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LEVERAGING ADVANCED DEEP LEARNING TECHNIQUES TO PRIORITIZE KEY FOCUS AREAS IN THE TEXTILE SECTOR FOR PROGRESS TOWARDS INDUSTRY 4.0

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ABSTRACT

Companies can increase their efficiency and competitiveness by implementing Industry 4.0 approaches. However, the Moroccan textile and apparel industry severely restricts the use of these technologies. Developing a logical implementation strategy, such as the proper emphasis areas prioritization, remains a contentious issue and a barrier for practitioners despite all the advancements in these theories and practical approaches. This article uses deep learning to successfully integrate the industry 4.0 paradigm and, based on an intelligent model, develops a support tool for the apparel stakeholders. With the help of SIRI Dimensions maturity and the advancement of a set of common key success factors (CSFs), a neural network was trained to forecast the tailoring of Industry 4.0 implementation focus areas priority. These SIRI Dimensions and CFSs were chosen as input data. The neural network model has since been trained, tested, and validated using the dataset. Twenty percent of the data was used to assess the trained network, and a tuning hyperparameter procedure was created to improve the model's performance. Accuracy, precision, and the specified loss function have all been assessed and optimized for performance indices including Categorical Cross Entropy (CCE). With an accuracy of 96.5% for the Organization focus area, 93.9% for the Technology focus area, and 92.8% for the Process focus area, the proposed model may then determine the appropriate priority of focus areas for Industry 4.0 deployment. The findings of this study could serve as a starting point for other researchers who wish to create a roadmap for successful digital transformation by developing initiatives tailored to each priority focus area.

Keywords: *Industry 4.0, Critical Success Factors, Implementation Priority, Neural Network, Textile And Clothing Industry*

1. INTRODUCTION

A disruptive phenomenon that has been extensively researched in recent years is Industry 4.0 [1]. As part of an initiative started by the German government to encourage digital technology in manufacturing to boost production efficiency in German industry, Industry 4.0 was initially presented at the Hannover Fair in 2011 (as discussed elsewhere [2,3,4]). This term refers to the fourth industrial revolution, which is being propelled by the advancement of digital technologies that are more potent and integrated. These technological developments are enabling the creation of an intelligent factory capable of bringing together the physical and virtual aspects of a manufacturing system to work flexibly. Massive product customization and the development of new operational capabilities are made possible by the adoption of Industry 4.0 [3, 5]. The United States, France, the United Kingdom, South Korea, China, Japan, and Singapore are among the nations that have included Industry 4.0 into their national strategic objectives [6].

For Morocco, the fourth industrial revolution, or Industry 4.0, makes it possible to boost the digital economy to produce Moroccan digital solutions and create value and jobs. It is one of the ways of accelerating the realization of Morocco's vision of becoming the 1st economic country in Africa on the digitization of public services by 2030. The Moroccan government has launched Digital Morocco 2030 to realize this vision. Digital Morocco 2030 gives first priority to the prerequisites for the digitalization of businesses through talent, Cloud services and an ecosystem of local companies producing digital solutions. The second priority is to support Moroccan SMEs in scaling up. The third priority is to assist SMEs in their digital transformation, through the implementation of a digital maturity assessment tool and participation in the financing of digital transformation projects [7]. Indeed, the Textile and Clothing sector is highly interested in these actions, given its predominantly SME composition. The Textile and Clothing industry has also been included in the World Economic Forum's global assessment of Industry 4.0 in 2022. Based on the results of the assessment, it appears that the Textile and Clothing industry has a relatively low level of Industry 4.0 readiness compared to more advanced industries [8].

Studies have been conducted by researchers to assess the level of Industry 4.0 readiness or maturity in the Textile and Clothing industry. A research conducted in Brazil, aims to contribute to organizational management by developing and applying a maturity model to assess companies in terms of technological maturity for Industry 4.0, using a multi-criteria approach to sorting problems. To demonstrate the applicability of the model, Brazilian textile companies were evaluated [9]. Another attempt [10] aims to present an instrument for diagnosing the maturity of Industry 4.0 technologies adapted to the textile and clothing sector and built based on technological references that support this industrial evolution process. Further research [11] presents the applications of Industry 4.0 in the apparel industry and the analysis of existing Industry 4.0 readiness assessment models based on a systematic literature review, evaluation criteria were proposed to assess the strengths and weaknesses of each model. The study conducted in Kazakhstan [12], focuses primarily on SMEs in the Textile sector, which account for almost 97% of all companies in the country.

As a result, there is discussion in the literature regarding appropriate and productive implementation priorities: Some writers highlight that companies for manufacturing sector need to prioritize investments in shop-floor digitalization (common fact in developing countries) and focus on understanding cybersecurity requirements (which hinders the implementation process) [13]. Another work [14] developed a decision-making system based on prioritization of the industry 4.0 design principles and characteristics including flexibility, self-adaptability, self-reconfigurability, context awareness, decision autonomy and real-time capabilities. However, others argue that considering the corporate strategy, a recommended Industry 4.0 roadmap is identified showing financial and strategic potential as well as implementation order and duration. In this context, the study [15] uses a Pythagorean fuzzy set (PFS) and Multi-Criteria Decision-Making (MCDM) to provide an analytical framework for prioritizing policy measures to address I4.0 transition barriers. The Thai food processing business in Portuguese serves as an example of the suggested structure that is described there. Thereby, the roadmap is a very effective tool to support management decision processes regarding a beneficial and tailored Industry 4.0 implementation [16]. Tortorella and Fettermann [17] argue the importance of better understanding how these technologies will be integrated in production systems. Several studies exist about the technology adoption process and the factors influencing it, including Tiwari et al. [18]. Despite diverse advances in this field, the literature lacks empirical studies mapping implementation priorities and difficulties in emerging countries, especially in Morocco. Understanding the adoption process in this context is important, since diverse emerging countries, and particularly Morocco, take part in major global supply chains, including Textile and Clothing, food, automotive, aerospace and other sectors. Then, a successful deployment of Industry 4.0 technologies depends on insightful implementing priority.

As a result, this achievement is also dependent on several criteria known as critical success factors (CSFs), which have been established as necessary for the successful implementation of industry 4.0 and have gained a wider scope through important research [18,19,20,21,22].

Based on the common properties of CSFs, this paper attempts to describe the selection and order for successfully implementing Industry 4.0. Based on its CSFs, this is the first study to employ a neural network model to suggest the key areas that must be prioritized to implement or enhance industry 4.0. The apparel industry will use the established model. Moreover, the choice of the implementation priorities of the sixteen Industry

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4.0 dimensions according to SIRI (Singapore Industry Readiness Index), could have a direct effect on the success of Industry 4.0 adoption [23]. Therefore, the primary goal of this study is to obtain the necessary data and connect them. (See **Figure1**).

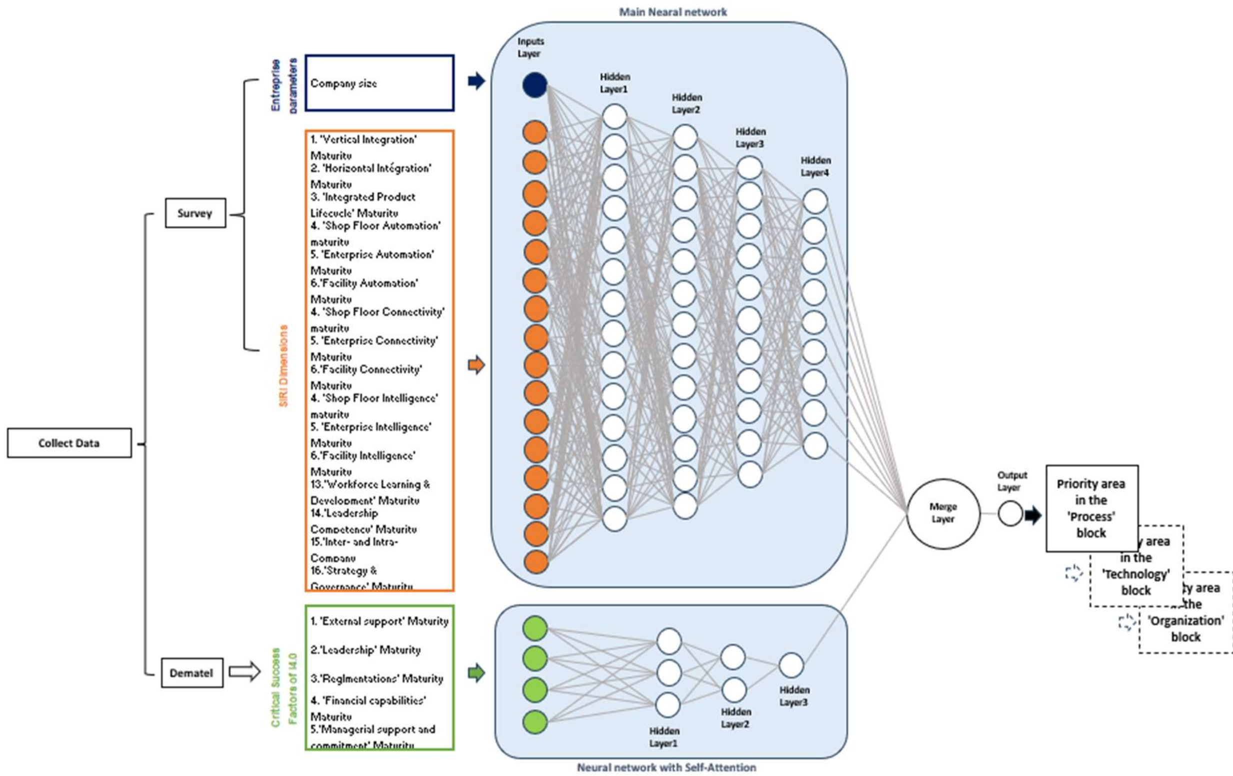

Figure 1: Neural network model input and output.

The data will be compiled from:

CSF maturity, which measures the amount of effort required to reach each CSF, will be addressed separately for Industry 4.0 common CFSs. The maturity of CSFs is correlated with their deployment level. It alludes to the extent to which each element is embodied into the business through its extension into the organization [24].

The companies under study select and put implementation priorities. Next, we set the aim wish is to prioritize one focus area per building block of the SIRI framework (Process, Technology, Organization). Naturally, a trained neural network model will supply the solution due to the problem's intricacy and the large number of variables (**Figure 1**). Furthermore, we decided to use this approach in the apparel and textile industry since, in Morocco today, this industry tends to increase its competitiveness by raising prices, and any waste or scraps that could compromise the desired profit margin are not tolerated. The results of this study could provide a foundation for other researchers looking to develop a roadmap for successful digital transformation through initiatives customized for each prioritized focus area, as Rahmatulloh et al. [34] did in their qualitative study.

The format of this document is as follows: Section 2 explains the SIRI Framework and presents the common CSFs of Industry 4.0 that were taken from the literature. The three steps of the technique are explained in Section 3: The experts who were interviewed verified the CSFs in the first step. They also recorded each CSF's maturity inside their organizations using a Likert scale. Additionally, they had used the SIRI Index to indicate the maturity of the SIRI Dimensions. The neural network is used as a novel technique to forecast the output's appropriate priority in the second stage. Then, using the trustworthy database

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of CSFs' maturity and dimensions maturity as inputs for every company size, we trained our neural network (**Figure 1**). The conversation and graphical and numerical results are best illustrated in Section 4. Additionally, a suggested way to expand on the created model in order to get ready for the Industry 4.0 implementation stage in a clothes company. Contributions to research and differences from prior work, also future research directions are provided in Section 5. The paper is concluded in Section 6.

2. INDUSTRY 4.0 CRITICAL SUCCESS FACTORS (CSFs) AND SIRI FRAMEWORK

2.1. Industry 4.0 Critical Success Factors

Critical success factors (CSFs) have been widely studied in multiple contexts. An example is the adoption of ERP systems in manufacturing companies [19]. In recent years, many researchers have studied CSFs for the transition to I4.0 in manufacturing SMEs. The identification of these CSFs has been the subject of several structured literature reviews [18,21], also through Delphi approaches with a list of experts [19,20] and case studies [25]. Using a Delphi study and the assistance of experts in digital transformation in manufacturing SMEs, researchers in [19] have listed ten CSFs and categorized them based on importance, starting with "conducting a study prior to embarking upon any Industry 4.0 project" and ending with "the importance of employee training". Cyberphysical systems implementation has also been studied through identification of ten critical success factors [18]. Finally, regarding Critical success factors for ERP implementation projects, 13 have been identified [23]. Overall, if we consider the overlaps between the CSFs identified for digital transformation projects and we can synthetize them into the following 15 CSFs in the context of manufacturing SMEs [26]: *I4.0 strategy alignment to business strategy*, *Leadership*, *Alignment along a hierarchical line*, *Study conduction prior to Industry 4.0 projects*, *Communication management*, *Project management*, *Financial capabilities*, *Culture and change management*, *Continuous improvement*, *Collaboration and Teamwork*, *Employee training and knowledge development*, *Managerial support and commitment*, *External support*, *Regulations*, *Supply chain alignment*.

Our previous DEMATEL analysis [26] reveals that among these 15 CSFs, five have fallen into the influencing group. It should be noted that improvements in the influencing factors result in advancements in the other ten influenced factors. As a result, we must initially concentrate on the five influencing factors. Then, successful adoption of industry 4.0, as previously said, depends on a set of CSFs to measure firms' readiness and assign the appropriate maturity to each one. These influencing CSFs have been selected for our study and are listed in **Table 1**.

Table 1: I4.0 critical success factors.

I4.0 Critical Succes Factors	References
External Support	[22, 27]
Leadership	[19,20,22,28]
Regulations	[27,29]
Financial Capacities	[22,30]
Managerial support and commitment	[31,32]

Additionally, managing the CSFs to get them ready for the pre-implementation stage involves preparing them for the implementation of I4.0 dimensions as a top priority. We had to prepare our data for this reason to make sure that all of the aforementioned variables were appropriate for our model. This will be done in the following section.

2.2. SIRI Dimensions

The aim of the study [33] conducted, is to assess the level of maturity of Moroccan apparel manufacturing companies and examine the disparities in the way they assess and execute their strategies to implement Industry 4.0. The Industry 4.0 Readiness Index for Singapore SIRI (also known as "the Index") is selected as the primary evaluation tool because of its multifaceted nature (**Figure 2**), which provides information on both current and future improvement plans. With government assistance, the Index is also tailored to small and medium-sized businesses (SMEs) and multinational corporations (MNCs) with an emphasis on practical application. The study focuses specifically on Moroccan companies, with a particular emphasis on apparel companies, to assess their maturity levels. Secondly, to prioritize the focus areas in order to improve the digital maturity, focuses on an empirical study to better understand the current level of Industry 4.0

preparedness and a suggested path for the textile and clothing industry in order to close the gap in the Industry 4.0 evaluation campaign. To ensure the best outcomes, the SIRI priority matrix insists on implementing the three Industry 4.0 building blocks concurrently, which raises the issue of appropriate and productive sequencing in the literature [23,34,35,36]. The main challenge is to define the most suitable priority of the 16 SIRI dimensions, in another words, to define a combination of three focus areas to improve digital maturity (1 priority focus area per building block). Then, a successful deployment of Industry 4.0 depends on insightful implementation priority.

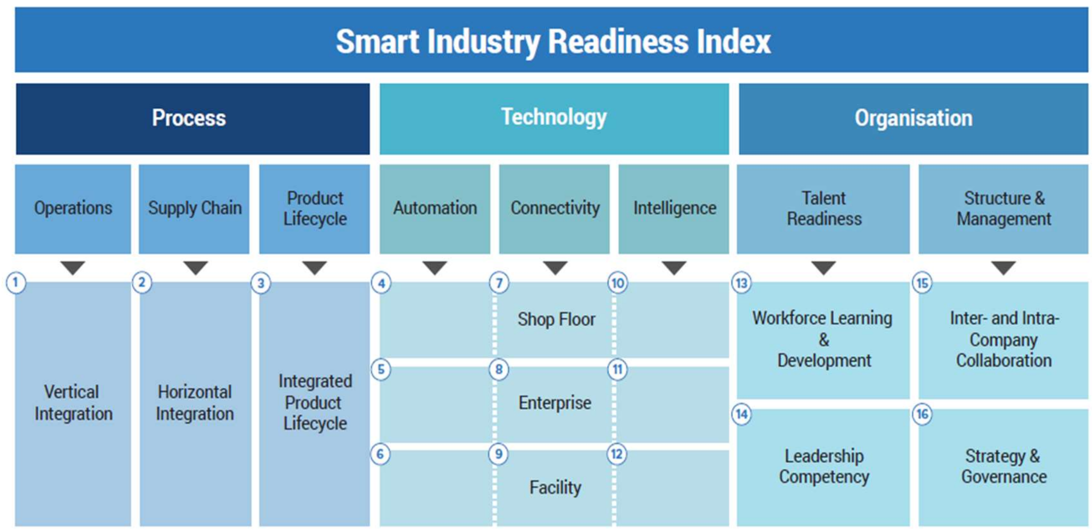

Figure 2: Singapore industry readiness index "SIRI" [34].

3. METHODOLOGY

Neural networks and deep learning algorithms are excellent substitutes for this type of issue that calls for training and data insight [37]. In contrast to many heuristic methods, deep learning is devoid of calculation rules and may be trained using data to find robust relationships between focus areas, priority (outputs), CSFs' maturity, and SIRI dimensions maturity (inputs).

According to the SIRI Framework, Industry 4.0 is built around 3 blocks which are: Processes, Technology, and Organization. Thus, our aim is to predict one area of intervention per Industry 4.0 building block, so we opted for a predictive model, based on a simple neural network, with self-Attention. Self-attention allows a model to weigh the significance of different elements in a sequence relative to each other. It computes attention scores based on the relationships between elements in the input sequence, enabling the model to capture long-range dependencies.

Value (V), Key (K), and Query (Q): Every input vector is converted into three vectors during self-attention:

- The element for which we are calculating attention is represented by the query (Q).
- Key (K): Indicates the components that will be contrasted with the query.
- The actual material that will be weighted and totaled according to the attention scores is represented by the value (V).

Formulas:

Weight Matrices (Eq. (1)): Each input vector x_i is transformed into its corresponding query, key, and value vectors using learned weight matrices:

$$V = XW_v \,,\ K = XW_k \,,\ Q = XW_q \qquad (1)$$

Where: W_q, W_k, W_v are weight matrices for queries, keys, and values respectively.

Attention Scores (Eq. (2)): The attention scores are calculated as the dot product of the query and key vectors:

$$w_{ij} = Q_i * K_j = q_i^T K_j \quad (2)$$

Where: w_{ij} represents the score between the i^{th} query and the j^{th} key.

Scaled Attention Scores (Eq. (3)): To prevent large values from causing instability during softmax computation, the scores are scaled by the square root of the dimension of the key vectors d_k:

$$\text{Scaled score}_{ij} = \frac{w_{ij}}{\sqrt{d_k}} \quad (3)$$

Softmax Normalization (Eq. (4)): The scaled scores are then normalized using the SoftMax function to obtain attention weights:

$$\alpha_{ij} = \text{Softmax}(\text{scaled score}_{ij}) = \frac{e^{\text{scaled score}_{ij}}}{\sum_k e^{\text{scaled score}_{ik}}}$$
(4)

Output Calculation (Eq. (5)): Finally, the output of the self-attention mechanism is computed as a weighted sum of the value vectors based on the attention weights:

$$z_i = \sum_j \alpha_{ij} * V_j \quad (5)$$

or in matrix form **(Eq. (6)):**

$$Z = AV \quad (6)$$

where $A = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})$ is the attention matrix.

In fact, self-attention is applied to the Critical Success Factors derived from our DEMATEL analysis. Simple neural network models are popular architectures in the field of deep learning. When Self-Attention mechanisms are added, these models can become even more powerful for certain tasks, especially those involving sequential or structured data. However, this approach's biggest drawback is the dearth of extensive datasets representing real-world Industry 4.0 implementation situations. The results of the maturity assessment study [33] of the Textile and Clothing sector in Morocco will be used as a basis for the training of our model. In conclusion, a variety of methods have been used in this work to gather and assess the data.

Then, as described in **Figure 1**, the predictive model of the focus area priority dimensions of the three building blocks, this model represents 22 input data and 1 output data; among the input data, 1 is linked to the size of the company, 16 to the maturity of the SIRI dimensions, and 5 to the maturity of the Critical Success Factors. The output is linked to the focus area priority of the building block dimensions. The model is computed 3 times, each time with a different output: The priority dimensions of the Process building block, the priority dimensions of the Technology building block, and the priority dimensions of the Organization building block.

3.1. Data collection

This step undertook a measurement of digital maturity for different company sizes, which addressed their implementation under different focus area priorities. To participate in this study, practitioners had to have managed at least one Industrie 4.0 project. Data was collected via an online survey. Digital maturity was measured using the SIRI model. Based on their positions, respondents were asked to rate the maturity of the following dimensions on a scale of 1 to 5 according to the SIRI index: Process block: 1 = vertical integration; 2 = horizontal integration; 3 = integrated product lifecycle - Technology block: 1 = shop floor automation; 2 = shop floor connectivity; 3= shop floor intelligence; 4= company automation; 5= company connectivity; 6= company intelligence; 7= facility automation; 8= facility connectivity; 9= facility intelligence - Organization block: 1= employee training and development; 2= leadership skills; 3= inter- and intra-company collaboration; 4= strategy and governance.

Figure 3 displays the average readiness index value for each dimension across the 252 participating businesses. An overview of the Industry 4.0 readiness index for Moroccan textile and apparel manufacturing enterprises is provided by the average value. Comparing the results of the Industry 4.0 readiness index in the same framework with global companies is essential to understanding the position of the Textile and Clothing industry in Morocco to achieve its goal "To become a benchmark for sustainable production, win back the local market and boost Morocco' s export performance by conquering new markets." In comparison with the global benchmark, additionally, **Figure 3** displays the

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best-in-class readiness index and the average value of the worldwide readiness index, which are based on the SIRI global assessment of 600 multinational corporations across 14 industrial sectors, including textiles and clothing [8].

Moroccan Textile companies have an average readiness index of **0.95**, while the average global Textile company has a readiness index of **1.04**, and global Textile companies in the “best in class” category have a readiness index of **3.19**. In general, the readiness level of Textile companies in Morocco is close to the world average. However, it is still much lower than that of companies in the best-in-class category.

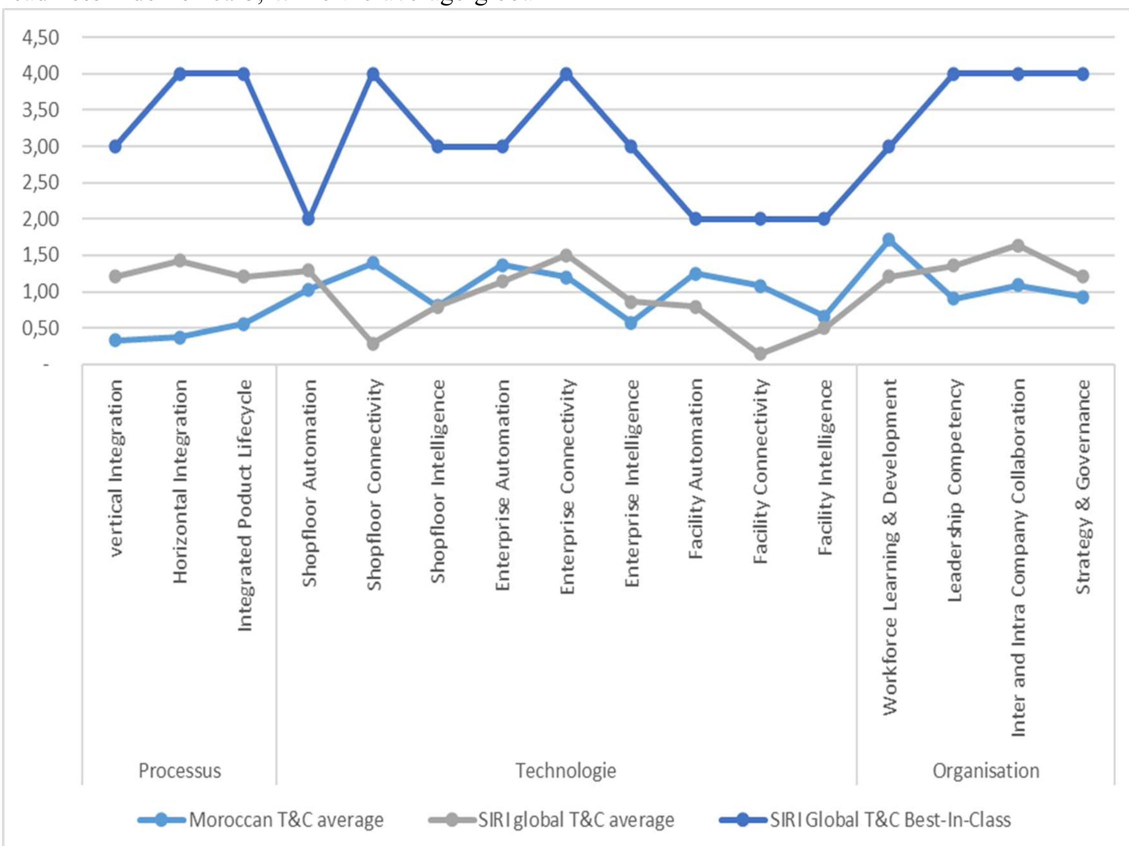

Figure 3: Industry 4.0 Readiness Index Benchmark Textile & Clothing (T&C)

(Source: Own elaboration; World Economic Forum [8]; Singapore economic development board [23])

In addition, survey participants were asked to measure, on a scale of 1 to 5, the maturity of I4.0 critical success factors (CSFs) within their respective companies. The five-point Likert scale was used to measure the CSFs scores. The following indications were presented to the respondents for selection: 1 = not Mature; 2 = Slightly Mature; 3 = Mature; 4 = Very Mature; and 5 = Totally Mature. All input variables were encoded as integers and converted to one-hot encoding format. According to the SIRI prioritization principle adopted in our study, the 3 building blocks must be developed simultaneously for a successful implementation of Industrie 4.0.

3.2. Data Pré-processing

To maintain data integrity, all values in the original data were converted to numeric format, and rows with missing values were eliminated. The Priority column was chosen as the target variable after irrelevant columns were eliminated from the features. The remaining columns were kept as the primary characteristics, but a particular subset of the features (FCSs maturity columns) was isolated

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for use in the attention mechanism. Label Encoder was used to encode the target variable in integers, and it was subsequently transformed into a one-hot encoding format for use in the classification model. To make sure that every feature was on a similar scale, StandardScaler was used to normalize the remaining features and attention columns independently. After combining normalized data, principal component analysis (PCA) was used to optionally reduce the number of dimensions while maintaining the most amount of information. To deal with uneven classes, data were balanced using RandomOverSampler's oversampling technique. Train_test_split was used to separate the balanced data into training and test sets, with 80% going to training and 20% to testing.

This meticulous pre-processing process ensures that the data is clean, normalized and correctly structured for the neural network model, improving the quality and performance of the predictions made by the trained model.

3.3. The neural network modeling and training

Neural networks are made up of a set of processing elements called “neurons”. This is a group of interconnected nodes used to establish complex relationships between inputs and outputs [38]. This neural network has a triple hidden layer - R inputs (I) and S outputs (O). When bias is present, each neuron adds up the input weights and sends the total to the activation function to produce the output. The main difficulty lies in choosing the right learning algorithm. The number of neurons in the hidden layer, the connection between neurons and the layer, the error function, and the activation function are only a few of the numerous variables that impact training activities, making neural network design extremely complex [39]. Thus, one of the most important steps in enhancing neural network outcomes is hyperparameter tweaking. This is a technique in which the algorithm parameters are chosen in such a way as to obtain the optimal solution, which depends essentially on the parameters of the hyperparameter [40]. In our case, the optimizer used is Adam.

Table 2 explains our neural network learning algorithm's hyperparameter combinations. In our setup, there are three hyperparameters to set per network, for the Main Network: Flattening Layers, Number of Dense Layers, Dropout, Learning Rate, which is 0.001 and after Dynamic Reduction becomes 0.0005, and for the self-Attention Network: Number of Dense Layers, Internal Attention Layers, Flattening Layers. Finally, a parameter for the fusion layer. There are many alternatives evaluated.

Table 2: Hyperparameters combinations

Model	Step	Layer type	Parameters of Layers
Neural Network with Self-Attention	Step 1	Flatten	Inputs Flatten (17)
		Dense	Units: 128, Activation: ReLU
		Dropout	Rate: 0.3
	Step 2	Dense	Units: 128, Activation: ReLU
		Attention (Self-Attention)	Applies self-attention to features
		Flatten	Inputs Flatten (5)
	Merge	Dense	Units: Nbr of classes (softmax output)

One of the most popular techniques for hyperparameter optimization, which has been demonstrated to produce good empirical results for hyperparameter tuning, will be employed in this study.

4. RESULTS AND DISCUSSION

4.1. The proposed framework

In phase 1, our algorithm continued to add layers until the test error stopped improving. We successively obtained 17 units, and 128 units located in the first and third hidden layers of the algorithm, respectively, in which the Relu function applies weights to the inputs; these two layers are separated by a flattening layer. The ideal value for dropout in a hidden layer was 0.3 in order to prevent overfitting and boost generalization power.

In phase 2, the algorithm continued to add layers until the test error stopped improving. We obtained successively 5 units, and 128 units located in the first and third hidden layers of the algorithm, respectively, in which the Relu function applies weights to the inputs; these two layers are separated by a flattening layer. A self-attention layer comes after these three layers.

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Adam was designated as the optimizer in order to train the neural network with various adaptive learning rates. Based on adaptive moments, Adam (Adaptive Moment Estimation) is a stochastic gradient descent optimizer. It combines the advantages of two other popular optimization methods: AdaGrad and RMSProp. Adam maintains an adaptive learning rate for each parameter by calculating moving averages of the first and second gradient moments. The learning rate was then set at 0.001, allowing the network to retain optimal weight management at the conclusion of each batch by appropriately updating its parameters. Additionally, it regulates how quickly or slowly a neural network model picks up on our issue. After that, the Adam optimizer keeps and modifies this specified learning rate for every weight in the model. If the input is positive, the linear function Relu outputs the value directly; if not, it outputs zero. By resolving the leaky gradient issue, this activation function helps models learn more quickly and function better. Neural network models that anticipate a multinomial probability distribution employ the softmax function as the activation function in the output layer for multiclass classification (see **Figure 4**). Overall, the hyperparameters were tuned via a multi-step process. The process of tuning the best combination of hyperparameters in terms of validation performance took place in several stages.

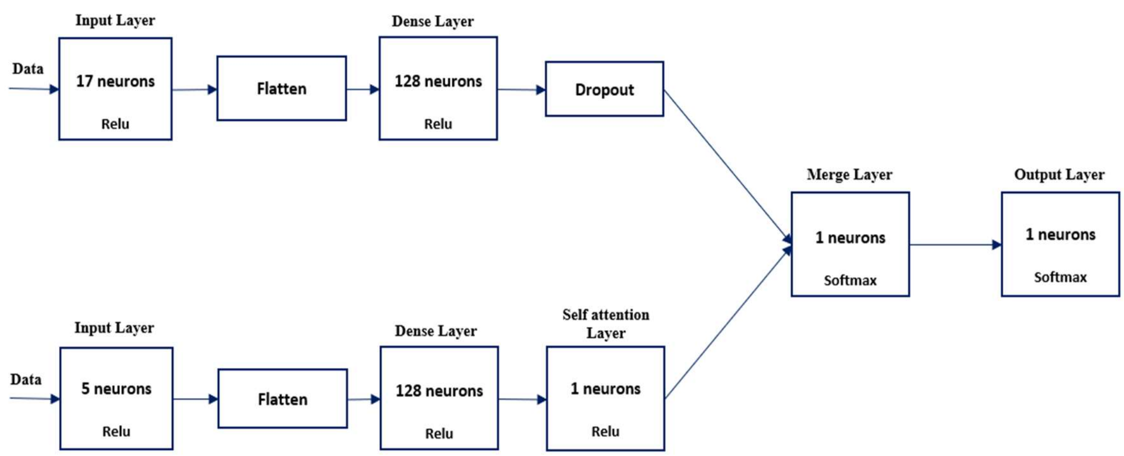

Figure 4: Architecture of our neural network model for predicting the priority of focus areas in I4.0 implementation/improvement.

Finally, evaluating performance by accuracy enabled us to draw conclusions about the efficiency of our network's performance. As previously discussed, we discovered that the greatest outcomes came from using these hyperparameter combinations:

Main Artificial Neural network :

- Number of hidden layers: 4
- Flattening layer: 1
- Number of units in first layer: 17
- Abandon: 0.3
- Learning rate: 0.001

Self-attention Network :

- Number of hidden layers: 4
- Flattening layer: 1
- Number of units in first layer: 5
- Self-attention layer: 1
- Learning rate: 0.001

4.2. Evaluation of the neural network model

One of the main indications of overfitting is the increase in validation errors. Some of the most popular criteria, such as categorical cross entropy, were selected for our multiclassification instance (CCE), Precision, Recall and F1 Score, to better assess the performance of the network model. In order to learn to assign a high probability to the correct digits and a low probability to other digits,

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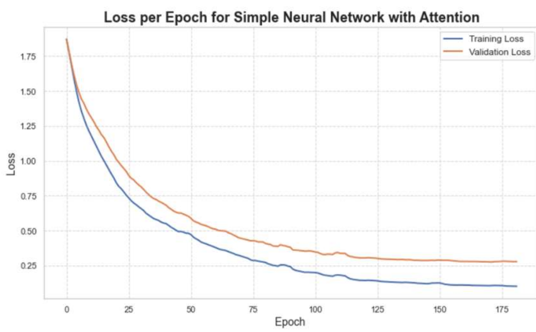
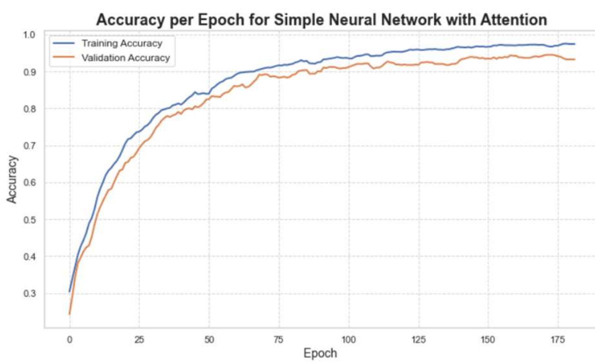
our model makes use of categorical cross entropy (CCE). In addition, precision evaluates the accuracy of our model in relation to real data points. The higher the precision, the more efficient the model [41]. The best neural network is characterized by low CCE and high accuracy.

Figures 5 compare and illustrate the evolution of CCE and accuracy as a function of the number of Epochs for the 3 outputs in question (Process Priority, Technology Priority, and Organization Priority). The accuracy achieves its best value (93.8%) and the CCE reaches its lowest value (0.120) for the Technology Priority output when the number of epochs hits 175. Accuracy achieves its best value (96.5%) and the CCE reaches its lowest value (0.100) for the Organization Priority output when the number of epochs exceeds 200. When there are 175 epochs in the Process Priority output, the accuracy reaches its maximum value of 92.8% and the CCE achieves its lowest value of 0.120.



a)



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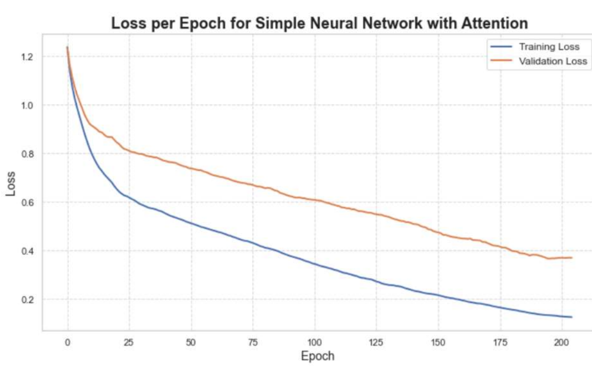

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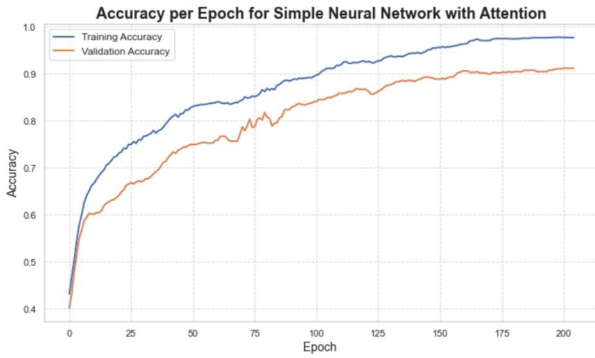

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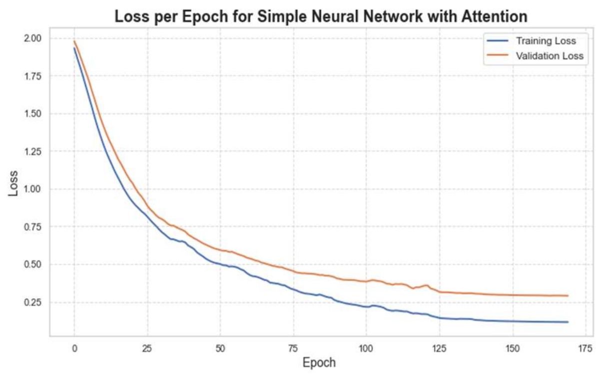

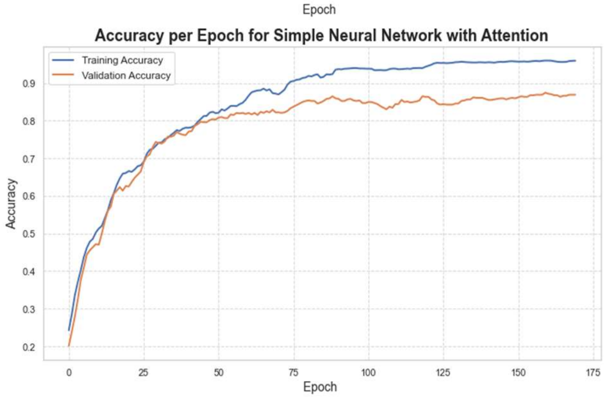

Figure 5: Evolution of CCE (Function Loss) and accuracy as a function of the number of Epochs for Priority: ***a)*** *Technology Priority,* ***b)*** *Organizational Priority,* ***c)*** *Process Priority*

For example, our model proposed 500 as the number of epochs for the three outputs, to obtain a smoother graph and good results with a high accuracy of up to 96.5%. Furthermore, four measures, in addition to classification accuracy, are generally required to evaluate the performance of a neural network model based on a test dataset [40].

The measures used are Test Loss, Accuracy, Precision, Recall and F1 Score (Results shown in **table 3**, **a)-b)-c)**):

- Precision is the proportion of samples that belong to a given class label and have a specific anticipated class label: Low false positive rates are linked to high precision. We achieved a very good precision of 93.3%, 93.8%, and 96.5% for the Process Priority, Technology Priority, and Organization Priority outputs, respectively.
- The percentage of samples of a class that were accurately predicted to belong to that class is known as recall. For the outputs Priority Process, Priority Technology, and Priority

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Organization, we obtained 92.8%, 93.9%, and 96.5%, respectively. This is good for this model because it is higher than 50%.

- The harmonic mean of a model's recall and precision is known as the F1 Score. These two criteria are combined to produce a single evaluation that shows how well the model balances avoiding false positives with identifying positive cases. By properly identifying a high percentage of positive cases while keeping a low rate of false positives, the model appears to have a solid capacity to balance precision and recall, according to the scores collected.
- The degree to which a measurement resembles the genuine or actual value is known as accuracy. To put it another way, it shows how closely a measurement's findings match what is deemed accurate or equitable. The model appears to function effectively in most situations, and the scores collected indicate good overall performance. Nearly 92% of priorities were accurately anticipated.
- Test Loss measures the discrepancy between the test set's actual values and the model's predictions. A loss function, which gauges the discrepancy between model predictions and actual targets, is used to calculate it. A low loss test shows that the model has a good generalization ability and produces few errors when applied to unidentified data. The results indicate that the model's degree of error is comparatively low for all tests. For process priority, the model can be improved.

In summary, the bias and weights were initially chosen at random; subsequently, the neural network will learn on its own through the application of multiple iterations, performing forward propagation while tagging the measures highlighted in this session.

*Table 3: Performance indicators of the neural network with self-attention model for predicting **a)** Technology Priority **b)** Process Priority **c)** Organization Priority*

a)

Model	Test Loss	Test Accuracy	Precision	Recall	F1 Score
Neural network with self-attention	0,26	93,9%	93,8%	93,9%	93,7%

b)

Model	Test Loss	Test Accuracy	Precision	Recall	F1 Score
Neural network with self-attention	0,17	92,8%	93,3%	92,8%	92,9%

c)

Model	Test Loss	Test Accuracy	Precision	Recall	F1 Score
Neural network with self-attention	0,18	96,5%	96,5%	96,5%	96,5%

4.3. Application of the trained neural network

The application of our developed neural network model will define the process, organizational and technological priorities for successful digital transformation within a given company. The model will help managers in the textile and clothing industry to develop a customized integration strategy during their transformation journey. Field data will be collected on the company's manufacturing site over a given period. The data collection exercise includes 22 input variables, 17 inputs for the classical neural network and 5 inputs for the self-attentive neural network, it will also have 1 output variable (priority of focus areas). The input data will be fed into our trained neural network model and will be used to define and predict the output data within the company (Results shown in **Figure 6**).

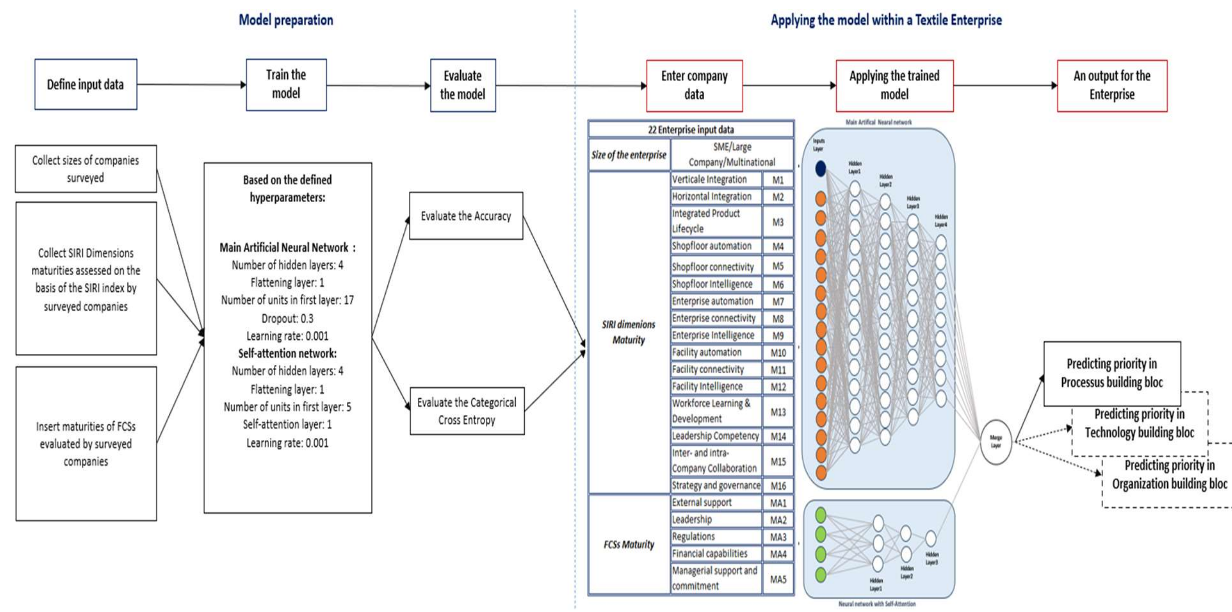

Figure 6: Flowchart of applying for the model within a T&C Company.

As we have seen, and according to the accuracy and CCE values, the neural network developed is a good approach for increasing the chances of success in digital transformation projects and achieving a better result. Indeed, the model achieved better results based on data from different companies. The neural network developed gives the company the ability to respect its CSFs and resources with better results. At the same time, the company can conduct continuous learning, which is another important advantage for prioritization, as training data is not limited, and new cases are continually encountered. For this reason, the use of a neural network can provide the company with a new approach to constantly improving the performance of its I4.0 implementation strategy, while increasing the inconsistency of correlations between CSFs and targeted performance.

5. CONTRIBUTION AND FUTUR RESEARCH

This study distinguishes itself from previous literature in several key aspects. First, while many prior studies have explored Industry 4.0 maturity assessment frameworks, they often relied on static models or manual prioritization methods [42]. In contrast, our approach employs a dynamic and adaptive neural network-based decision support system that integrates company size, SIRI dimension maturity, and critical success factors (CSFs) to prioritize focus areas effectively. This integration addresses the limitations of static models by offering a scalable and customizable solution that evolves with varying organizational contexts.

Second, existing studies typically focus on specific dimensions of Industry 4.0 maturity or provide generic recommendations without tailoring them to the unique needs of companies of different sizes or maturity levels [9]. Our study bridges this gap by emphasizing the nuanced relationship between input variables and their impact on prioritization, thereby enabling actionable insights tailored to organizational characteristics.

Third, most prior works concentrate on theoretical frameworks or qualitative analyses [43]. By incorporating advanced deep learning techniques, our methodology moves beyond conceptual discussions to provide a practical, data-driven tool. This shift not only improves the precision of focus area prioritization but also ensures robustness and reliability in real-world applications.

Limitations and Future Research Directions

- **Industry-Specific Data**: The dataset used in this study is specific to the Moroccan textile and apparel industry, which may limit the generalizability of the findings. Future research could apply this methodology to other industries and geographic regions to validate and extend its applicability.
- **Data Availability**: The reliance on a high-quality training and validation dataset poses challenges in contexts with limited data availability. Addressing this issue through synthetic data generation or data augmentation techniques could enhance the model's usability.
- **Hyperparameter Optimization**: While this study identified optimal hyperparameters for the neural network, future research could explore automated optimization methods, such as Bayesian optimization, to further refine model performance.
- **Dynamic Factors**: The model does not currently account for dynamic external factors, such as market trends or regulatory changes. Including these factors could enhance its prediction accuracy.
- **User Interaction**: The decision support tool's interface and usability were not a primary focus of this study. Future work could explore user-friendly interfaces and real-time feedback mechanisms to enhance adoption by industry practitioners.

By addressing these limitations, future research can build upon our findings to further refine and expand the scope of neural network-based decision support systems for Industry 4.0 maturity enhancement.

6. CONCLUSION

This study addresses the challenge of prioritizing focus areas for Industry 4.0 maturity enhancement by developing a dynamic, neural network-based decision support tool. The primary contribution lies in its ability to integrate company size, SIRI dimension maturity, and critical success factors (CSFs) into a robust framework that provides tailored recommendations for decision-makers. Unlike static models or generic frameworks prevalent in prior research, this adaptive approach offers actionable insights that evolve with organizational needs, particularly in the textile and apparel sector.

Despite its strengths, the study has limitations. The data used was industry-specific, focusing on the Moroccan textile and apparel sector, which may limit generalizability. Expanding the dataset to include diverse industries and regions could improve the model's applicability. Additionally, while the neural network's performance was validated, external dynamic factors such as market trends and regulatory changes were not incorporated, which could enhance predictive capabilities. The reliance on high-quality training data also poses challenges in data-scarce environments, and future research should explore synthetic data generation to address this issue.

In summary, this work offers a novel approach to prioritizing Industry 4.0 focus areas and serves as a foundation for developing scalable, adaptable tools applicable across industries. Future studies could build on this framework to refine its scalability, usability, and applicability to varied organizational contexts, further contributing to the advancement of digital transformation initiatives.

Authors contributions

Conceptualization, Methodology, Software: *Younes JAMOULI and Mouhsene FRI.*

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