Artificial Intelligence and Machine Learning for Maturity Evaluation and Model Validation

Thomas Hanne*
University of Applied Sciences and Arts Northwestern Switzerland, Olten, Switzerland
thomas.hanne@fhnw.ch

Phillip Gachnang
University of Applied Sciences and Arts Northwestern Switzerland, Olten, Switzerland
phillip.gachnang@fhnw.ch

Stella Gatziu Grivas
AbiliCor & University of Applied Sciences and Arts Northwestern Switzerland, Olten, Switzerland
stella.gatziugrivas@fhnw.ch

Ilyas Kirecci
ZHAW School of Life Sciences and Facility Management, Institute for Facility Management, Wädenswil, Switzerland
ilyas.kirecci@zhaw.ch

Paul Schmitter
ZHAW School of Life Sciences and Facility Management, Institute for Facility Management, Wädenswil, Switzerland
paul.schmitter@zhaw.ch

ABSTRACT

In this paper, we discuss the possibility of using machine learning (ML) to specify and validate maturity models, in particular maturity models related to the assessment of digital capabilities of an organization. Over the last decade, a rather large number of maturity models have been suggested for different aspects (such as type of technology or considered processes) and in relation to different industries. Usually, these models are based on a number of assumptions such as the data used for the assessment, the mathematical formulation of the model and various parameters such as weights or importance indicators. Empirical evidence for such assumptions is usually lacking. We investigate the potential of using data from assessments over time and for similar institutions for the ML of respective models. Related concepts are worked out in some details and for some types of maturity assessment models, a possible application of the concept is discussed.

CCS CONCEPTS

• **Computing methodologies** → Modeling and simulation; Model development and analysis; Model verification and validation; Machine learning; Machine learning algorithms.

KEYWORDS

Maturity model, Maturity evaluation, Model validation, Machine learning

ACM Reference Format:
Thomas Hanne, Phillip Gachnang, Stella Gatziu Grivas, Ilyas Kirecci, and Paul Schmitter. 2022. Artificial Intelligence and Machine Learning for Maturity Evaluation and Model Validation. In *2022 13th International Conference on E-business, Management and Economics (ICEME 2022), July 16–18, 2022, Beijing, China.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3556089.3556102

*Corresponding author.

ICEME 2022, July 16–18, 2022, Beijing, China

ACM ISBN 978-1-4503-9639-4/22/07.
https://doi.org/10.1145/3556089.3556102

1 INTRODUCTION

Maturity evaluation or assessment is an activity which is frequently done for different types of organizations and in different industries. This is especially useful for finding out where a company currently stands relative to its competitors on its path to excellence and how it could improve. Maturity assessments often focus on the adaptation of novel technologies and related innovations, especially regarding the adaption of information and communication technologies (digitalization).

A model is needed, which specifies how maturity is measured or calculated and what data is used for this purpose. In the academic literature and in more practice-related publications, a wide variety of different models is suggested [2] [8] [20] [30]. As we show with some examples, in most cases the suggested and employed models lack empirical evidence and are rather simplistically formulated and/or make some ad-hoc assumptions regarding the model parameters used.

With the project Digital Competence for Healthcare (DC4HC) we develop a maturity model for the assessment of non-medical support services within the healthcare sector. The model will be used to develop a platform offering tools to support health institutions to analyze their digital maturity based on assessed data and receive recommendations depending on their maturity level. Developing a maturity model includes the definition of dimensions, representing the areas covered by the model, the definition of indicators representing the items to be analyzed in each dimension and a logic for calculating the assessment levels.

For this logic, our approach goes one step beyond existing approaches. We use data collected over time on the platform where institutions use the model to measure their maturity and we provide an empirical foundation for the model used to measure maturity. Starting from a model that was initially created based on reasonable assumptions (e.g., by domain experts) as is the case with various other models in the literature, our idea is to use data collected over time and from various institutions to provide an empirical basis for the maturity measurement model used.

In particular, data collected on the platform is analyzed with machine learning (ML) techniques. ML is considered a part of Artificial Intelligence (AI) research and can be defined as "the science (and art) of programming computers so they can learn from data" [9]. In our project, ML algorithms are used to build and improve a model based on sample data collected on a maturity assessment platform. As a result, evidence-based relationships are determined from the data such as the impact of assessed features related to the adoption of information technology (answers to maturity assessment questions), and maturity levels and possibly other key performance indicators (KPIs). This also supports the benchmarking within the user group (e.g., healthcare institutions, specific types of healthcare institutions, and across national healthcare sectors) and provides a validation and an enhancement of the a priori maturity model. In this paper, we describe the concept of the related research and development.

2 RELATED WORK

The approach of validating maturity models using empirical data has not yet been sufficiently explored. Apart from the AI based contribution discussed above, validation is mostly performed through literature review or expert interviews, while empirical evidence is still pending [27]. While the best empirical evidence is available for maturity models in software development [14] [25], the situation appears unsatisfactory in other technology-related areas such as Industry 4.0 [27].

Currently, the use of advanced techniques from data analytics, and ML approaches in particular, are rarely used in connection with maturity assessment. Vlahovic, Milanovic, and Skrinjar [29] analyzed the maturity of business process orientation using data from 204 Croatian and Slovenian companies based on 51 questions. They employed ML using a decision tree model to classify the companies according to maturity levels and obtained very accurate results. Similar results were also presented in [10].

Liu et al. [19] studied the maturity of open-source software projects using time series data extracted from GitHub projects and a support vector machine for ML. The results provided a high degree of accuracy and highlighted advantages over a traditional maturity assessment model.

Dissanayake and Ramachandran [6] followed a similar line of research and studied ML in maturity assessment in the context of software process improvement. They proposed a linear regression methodology and compared it to traditional approaches. Similar research was conducted by Raza and Faria [26] who also use a linear regression model to assess software process performance.

Specific research or technological solutions based on ML for maturity assessment in the healthcare sector were not found.

3 BASIC APPROACH

3.1 Maturity Model

Let us assume that the maturity model can be described as follows: Based on several variables $x_1, \ldots, x_n$, which can be denoted as a vector $x = (x_1, \ldots, x_n)$, a maturity score or level $y \in \Re$ is calculated by a function f, i.e.

$$y = f(x) \tag{1}$$

Instead of a maturity score or level which requires further definition, y could also be any other suitable performance indicator of the entity to be analyzed, e.g., something which is more easily measurable such as indicators based on accounting data. Some examples of empirically measurable and relevant KPIs could be throughput-times of processes, quality issues as measured for example by open IT tickets, investment amount, return on (invested) capital, growth rates (e.g., related to turnover or number of patients) or customer satisfaction (if assessed regularly).

The model could also be generalized in a straight-forward way by assuming a multicriteria evaluation of maturity instead of a scalar value, or the consideration of several performance indicators by assuming a vector y comprising q indicators or criteria, i.e., $y \in \Re^q$

Without loss of generality, we can assume, that the model is based on several parameters $p_1, \ldots, p_m$, such as weights, importance indicators etc. which adapt a general type of model to a specific application or domain. Using the vector notation $p=(p_1, \ldots, p_m)$ for the parameters, this leads to the following model formulation:

$$y = f(x, p) \tag{2}$$

3.2 Machine Learning for Model Adaptation

Assume that empirical data from several entities is available. Let us denote the entities to be evaluated by an ID, e.g., a user ID or customer ID, denoted as $id \in \{id_1, \ldots, id_k\}$. In addition, we assume that empirical data from one entity id is assessed at different times $t \in \{t_{1,id}, \ldots, t_{T,id}\}$. For instance, maturity assessment is conducted each year.

For simplicity, we assume that all assessed data will be used for ML without considering specific entity relationships and time aspects. Assuming that in total z data sets are available, the data can be described as follows: $X = \{x^1, \ldots, x^z\}$ are the data of the variables for the maturity model, $Y = \{y^1, \ldots, y^z\}$ are the corresponding maturity scores (or other performance indicators) measured or otherwise assessed, i.e., a correct maturity model f should deliver a corresponding maturity score for each of the variable settings that is identical to the measured value:

$$y^i = f\left(x^i, p\right) \text{ forall } i \in \{1, \ldots, z\}\,. \tag{3}$$

Of course, it cannot be assumed that such a model is perfectly accurate for every data item. Therefore, the deviation between calculated and measured score is expected to be reasonably small which leads to an optimization problem (as usual in ML applications). This results in the usually used formulation for a general problem in regression analysis

$$y^i = f\left(x^i, p\right) + e^i \text{ forall } i \in \{1, \ldots, z\}\,. \tag{4}$$

with e^i representing an additive error term which should be as small as possible.

4 DISCUSSION OF THE APPLICABILITY TO SOME MATURITY MODELS

In this section, we discuss a few selected maturity assessment models in terms of their suitability for machine learning applications.

A more comprehensive recent survey of such models is included in [16]. A survey related to maturity models with focus on healthcare information systems is given by Carvalho, Rocha and lvaro [4]. Another recent review of maturity models related to the context of our project is given by Kirecci et al. [17]. Ongoing major research and development projects such as the digital maturity tool and the Innovation radar developed under the Digital Europe programme [7] are also not covered in the following.

An example of existing maturity models is the National Health Service model (NHS) [21]. It consists of 179 scored questions related to three themes (readiness, capabilities, and infrastructure), which in turn are divided into fourteen sections. Each question is evaluated on a score from 0 to 100. Section scores are calculated as average scores from all scored questions within the relevant section, rounded to the next integer. Theme scores are determined as rounded average scores from all scored sections under the theme in question.

With a slight simplification of the model (leaving out the rounding and the consideration of missing questions scores), the model can be written as in (2) assuming that the variables are aggregated in a linear fashion using given constant weights p_i

$$y = \sum_{i=1}^{n} p_i x_i \tag{5}$$

In the formulation (5), the parameters serve as variable-specific weights and their number equals the number of variables, i.e., n=m. Mostly, these weights are identical and different values are only used to take care for a different number of variables (questions) relating to each section. In addition, let us note, that overall scores are calculated for each theme resulting in three overall score values. It would, of course, be possible to calculate a unique maturity score following the same model ideas, i.e., using an average value of the three scores.

A similar model is suggested by NSW [15], which considers five maturity pillars such a governance and leadership, people and culture, capacity and capability, innovation, and technology. For each of these pillars, several statements have to be considered true or false, e.g., 27 statements for governance and leadership, each of them associated with a maturity level from 1 to 5. Thus, the assessed variables x_i are binary and weighted level factors are specified by the model creators. Users of the model are advised for each pillar to "look at the pattern of ticks" regarding the statements, and then to "estimate a rating 1 – 5", e.g., considering where most ticks appear. However, the option to specify levels between two integer values is also offered. In addition, it is mentioned that users could consider "greater weighting than others for [their] organization". In the end, it is suggested to determine an overall digital maturity rating by "[adding] pillars then divide by 5".

Applying a more precise mathematical notation and omitting simplifications such as rounding, the model can be described as follows:

$$y_j = \sum\nolimits_{i=1}^{nj} p_i x_i^j / \sum\nolimits_{i=1}^{nj} x_i^j \tag{6}$$

y_j is the pillar-specific score, $x^j{}_i$ are the binary variables relating to pillar j with $x^j{}_i$ =1 if the respective statement is evaluated as true and 0 otherwise. nj is the number of statements relating to pillar j. The p_i are the specified maturity levels for each statement. The overall score is then calculated as follows:

$$y = \sum_{j=1}^{5} 0.2 y_j \tag{7}$$

Ustaoğlu [28] suggests a maturity model considering the following five dimensions: leadership, strategy, people, process/product/services, partnership/resources. Each of these dimensions is subdivided into several more specific topics (e.g., five for the leadership area) with a number of criteria (e.g., in total sixteen criteria (variables) for the leadership area). The criteria are always measured on a scale from 0 to 4. In total there are 76 questions and corresponding variables. As the five main areas are equally weighted for the overall score, the specific weights with which the individual variables are to be multiplied are different due to the varying number of criteria corresponding to each area. Basically, the model can be described as in (4).

The Accenture model [1] is similar in structure to (4): Maturity related questions are organized in the three dimensions: identification and design of business transformations, characteristics of Latin America for business transformations, and execution of business transformations. These dimensions are further subdivided into a total of eight groups. Due to some inconsistencies of the model (incorrect numbering of questions, missing cells of question data in the Excel file, incorrect consideration of assessed relevance data in final scores) the model is not further discussed here.

The Deloitte [5] model considers five main dimensions of maturity: customer, strategy, technology, operations, and organization & culture. These five core dimensions are divided into 28 subdimensions, for which a total of 179 digital criteria (variables) are suggested. The maturity questions are evaluated on a 5-point Likert scale. We note that further details of the model were not found, and that Deloitte used variants of maturity models in other studies.

The model by pom+Consulting AG [24] refers to Building Information Modeling (BIM). Digital maturity is measured on a scale from 1 to 10. For some topic areas (ten selected BIM areas) it is said that maturity evaluation is done on a scale from 1 to 5. It is also mentioned that assessment is done on a four-point scale with additional response option "not relevant". Further details of the model are not provided.

A more complex maturity model is discussed by Kljajić Borštnar and Pucihar [16] with focus on small and medium-sized enterprises (SMEs). The model is based on concepts from multi-attribute decision making methodologies and uses 34 basic attributes (assessment indicators) which are aggregated over several hierarchies to 17 higher level attributes. Utility functions in the form of simple "if–then" rules are used for aggregation. In their approach, the utility functions are determined by experts and validated by exploring them on a sample of eight SMEs. For the suggested model, machine learning could automatically generate a specification of the model hierarchy and related rules from the data, and a test set could provide a respective validation, possibly from a much larger set of involved companies.

The maturity model by University St. Gallen [3] is a more complex model that considers nine dimensions divided into a total of 64 indicators measured on a 5-point Likert scale. Five maturity levels are derived from a cluster analysis based on the weighted data obtained from a survey study. Indicators that are fulfilled by many study participants are assigned an easy level of difficulty corresponding to maturity level 1 while difficult indicators that are fulfilled by only a few participants are assigned to maturity level 5.

A cluster maturity degree is calculated considering the subsequent fulfilment of indicators starting with lower-level clusters. This means that the fulfilment of higher-level indicators is not considered when lower-level indicators are not fulfilled. However, the details of this concept, which uses ad-hoc threshold values specifying the fulfillment of indicators in a cluster to indicate that the next level is reached (but not one level further) appear arbitrary. In addition, a second maturity degree, the so-called point maturity degree, is calculated as considering all indicator values (in relationship to the maximum reachable values). An overall maturity degree is calculated as the average of the other two maturity degrees.

The authors also mention that the maturity model is revised from year to year, e.g., by adding new indicators. This fact and the expected modification of the maturity degree measurement due to varying clusters over time (as revealed by the specific survey data) do not make the model a good candidate for ML, which assumes a constant model when training data from different time periods are used.

The ABILI maturity model developed at the University of Applied Sciences and Arts Northwestern Switzerland [11] [12] considers four dimensions, structured as a matrix along the two axes consisting of internal and external factors and human and organizational factors: customer centricity, business model, operational excellence, and organizational excellence. These dimensions are further divided into four to five sub-dimensions each. Like the maturity model from the University of St. Gallen these sub-dimensions are further divided into 56 indicators measured on a 5-point Likert scale. The indicators are measured twice, on the one hand along the current strategy goals of the companies and on the other hand along the current implementation success. This differentiated consideration is not offered by the other models. The calculation of the maturity takes place as described in (5).

An alternative to this calculation approach would be to use the data from the current implementation success for maturity assessment whereas data relating to the current strategy goals of the companies could be used for weighting the other data in order to assess maturity levels. This approach would imply that there are no general weights for different maturity-related aspects among different institutions, but each institution would need to set up and tune their individual model. This would impede the machine learning approach as a larger number of training data would be required for each individual institution which could only be collected during a large number of years. In addition, this approach would complicate possibilities of comparing and benchmarking institutions as they usually assign different priorities to different aspects related to maturity.

Based on the original suggestions of maturity assessment by Nolan [22, 23] and as emphasized by . Carvalho, Rocha and lvaro [4], maturity is often measured on a discrete scale denoted as maturity stages, levels, or classes. For instance, Nolan originally suggested a four stages maturity model [22] which was later extended to a six stages model [23]. In their survey comprising 14 maturity models, Carvalho, Rocha and lvaro [4] find models with three to nine stages, where models with five stages dominate. This is probably caused by the influence of the well-known Capability Maturity Model as originally described by Humphrey [13].

As mentioned before and discussed for some of the above models, an easy and frequently used approach is to calculate a score as in Eg. (5) or (6)-(7) and then use rounding to achieve an integer valued maturity level. Another similar approach is to define maturity levels by intervals of maturity scores. For instance, in [31] it is shown how intervals of maturity scores (which cover the full range of achievable scores) can be mapped to integer valued maturity levels. It would be straightforward to include a respective rounding or mapping from maturity scores to levels in a machine learning based model.

However, an alternative approach would be not to apply the regression model as in (4) but to apply a classification method for machine learning. While clustering is an unsupervised approach for categorizing items based on similarity, classification is usually done in a supervised fashion assuming given categories for assigning items. This means, for the assessed institutions, both the basic maturity data and maturity levels based on them must be assessed. For the machine learning related to classification different methods can be used as discussed for instance, in [18]. After training the model can then classify new data items based on the learned model. In contrast to standard models as assumed in the literature, there is no predefined influence on the basic maturity data on the maturity levels. For instance, it could be possible that some ground data have no significant influence on the maturity level or that it influences the maturity level in a counterintuitive way. It would also be possible that some ground data which would manually be classified as relevant for a different maturity-related aspect have an influence on another unexpected aspect. However, such promising discoveries can also be made in the context of a regression model, which appears in general more attractive as the assumed maturity levels in the suggested models are usually based on an ordinal scale which allows a rounding or mapping approach based on a regression model.

5 CONCLUSIONS

As can be seen (and occasionally mentioned by the model creators themselves) the consideration of the specific importance of the variables used is insufficient. Frequently, the different variables are considered in an identical way, which may appear to be "fair" but does not consider expectable differences in their importance or interdependencies among the variables. In some cases, different weights are used, but in a rather ad-hoc way, e.g., to make main areas including different numbers of variables equally important or based on a rough classification of statements regarding maturity levels as in (4).

Thus, the use of empirical data for ML appears promising to achieve more differentiated models. In addition, no sufficient reason is provided why the models should have the rather simple linear structure usually assumed. In reality, more complex and in particular also nonlinear relationships could exist between basic variables and derived maturity assessments. This also reflects the requirements for organizations to individualize their maturity assessments, as shown by Felch et al. [8]. For that reason, a ML approach could also consider more general functions describing related connections. For instance, neural networks could be a sufficiently general type of function to model such complex relationships and support their assessment by ML. Using standard libraries with ML methods, it should be possible to try out a variety of further ML algorithms (e.g., logistic regression, decision trees, random forest, support vector machines, or naive Bayes). With the help of a dynamic model based on empirical data, as proposed in this paper, it is possible to meet the capabilities and requirements of maturity models expected in practice.

ACKNOWLEDGMENTS

This publication has been supported by Innosuisse Innovation project 50775.1 IP-SBM

REFERENCES

[1] M. Angelastro. n.d. Connecting Expertise and Innovation Across a Diverse Latin America, https://www.accenture.com/ t20170601t203531__w__/cr-en/_acnmedia/pdf-53/accenture-transforming-and-digitizing-maturity-quest.pdf
[2] S. Berghaus and A. Back. 2016. Gestaltungsbereiche der Digitalen Transformation von Unternehmen: Entwicklung eines Reifegradmodells. Die Unternehmung, 70(2), 98–123. https://doi.org/10.5771/0042-059X-2016-2-98
[3] S. Berghaus, A. Back, and B. Kaltenrieder. 2017. Digital Maturity & Transformation Report 2017. Universität St.Gallen
[4] J. V. Carvalho, Á. Rocha and A. lvaro. 2016. Maturity Models of Healthcare Information Systems and Technologies: a Literature Review. In: J Med Syst 40 (6), 1-10. DOI: 10.1007/s10916-016-0486-5.
[5] Deloitte. 2018. Digital Maturity Model. https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Technology-Media-Telecommunications/deloitte-digital-maturity-model.pdf
[6] S. Dissanayake and M. Ramachandran. 2020. Machine learning as a service for software process improvement. In Software Engineering in the Era of Cloud Computing. Springer, Cham. 299-326.
[7] European Commission. 2021. Digital Maturity Tool and the Innovation Radar. https://digital-strategy.ec.europa.eu/en/events/digital-maturity-tool-and-innovation-radar
[8] V. Felch, B. Asdecker, and E. Sucky. 2019. Maturity models in the age of Industry 4.0: Do the available models correspond to the needs of business practice? In T. Bui (Ed.), Proceedings of the Annual Hawaii International Conference on System Sciences, Proceedings of the 52nd Hawaii International Conference on System Sciences. Hawaii International Conference on System Sciences, 5165–5174.
[9] A. Géron. 2019. Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems. O'Reilly Media, Inc.
[10] L. M. Glavan, V. B. Vukšić, and N. Vlahović. 2015. Decision tree learning for detecting turning points in business process orientation: a case of Croatian companies. Croatian Operational Research Review, 207-224.
[11] M. Graf, M. Peter, and S. Gatziu Grivas. 2018. Foster strategic orintation the digital age – a methodic approach for guiding SME to a digital transformation. In 21st International Conference on Business Information Systems. In Abramowicz, W., Paschke, A. (eds.) Business Information Systems Workshops. Springer, Heidelberg, 420–432.
[12] M. Graf, M. Peter, and S. Gatziu Grivas. 2019. Foster strategic orientation in the digital age. In: Business Information Systems Workshops. Springer International Publishing. DOI: https://doi.org/10.1007/978-3-030-04849-5_37
[13] W. S. Humphrey. 1988. Characterizing the software process: a maturity framework". IEEE Software. 5 (2): 73–79. doi:10.1109/52.2014.
[14] J. C. Jacobs and J. J. Trienekens. 2002 (October). Towards a metrics based verification and validation maturity model. In 10th International Workshop on Software Technology and Engineering Practice. IEEE, 123-128.
[15] KPMG Australia and the South Australian Government. n.d. Digital Transformation Toolkit Guide. https://www.dpc.sa.gov.au/__data/assets/pdf_file/0008/46565/Digital_Transformation_Toolkit_Guide.pdf
[16] M. Kljajić Borštnar and A. Pucihar. 2021. Multi-attribute assessment of digital maturity of SMEs. Electronics, 10(8), 885.
[17] I. Kirecci, P. Schmitter, S. Gatziu Grivas, T. Hanne, P. Gachnang. 2022. Towards the Development of a Digital Maturity Framework for Facility Management in Healthcare – An Integrative Review. Paper presented at the 15th International Facility Management Congress, November 17-18, 2022, Vienna, Austria.
[18] S. B. Kotsiantis, I. Zaharakis and P. Pintelas. 2007. Supervised machine learning: A review of classification techniques. Emerging artificial intelligence applications in computer engineering, 160(1), 3-24.
[19] Q. Liu, X., Li, H. Zhu, and H. Fan. 2017. Acquisition of open source software project maturity based on time series machine learning. In 2017 10th International Symposium on Computational Intelligence and Design (ISCID) (Vol. 1, pp. 296-299). IEEE.
[20] T. Mettler and R. Pinto. 2018. Evolutionary paths and influencing factors towards digital maturity: An analysis of the status quo in Swiss hospitals. Technological Forecasting and Social Change, 133, 104–117; https://doi.org/10.1016/j.techfore.2018.03.009
[21] NHS. 2017. Digital Maturity Self-Assessment: Data Model/Structure https://www.england.nhs.uk/wp-content/uploads/2017/08/digital-maturity-data-model_v2.pdf
[22] NHS. 2017. Digital Maturity Self-Assessment: Data Model/Structure https://www.england.nhs.uk/wp-content/uploads/2017/08/digital-maturity-data-model_v2.pdf
[23] NHS. 2017. Digital Maturity Self-Assessment: Data Model/Structure https://www.england.nhs.uk/wp-content/uploads/2017/08/digital-maturity-data-model_v2.pdf
[24] pom+Consulting AG. 2021. Digitalisierung der Bau- und Immobilienwirtschaft https://www.pom.ch/fileadmin/doc/04_ueber_uns/03_medienmitteilungen/2021/6-DRE_Umfrage_2021_final.pdf
[25] D. Proença and J. Borbinha. 2016. Maturity models for information systems-a state of the art. Procedia Computer Science, 100, 1042-1049.
[26] M. Raza and J. P. Faria. 2020. The ProcessPAIR Method for Automated Software Process Performance Analysis. IEEE Access, 8, 141569-141583.
[27] A. Schumacher, S. Erol, and W. Sihn. 2016. A maturity model for assessing Industry 4.0 readiness and maturity of manufacturing enterprises. Procedia Cirp, 52, 161-166.
[28] N. Ustaoğlu. 2019. A maturity model for digital transformation (Doctoral dissertation).
[29] N. Vlahovic, L. Milanovic, and R. Skrinjar. 2010. Turning points in business process orientation maturity model: an east European survey. WSEAS transactions on business and economics, 7(1), 22-32.
[30] F. L. V. Voßand J. M. Pawlowski. 2019. Digital Readiness Frameworks. In L. Uden, I.-H. Ting, & J. M. Corchado (Eds.), Communications in Computer and Information Science. Knowledge Management in Organizations (Vol. 1027). Springer International Publishing. 503–514. https://doi.org/10.1007/978-3-030-21451-7_43
[31] A. A. Wagire, R. Joshi, A. P. S., Rathore and R. Jain. 2021. Development of maturity model for assessing the implementation of Industry 4.0: learning from theory and practice. Production Planning & Control, 32(8), 603-622.