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Maturity Levels Evaluation of Smart Factories through Fuzzy Cognitive Maps

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Abstract

In today's industrial environment, digital transformation is crucial for companies aiming to remain competitive and embrace smart manufacturing practices. Within this context, Maturity Models (MMs) have become valuable instruments for guiding smart evolution and ongoing improvement. Nevertheless, the effectiveness and practical use of an MM largely rely on the presence of web-based tools that present evaluation outcomes in a clear and user-friendly manner, enabling effective self-assessment or third-party evaluation. This paper introduces SM-FCM, a novel interactive web-based application designed to facilitate the implementation of an MM utilizing Fuzzy Cognitive Maps (FCMs), which helps in representing complex causal relationships between concepts. The presented platform simplifies the process of configuring model inputs, clearly shows the results of the assessment, and enables users to simulate and compare multiple scenarios with ease.

Keywords: Smart Manufacturing; Maturity Model; Fuzzy Cognitive Map; Assessment Tool

1. Introduction

In the contemporary industrial landscape, digitization is essential for the survival and growth of companies, regardless of their size [1, 2]. This transformation encompasses the adoption of new digital technologies, processes, organizational structures, work methods, and business strategies [3, 4, 5, 6], along with the need to adopt both an intra- and inter-organizational perspectives [7, 8]. As such, this process is considered a critical decision-making problem, requiring a multi-way perspective to obtain an effective roadmap [9], as well as tools and guidelines to assess the digital maturity and identify critical areas for improvement [10, 11]. Among others, the literature repeatedly empha-

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sized the importance of evaluating and measuring a digital transformation path to what is defined *smart manufacturing* [12, 13].

Maturity Models (MMs) have emerged as powerful tools to support smart development and continuous improvement across various fields. Typical use of MMs is to support companies willing to start their digitization journey, helping them to understand where to begin, measure their current position, and assess various alternatives [14, 15, 16, 17].

Despite the availability of numerous MMs [11], there are notable limitations in their current applications. A primary limitation is the inadequate consideration of existing IT systems within organizations. Traditional MMs tend to focus on the presence and extent of specific digital manufacturing technologies, e.g., additive manufacturing [18] or artificial intelligence [19], often neglecting the Information Technology (IT) systems that are already integrated into the company's infrastructure [20, 21]. Additionally, conventional MMs often assess individual elements without adequately accounting for the causal relationships between them [22, 23]. This approach fails to recognize that technologies often serve as platforms that enable and enhance other technologies, creating a dynamic and interdependent ecosystem. As a result, there is a need for a more comprehensive model that considers these interconnections and provides a holistic view of digital maturity.

The above-mentioned gaps have been recently tackled in [24], where an MM that incorporates IT systems as integral components driving digitization in smart manufacturing has been proposed. The MM is based on Fuzzy Cognitive Maps (FCMs) [25], which are well-suited for representing complex causal relationships among factors. By leveraging FCMs, it is possible to take into account the intricate interplay between IT systems and enabling technologies. Also, the employment of FCMs makes the proposed MM suitable for simulation and what-if analysis.

However, the real impact and applicability of an MM strongly depend on the availability of web tools that make the result of the evaluation and, in the case of [24], of the what-if analysis clear and immediate to the final users for self-assessment [26]. In this paper, we propose SM-FCM, a graphical web application that supports the application of the MM proposed in [24]. This application allows for easily setting up the input for an MM built following the FCM-based approach and for comparing simulation scenarios.

The paper is structured as follows. Section 2 introduces the MM and preliminary notions to understand its internals. Section 3 describes the SM-FCM tool. Section 4 shows the results of a user study conducted on the tool. Section 5 compares the tool with relevant works in the literature. Finally, Section 6 concludes the paper with future works.

2. The Maturity Model

The SM-FCM tool supports the application of the FCM-based maturity model (MM), introduced in [24], which enables the assessment of IT systems and smart manufacturing enabling technologies within a company. It estimates the current maturity level and supports simulations and what-if analyses to guide digital growth. The remainder of this section first introduces the concept of FCM, and then describes the FCM-based MM proposed in [24]. However, this model should be considered a tool in continuous evolution, as the impact of information systems and technologies on smart manufacturing changes over time. Nevertheless, the methodology proposed in [24] allows the model to be easily updated to accommodate evolving requirements.

2.1. Fuzzy Cognitive Maps

Fuzzy Cognitive Maps (FCMs) are soft computing tools that combine elements of Fuzzy Logic and Neural Networks (NNs). An FCM is a type of network that offers a flexible and powerful framework for representing knowledge and reasoning in complex, real-world scenarios. In practice, it is a directed graph where nodes represent concepts within a domain of interest, and weighted edges describe the causal relationships among them. The structure of an FCM can be viewed as a neural network in which concepts function like neurons, and their activation is determined by the transformed weighted sum of inputs received from connected nodes. Unlike traditional neural networks, which often function as black boxes with hidden neurons and connections lacking explicit meaning, the neurons and connections in an FCM have clear and interpretable semantics.

Formally, a FCM is defined as $FCM = (C, W, A, f)$, where: *(i)* $C = \{C_1, \cdots, C_n\}$ is the set of n concepts; *(ii)* $W : C \times C \to [-1, 1] \subset \mathbb{R}$ is the *adjacency matrix* of the FCM which contains the weights w_{ij} (i.e., the causal relationships) assigned to each pair of concepts (C_i, C_j) and determining the sign and intensity of the edges connecting

Table 1. Concepts of the FCM-based MM

Concept	Level	Type	Name
SM	0	Main	Smart Manufacturing Maturity Level
CAD/CAM/PLM	1	IT system	Computer-Aided Design (CAD), Computer-Aided Manufacturing (CAM), Product Lifecycle Management (PLM)
CRM	1	IT system	Customer Relationship Management (CRM)
ERP/SCM	1	IT system	Enterprise Resource Planning (ERP), Supply Chain Management (SCM)
WMS/TMS	1	IT system	Warehouse Management System (WMS), Transportation Management System (TMS)
MES	1	IT system	Manufacturing Execution System (MES)
IIoT	2	Technology	Industrial Internet of Things (IIoT)
Cloud	2	Technology	Cloud Services
AI	2	Technology	Artificial Intelligence (AI), Computer Vision (CV), Process Mining (PM), Robotic Process Automation (RPA)
CS	2	Technology	Cyber Security
Robot	2	Technology	Robotics
AR/VR	2	Technology	Augmented Reality (AR), Virtual Reality (VR)
DT	2	Technology	Digital Twin
DM	2	Technology	Business Intelligence (BI), Data Management

the cause concept C_i with the effect concept C_j; *(iii)* $A : C \to A^{(t)}$ represents the *activation function* (also called *inference rule*) computing the activation vector $A^{(t)} = (A_1, \cdots, A_n)$ depicting the activation value, or strength, of each concept $C_i \in C$ at time step $t = \{1, \cdots, T\}$; *(iv)* $f : \mathrm{Re} \to I$ is the *transfer function* which maps the aggregated impact of the causal input (derived from A) into the predefined operating range (in other words, at any time t, each concept C_i has an activation value restricted to the predefined operating range). Usually, concepts' values are bounded within $[0, 1]$ or $[-1, 1]$.

The execution of an FCM begins with a specific initial condition, represented by the initial activation vector $A^{(0)}$. The inference rule is then applied iteratively until a stop condition is met, i.e., either reaching the maximum number of iterations T, or achieving an equilibrium state. The literature proposes several inference rules [25, 27, 28, 29]. Additionally, various transfer functions f can be used to constrain the computed activation values of concepts to a desired interval (e.g., $[0, 1]$ or $[-1, 1]$), such as the sigmoid, hyperbolic tangent, step, and threshold linear functions [30]. The choice of functions depends on the specific problem being modeled.

2.2. FCM-based Maturity Model

The MM is developed by building on FCM theory following the construction methodology presented in [24][1]. In the following, the various components that characterize the FCM behind the MM are described.

Concepts C and structure of the FCM. The concepts identified for the MM are inferred from the existing literature on Smart Manufacturing. Specifically, they are selected from a set of IT systems and enabling technologies that support smart manufacturing. Table 1 lists the identified concepts, presented in both abbreviated form (*Concept* column) and extended form (*Name* column). When evaluating a company's maturity, (activation) values are assigned to a subset of nodes and propagated through the map according to the defined structure.

This structure is organized into two levels: Level 1 comprises IT systems, and Level 2 comprises the technologies employed within these systems. In addition, a central concept, named "Smart Manufacturing Maturity Level", is defined to represent the primary outcome of the MM. Table 1 provides information on the levels of the concepts. The structure of the map is illustrated in Figure 1, where Level 1 concepts are shown in light blue and Level 2 concepts in light green.

[1] The version of the MM presented here follows the construction methodology outlined in [24], which provides a step-by-step guide for developing an FCM-based MM, reflects the insights of experts at the time of writing. However, the construction methodology can be easily reapplied, ensuring that the model remains up-to-date.

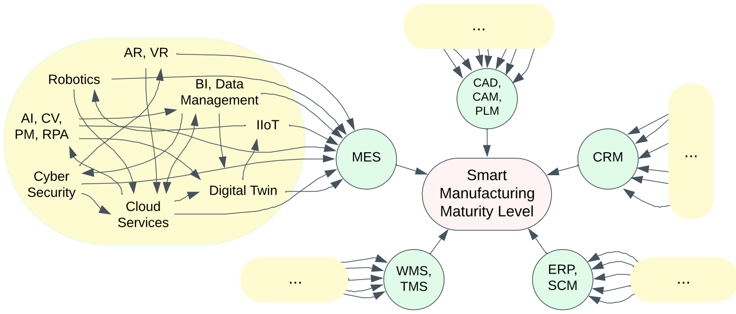

Fig. 1. Structure of the FCM-based MM

Table 2. Activation levels meaning

Level	LT	Description
Absence	VL	The technology is currently not used in the system.
Planned	L	Design and planning phase for the implementation of the technology, but it has not yet been implemented.
Just Started	M	Initial phase of technology implementation (e.g., pilot project) and first test conduction.
Under Development	H	The technology has been implemented and integrated into the system, but is still in development and used only by a limited number of users.
Developed and Ongoing	VH	The technology has been fully implemented and integrated into the system (in at least one process) and activities of monitoring and continuous improvement are underway.

Table 3. Technologies per system consensus

	CAD/CAM/PLM	CRM	ERP/SCM	WMS/TMS	MES
IIoT	✓	✓	✓	✓	✓
Cloud	✓	✓	✓	✓	✓
AI	✓	✓	✓	✓	✓
CS	✓	✓	✓	✓	✓
Robot	–	–	✓	✓	✓
AR/VR	✓	✓	✓	✓	✓
DT	✓	–	✓	✓	✓
DM	✓	✓	✓	✓	✓

Each Level 1 concept is shared with a sub-FCM composed of its related Level 2 concepts. The underlying rationale for this organization is to analyze the impact of the various technologies (Level 2 concepts) used within a specific IT system (Level 1 concepts) in the company being evaluated. Each sub-FCM is executed independently until equilibrium is reached, and the computed activation levels of shared concepts are then propagated upward to the corresponding higher-level sub-FCMs.

Adjacency matrix W**.** To represent the causal relationships and activation levels among the concepts, a 5-point linguistic scale is adopted, with specific membership functions defined over the interval [0, 1]. In particular, the selection of linguistic terms for the activation levels of the enabling technologies is inspired by the five-level assessment scale proposed in [31]. Table 2 presents the linguistic terms, their corresponding activation levels, and the meanings associated with each level. The activation level reflects the extent to which experts report the implementation of the processes within the company.

The adjacency matrix consensus is derived from interviews with a set of 19 experts actively involved in both the development and application of IT systems. These experts include industry professionals, IT system developers, and academics. Table 3 shows the final list of the technologies examined within each specific IT systems. For each identified relationship, the average values of relationship intensity (ranging from low to high or neutral) is calculated based on the expert assessments.

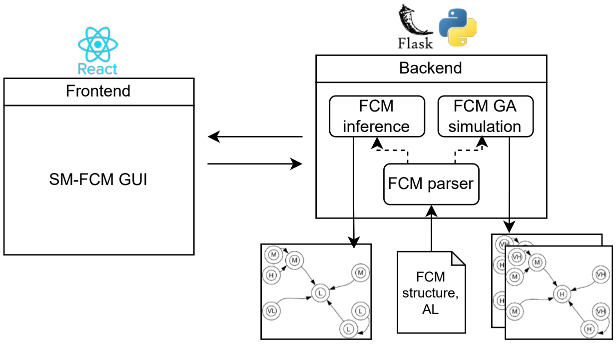

Fig. 2. SM-FCM architecture

Inference rule A and transfer function f. Since the chosen activation values lie within the interval $[0, 1]$, the sigmoid function $f(x) = 1/(1 + e^{-\lambda x})$ is selected as the most suitable transfer function. The λ values[2] used for the sigmoid function are $\lambda = 0.83$ for CAD/CAM/PLM sub-FCM, $\lambda = 0.85$ for CRM sub-FCM, $\lambda = 0.81$ for ERP/SCM sub-FCM, $\lambda = 0.91$ for WMS/TMS sub-FCM, and $\lambda = 0.75$ for MES sub-FCM.

Furthermore, the inference rule adopted[2] is the one proposed in [29], i.e., $A_i^{(t+1)} = f(\sum_{j=1, j\neq i}^{k} w_{ji}(2A_j^{(t)} - 1) + (2A_i^{(t)} - 1))$, which supports scenarios in which some concepts may lack initial activation values, as in the case for Level 1 concepts.

How to use the MM. The MM can be utilized in two distinct modes. First, it can be employed to determine a company's current level of SM maturity. Second, it supports what-if analysis, enabling users to simulate various scenarios and evaluate how improvements in specific technologies could enhance the overall SM score. This dual functionality makes the tool versatile, serving both as an assessment framework for the current state and as a strategic instrument for planning future advancements in smart manufacturing.

To assess the As-Is SM level, the user must provide its current activation levels (see Table 2) for each of the enabling technologies within its IT systems. Based on these values, the MM is executed to determine the overall SM activation level. In contrast, the what-if analysis is conducted using a Genetic Algorithm [32], which automatically generates multiple solutions by iteratively running the MM with evolving activation levels. These final solutions can then be analyzed to identify the optimal path for future development.

3. SM-FCM tool design and implementation

Figure 2 illustrates the architecture of SM-FCM. The system includes a front-end with a graphical user interface (GUI) developed using React[3], and a back-end implemented in Python. The back-end is a Flask[4] web application responsible for processing user inputs and returning the results from the application of the MM. A demo of SM-FCM is available online[5], and the source code can be accessed in GitHub[6], from which a local version can be deployed.

The SM-FCM graphical user interface (GUI) (see Figure 3) enables users to load the MM using the controls located in the orange block A. As described in Section 2, the MM proposed in this paper reflects the insights of the experts at the time of writing. However, alternative MMs developed using the construction methodology outlined in [24] can also be imported. The required format for the FCM-based MM is a .json file. Further details on the file structure are available in the GitHub repository.

Once the MM is loaded, the user can view a graphical representation of the FCM (see the green dotted box B in Figure 3). This visualization clearly depicts the different levels of the sub-FCM concepts and the weighted connections

[2] The validation of the values selected for λ and of the adoption of the selected inference rule is detailed in [24].
[3] https://react.dev
[4] https://flask.palletsprojects.com
[5] http://94.177.218.70:3000
[6] https://github.com/DIAG-Sapienza-BPM-Smart-Spaces/SM-FCM

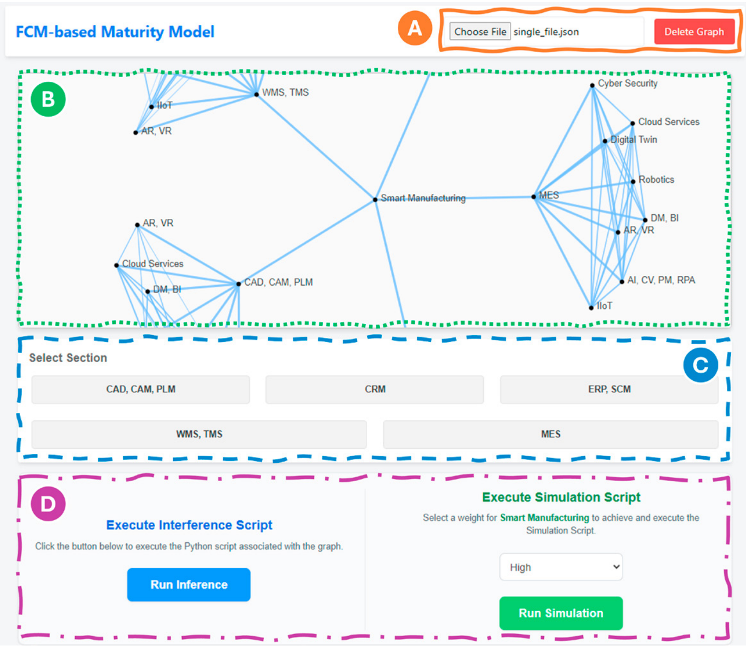

Fig. 3. SM-FCM GUI interface

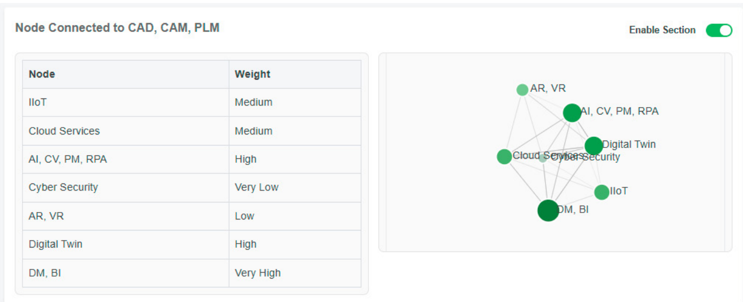

Fig. 4. Activation level setting

between them. Along with the functionalities provided in the blue dashed box C, this view enables the user to input the initial activation levels of the Level 2 concepts corresponding to each Level 1 concept. By clicking one of the buttons associated with a Level 2 concept, the section shown in Figure 4 appears, allowing the user to select the desired activation level. Upon selection, the size and color of the corresponding node are updated, enhancing the visual presentation of the MM.

The final functionality provided by the GUI involves interaction with the backend, using the controls located in the purple dashed block D in Figure 3. Specifically, the backend offers two core operations: inference and simulation. Inference refers to the computation of the company's current SM maturity level, while simulation focuses on generating alternative configurations through what-if analysis. A key internal component of the backend is the FCM parser, which processes the contents of the .json file uploaded by the user via the GUI (cf. orange block A in Figure 3). This file encodes the structure of the FCM underlying the maturity model, including its concepts and their causal relationships. The parser interprets both the FCM structure and the user-defined activation levels, converting them into a format suitable for processing by the inference and simulation engines.

More specifically, inference triggers the execution of the FCM-based MM, where the inference rule is applied iteratively, starting from the initial activation levels of the concepts, until either an equilibrium state is reached or the maximum number of iterations is completed.

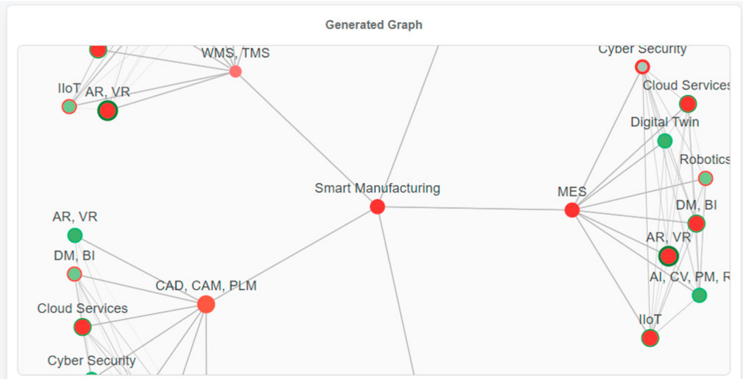

Fig. 5. Inference output

Simulation, on the other hand, employs a Genetic Algorithm to generate multiple alternative paths for achieving a specific maturity level defined by the user through the GUI. In this process, the FCM is executed across successive generations of evolving populations. The best individual from each generation is selected to construct a solution roadmap toward the desired maturity level. Consequently, the company is presented with various improvement paths, each offering a distinct strategy to reach the targeted maturity value.

Figure 5 presents the graphical output generated by the inference and simulation processes. Specifically, the figure illustrates the results of the inference functionality, where the displayed FCM highlights both the initial and final activation values of each concept. These values are visually distinguished through color coding (green for initial values and red for final values) and by varying node sizes. For example, the AR, VR technology in the MES IT system is represented by both a small red circle and a larger green circle, indicating that the concept started with a lower activation value and ended with a higher one. This change is due to the application of the inference rule, which combines the values of the nodes and arcs during execution. For the simulation, the GUI allows the user to explore the set of generated alternative solutions.

4. SM-FCM Usability

In [24], the MM integrated in SM-FCM (cf. Section 2) has been validated with graph theory analysis and FCM-based theory. Furthermore, the MM was also applied in a real case study, demonstrating its practical applicability and relevance for assessing manufacturing contexts.

In this paper, we evaluate the usability of the tool through a System Usability Scale (SUS) test involving 13 users from both the industry and academia. Users were initially instructed on the SM-FCM functionalities through a short training session, followed by an interactive session with the tool and the administration of the 10-item SUS questionnaire, which rates responses on a five-point Likert scale from 1-*strongly disagree* to 5-*strongly agree*. The overall SUS score (cf. [33] for instructions on how to compute it), considered a reliable measure of perceived usability and user experience, was benchmarked against literature standards to determine the tool's usability. The SUS score was 86.53, corresponding to an A+ rank according to the selected benchmark [33], indicating excellent usability.

5. Related Works

Scientific literature is witnessing exponential growth in the number of MMs [34, 35]. However, only a limited number of works make a web assessment tool available to end users. In the following, we present works that do so. The majority of these come from consulting firms. Other solutions are proposed by academia but they often lack an accessible assessment tool and instead provide only a Likert-scale questionnaire on request [36, 37, 38, 39, 40].

Table 4 presents a set of smart manufacturing MM assessment tools currently available. These tools can be categorized into web-assessment tools and self-assessment tools. Specifically, by web-assessment tools we refer to tools that are available online, while by self-assessment tools we refer to tools that can be used offline.

Table 4. Smart Manufacturing MM assessment tools

Tool	URL	Characteristics
IMPULS [41]	https://www.industrie40-readiness.de/?sid=62931&lang=en	Web-assessment
ERICSSON[7]	https://www.ericsson.com/en/industries/manufacturing/smart-manufacturing-maturity-assessment#	Web-assessment
L2L[8]	https://www.l2l.com/resources/digital-maturity-assessment	Web-assessment
Warwick [42]	https://warwick.ac.uk/fac/sci/wmg/research/scip/reports/final_version_of_i4_report_for_use_on_websites.pdf	Self-assessment
SMSRL [43]	https://www.nist.gov/services-resources/software/smart-manufacturing-systems-readiness-level-smsrl-tool	Self-assessment

The IMPULS Industry 4.0 – Readiness Online Self-Check [44] is a web-assessment tool developed by VDMA (Mechanical Engineering Industry Association), with a particular focus on small and medium-sized enterprises. It assesses the following dimensions: Strategy and Organization, Smart Factory, Smart Operations, Smart Products, Data-Driven Services, and Employees.

ERICSSON[7], in collaboration with inCode Consulting, developed the Ericsson Smart Manufacturing Maturity web-assessment tool consisting of 23 questions. It generates a detailed report outlining a company's smart manufacturing maturity level and comparing it to other companies that have completed the assessment. The report also includes recommendations to help companies grow their smart manufacturing capabilities, maximize return on investment, and ultimately deliver business value.

The Digital Maturity Assessment proposed by L2L[8] evaluates an organization's digital maturity across seven key areas of manufacturing operations, including Training & Skills Management, Standardized Work, Asset & Maintenance Management, Production Execution, Quality, Safety, and Continuous Improvement. It provides a personalized score, comparisons to industry and L2L customer benchmarks, and insights to strengthen an organization's digital transformation journey.

The Warwick Industry 4 Readiness Assessment tool [42] is a self-assessment tool, which considers six core dimensions with 37 sub-dimensions of Industry 4.0 readiness. The core dimensions include Products and Services, Manufacturing and Operations, Strategy and Organisation, Supply Chain, Business Model, and Legal Considerations. The tool is provided as a PDF template that can be completed to derive the maturity score.

NIST proposed the Smart Manufacturing Systems Readiness Level (SMSRL) [43], which measures maturity across four dimensions: Organizational, IT, Performance Management, and Information Connectivity. It is provided as a macro-enabled Microsoft Excel file that can be downloaded and self-executed by users.

Unlike the tools discussed above, SM-FCM, which can be classified as both a web-assessment and a self-assessment tool, specifically focuses on the IT systems and technologies employed within a smart manufacturing company, an aspect that is not, or only partially, addressed by any other tool. Similar to the other tools, the proposed tool also supports simulation. However, it offers additional advantages, as it enables users to visualize and analyze how changes in specific concepts affect overall maturity levels through the causal relationships captured by the FCM. Furthermore, unlike other tools that are designed for specific maturity models, the proposed tool is designed to be compatible with any FCM-based MM, offering broader applicability and flexibility to be employed in other domains.

6. Conclusions and Future Works

In this paper, we introduced SM-FCM, a web application that supports users in applying an FCM-based maturity model, as described in [24], to assess a company's current maturity from the perspective of smart manufacturing. The tool considers the support provided by existing IT systems and helps users identify ways to improve their maturity

[7] https://www.ericsson.com/en/industries/manufacturing/smart-manufacturing-maturity-assessment#/ (acc. June 2025)
[8] https://www.l2l.com/blog/digitalization-transformation-roadmap-for-manufacturing (acc. June 2025)

score by implementing or deploying new IT solutions. This helps organizations align their IT investment with their maturity objectives. Different from existing maturity model tools, SM-FCM stands out for its ability to capture and represent causal interdependencies between technologies, while also enabling scenario analyses that are adaptable and generalizable to alternative FCM-based maturity models. Furthermore, the tool is designed to require minimal technical expertise and is freely accessible online, making it a practical and scalable solution for both academic and industrial contexts.

As a first consideration for future works, the recommender algorithm may yield a multitude of different solutions to reach a specific maturity. It could be useful to this aim to introduce additional metrics to help users navigate them. These metrics may include implementation cost, deployment efforts, risk, or organizational readiness.

From the point of usability, possible improvements may also include the employment of Large Language Models to simplify the assessment, by, for instance, extracting information from documents, and the decision making process, through, for instance, generating a natural language explanation of why a roadmap could raise maturity, by supporting a conversation between the tool and the human user.

Finally, in its current state, the tool mainly supports the application phase, i.e., the use of an already existing maturity model, which is loaded as an input file. However, the methodology proposed in [24] allows for updating the maturity model by adding new classes of IT systems and areas, and fine-tuning the relationships between them. As the definition of a new or updated maturity model requires the involvement of experts, the tool could be integrated with a crowdsourcing platform, allowing for the involvement of stakeholders, thus simplifying the entire process and making it more sustainable with respect to point-to-point interactions and interviews.

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