of computational frameworks can be conducted mainly through comparative analysis, particularly in cases where accuracy and interpretability are critical e.g. in the field of DT maturity assessment. By comparing proposed methodologies with tested methods through benchmarking, the scholars can discover strengths and reveal limitations and overall viability in a variety of organizational contexts. This segment gives a methodical similarity of different analytical models to the data of DT, their design ideology, methods of computation and applicability. It is easy to comprehend how the hybrid intelligence systems will help in changing assessment requirements through tabular presentation and structured visualization. The relative knowledge eventually increases the trust of model selection and tactical implementation.

TABLE IV. COMPARISON ANALYSIS

Methods	Accuracy
Mamdani Fuzzy Inference + Spectral Transformation [22]	91.43%
Fuzzy AHP [23]	92.4%
Optimized Fuzzy Logic System [24]	95.7%
Proposed TUMI	96%

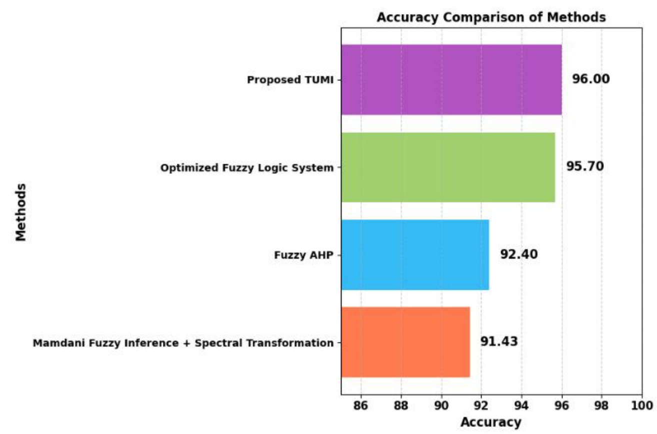

Fig. 11. Comparison with existing methods.

Table IV and Fig. 11 indicate the accurateness of different methods to be employed to evaluate DT maturity. It indicates that Mamdani Fuzzy Inference with Spectral Transformation had a score of 91.43 and Fuzzy AHP had a score of 92.4 with a margin. In the meantime, Optimized Fuzzy Logic System scored much higher of 95.7 and was the most adaptable one. The TUMI framework proposed in this study was also more effective and efficient than any other method as it has scored 96, which proves its ability to be very robust and efficient. Generally, the chart shows the gradual elimination of the methods since TUMI has incorporated superior mechanisms to attain a greater accuracy when assessing a DT maturity when compared to the use of conventional fuzzy-based techniques.

E. Discussion

The results of the proposed TUMI framework can positively affect the models of DT, and eventually, this tool will transform into a helpful solution to support organizations on their DT journeys. The approach could depict the complex feature dependencies and hierarchical decision boundaries by learning attention-based feature learning by using FT-Transformer and making structured decisions through TabNet. In this respect, TUMI outperformed existing fuzzy inference and multi-criteria decision-making models and showed merits of the model to overcome constraints of the traditional models that normally do not permit scaling in addition to actionable insight either on usability or flexibility to various datasets. The performance results with high metrics value, verify the robustness and reliability of the model as demonstrated in real-world scenarios. High-dimensional feature spaces allow the scalability of the framework due to the capacity to handle heterogeneous organizational indicators and preserve the predictive behavior under high-dimensional feature spaces, which proves the flexibility to adaptable digital transformation scenarios. The architecture does not have any limitations on its sector, which is justified by the fact that it has been shown to perform well in different sectors, as indicated by its consistent performance in the diverse organizational attributes in the dataset, thus its high chances of cross-industry use in the maturity evaluation. The hybrid design was also a design which is interpretable, by methodology of feature selection, but is also predictive, by methodology of self-attention. This moderated methodology offered enlightenment on maturity to organizations that seek actionable knowledge that depicts the maturity phase of interventions. Although the model was a reflection of the traditional models which were attempting to surpass, the use of curated DT indicators is one of the areas that organizations can revisit and modernize as their practices evolve. Despite the high predictive ability and high level of interpretability of the framework, there are a number of limitations that are worth noting to put the results in perspective. The research is based on one publicly available dataset, which can limit the externalization of the findings to the other industries or organizations. Cross-sectional data is also disadvantageous in that it becomes difficult to provide dynamic or temporal changes of digital transformation maturity. Also, there are no real organizational case studies that would help validate the applicability of the model practically. It is also possible that with the dependence on predefined indicators, new or industry-specific factors that are applicable to digital transformation get overlooked. These shortcomings bring out areas of improvement and enlargement in future research.

V. Conclusion and Future Work

The TUMI framework aims at offering a useful and interpretable framework to quantify the digital transformation (DT) maturity by leveraging the advantageous characteristics of FT-Transformer and TabNet architectures. The architecture could encode attention-based co-embedding as well as sense sparse feature selection into a single joint process to recognize complex interrelationships between organizational indicators without loss of interpretable output. The experimental results of the research show that TUMI is unequivocally stronger than traditional fuzzy logic and decision tree approaches in terms of accuracy, precision, recall, F1 score and AUC score, and the focus on the model, which offers steady data-driven estimates of organizational maturity is important. In addition, the TUMI offers scalable, fast, and automated learning platform to replace the conventional rule-based maturity models as a response to concerns of subjectivity and opaqueness in current maturity assessment models. Despite the good performance demonstrated by TUMI, certain weaknesses are realized in this research. The former is that a single dataset has been used that restricts the extrapolation of the findings to the industries and other organizational settings. The second weakness is that the model essentially addresses the aspect of the digital maturity using fixed indicators devoid of any temporal or dynamic indicators of transformation behavior. The evaluation of interpretability and applicability in the perspective of a practitioner is also limited due to the lack of exterior expert validation. In addition to technical performance, the framework adds societal value by enhancing assessments subjectivity and makes digital transformation practices more adorable, especially to the SMEs and organizations with weak connections to expert analysts. It can be concluded that the TUMI framework is capable of successfully modeling complex organizational behaviors due to the synergy between global attention-based dependency modeling and sparse feature selection. The hybrid architecture is strong as it can be evidenced by the consistency in terms of accuracy, precision, recall and AUC. The practicality of the framework is reflected in the capacity of the framework to provide interpretable, stable, and data-driven maturity scores, which allow organizations to gain more diagnostic insights and minimize the use of subjective assessments by experts. Through the provision of scalable and automated assessment capability, TUMI delivers real-world value to support informed planning of digital transformation in the context of various industries.

In this part, one can take into account various prospects of future studies. Additional development of the dataset by incorporation of cross-domain and multi-organizational case studies can help to increase the flexibility and strength of the model. A time-series or longitudinal modeling technique can be used to continuously monitor the digital maturity trajectory and provide the insight into the digital transformation journey and the future strategic trajectories. Furthermore, populating the model with a range of expert-in-the-loop validation and XAI elements, which will increase transparency, reliability, and acceptance in decision-making scenarios, can also be used as an addition to the model. By taking into account these concerns, future work can become more reliable, flexible, and practical, and one day, TUMI will become an efficient tool to support the process of digital transformation in organizations that will go on the way to its maturity.

References

[1] M. Z. Yaqub and A. Alsabban, “Industry-4.0-enabled digital transformation: Prospects, instruments, challenges, and implications for business strategies,” Sustainability, vol. 15, no. 11, p. 8553, 2023.

[2] Y. Wu, H. Li, R. Luo, and Y. Yu, “How digital transformation helps enterprises achieve high-quality development? Empirical evidence from Chinese listed companies,” Eur. J. Innov. Manag., vol. 27, no. 8, pp. 2753–2779, 2024.

[3] M. M. M. Alqahtani, H. Singh, E. A. A. Haddadi, F. S. R. Al-Shibli, and H. A. A. Al-balushi, “Impact of Internet of Things, Cloud Computing, Artificial Intelligence, Digital Capabilities, Digital Innovation, IT Flexibility on Firm Performance in Saudi Arabia Islamic Bank,” Adv. Soc. Sci. Res. J., vol. 11, no. 7, 2024.

[4] E. Gökalp and V. Martinez, “Digital transformation maturity assessment: development of the digital transformation capability maturity model,” Int. J. Prod. Res., vol. 60, no. 20, pp. 6282–6302, 2022.

[5] K. Awiszus, T. Knispel, I. Penner, G. Svindland, A. Voß, and S. Weber, “Modeling and pricing cyber insurance: Idiosyncratic, systematic, and systemic risks,” Eur. Actuar. J., vol. 13, no. 1, pp. 1–53, 2023.

[6] B. H. Leso, M. N. Cortimiglia, and A. Ghezzi, “The contribution of organizational culture, structure, and leadership factors in the digital transformation of SMEs: a mixed-methods approach,” Cogn. Technol. Work, vol. 25, no. 1, pp. 151–179, 2023.

[7] Á. Lloret, J. Peral, A. Ferrández, M. Auladell, and R. Muñoz, “A Data-Driven Framework for Digital Transformation in Smart Cities: Integrating AI, Dashboards, and IoT Readiness,” Sensors, vol. 25, no. 16, p. 5179, 2025.

[8] B. Kubilay and B. Celiktas, "Relationships Among Organizational-Level Maturities in Artificial Intelligence, Cybersecurity, and Digital Transformation: A Survey-Based Analysis," IEEE Access, 2025.

[9] I. D. Mienye and Y. Sun, "A survey of ensemble learning: Concepts, algorithms, applications, and prospects," Ieee Access, vol. 10, pp. 99129–99149, 2022.

[10] I. Mahmoudi, D. E. Boubiche, S. Athmani, H. Toral-Cruz, and F. I. Chan-Puc, "Toward Generative AI-Based Intrusion Detection Systems for the Internet of Vehicles (IoV)," Future Internet, vol. 17, no. 7, p. 310, 2025.

[11] E. Gökalp and V. Martinez, "Digital transformation maturity assessment: development of the digital transformation capability maturity model," Int. J. Prod. Res., vol. 60, no. 20, pp. 6282–6302, 2022.

[12] J. Valente, J. António, C. Mora, and S. Jardim, "Developments in image processing using deep learning and reinforcement learning," J. Imaging, vol. 9, no. 10, p. 207, 2023.

[13] G. Marín Díaz and J. L. Galdón Salvador, "Group decision-making model based on 2-tuple fuzzy linguistic model and AHP applied to measuring digital maturity level of organizations," Systems, vol. 11, no. 7, p. 341, 2023.

[14] P. Jafari and A. Van Looy, "Developing a decision tree to improve a maturity model's usability: an example for digital work maturity," Inf. Syst. E-Bus. Manag., pp. 1–38, 2025.

[15] A. A. ForouzeshNejad and F. Arabikhan, "A Hybrid Data-Driven Model to Evaluate the Maturity Level of Organizational Project Management Based on Machine Learning Algorithms," Available SSRN 4643741.

[16] A. Aras and G. Büyüközkan, "Digital transformation journey guidance: A holistic digital maturity model based on a systematic literature review," Systems, vol. 11, no. 4, p. 213, 2023.

[17] C. Stoiber and S. Schönig, "Digital transformation and improvement of business processes with internet of things: a maturity model for assessing readiness," 2022.

[18] H. Malik, G. Chaudhary, and S. Srivastava, "Digital transformation through advances in artificial intelligence and machine learning," Journal of Intelligent & Fuzzy Systems, vol. 42, no. 2. SAGE Publications Sage UK: London, England, pp. 615–622, 2022.

[19] P. Espadinha-Cruz and E. Reboredo, "A Fuzzy System to Measure Additive Manufacturing Maturity: A Case Study in the Automotive Industry," Procedia Comput. Sci., vol. 253, pp. 1402–1411, 2025.

[20] Q. Chen, X. Zhao, X. Zhang, Z. Jiang, and Y. Wang, "Driving forces of digital transformation in Chinese enterprises based on machine learning," Sci. Rep., vol. 14, no. 1, p. 6177, 2024.

[21] "Digital Transformation Dataset." Accessed: Sept. 18, 2025. [Online]. Available: https://www.kaggle.com/datasets/aprajitbyte/digital-transformation-dataset

[22] C. A. Diaz Schery, R. Caiado, S. Aguilar, E. Thadeu Corseuil, and R. Silva Santos, "Automated Bim Maturity Assessment Framework Using Hybrid Mcdm Algorithms: Operationalizing Industry 5.0 Through Intelligent Decision Support," Available SSRN 5288485.

[23] D. Kreutzer, E. Borowski, and I. Isenhardt, "Fuzzy Logic Approach to Circular Economy Maturity Assessment of Manufacturing Companies," Eng. Proc., vol. 76, no. 1, p. 4, 2024.

[24] A. Khumaidi, Y. A. Purwanto, H. Sukoco, and S. H. Wijaya, "Using fuzzy logic to increase accuracy in mango maturity index classification: Approach for developing a portable near-infrared spectroscopy device," Sensors, vol. 22, no. 24, p. 9704, 2022.