ARTIFICIAL INTELLIGENCE (AI) - APPLICATION FOR EVALUATING THE ENTERPRISE'S DIGITAL TRANSFORMATION CAPACITY

Nguyen Thi Thanh Huong[1]
Posts and Telecommunications Institute of Technology
- Ho Chi Minh City Branch

Tran Quang Huy
FPT University

Summary:

We are living in a period of digital transformation, in the 4.0 industrial revolution, the age of information is developing rapidly, so corporations and businesses can no longer exploit sustainably the competitive advantages if they only rely on the tangible assets of technology and the exploitation and mobilization of the intangible assets of technology are becoming increasingly more decisive factors. Digital transformation is an inevitable trend, contributing to promoting economic growth, improving labor productivity, competitiveness, production, and business efficiency, and lowering product costs, reducing administrative procedures, time, and costs. To evaluate the digital transformation capacity of businesses, traditional measures that are based on financial indicators are no longer strong enough and are not suitable to control and accurately control the performance of businesses in the new circumstances. Businesses need a new tool that can use artificial intelligence (AI) to provide a balanced view of all qualitative influencing factors and identify decisive capacity parameters in a more relevant and smarter manner. This article provides an overview of digital transformation perspectives and enterprise digital transformation capabilities, factors affecting digital transformation capabilities, and the application of language-based machine learning algorithms: ontology and fuzzy logic to evaluate the digital transformation capacity of enterprises.

Keywords*: Machine learning; Digital transformation capabilities; Enterprises.*

Code*: 24020101*

1. Concept of digital transformation and enterprise’s digital transformation capacity

The concept of digital transformation has been mentioned and researched many years ago, but up to now, there is still no unified concept. At different stages and associated with a different perspective, the authors introduce a different concept. But from a business perspective, the authors share the same point of view that digital transformation is the application of new technology to optimize resources, and operational processes and better satisfy the customer needs. According to Stolterman and Fors (2004), digital transformation is defined as the use of technology to radically improve the enterprise’s performance or reach of business.

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[1] Author’s contact: huong0312@ptithcm.edu.vn

McDonald and Rowsell-Jones (2012) believe that digital transformation is not simply the digitization of resources; the value created by businesses must be based on digital assets. Also following this point of view, Fitzgerald (2013) defines digital transformation in business as the use of new digital technologies, such as social media, mobile devices, new analytical techniques or automatedly linked systems to make major changes in business operations such as enhancing customer’s experience, optimizing operations, and creating new business models. Hess et al (2016) said that digital transformation is the changes that digital technology can bring in business models, leading to changes in products or organizational structures or automation of business processes. According to VCCI and USAID (2021), digital transformation in businesses is defined as “the integration and application of digital technology to improve business efficiency, management efficiency, capacity and competitiveness of enterprises and create new values”. Digital transformation activities can range from digitizing an enterprise's management and business data, applying digital technology to automate and optimize business processes, management processes, production processes, and reporting processes, and coordinating work within the enterprise to transforming the entire business model, creating new value for the enterprise.

The enterprise’s digital transformation capacity is the ability to apply new digital technologies in organization, operation, and management, and at the same time to create valuable assets from the application of digital technology to help the enterprise optimize resources, to better meet market needs and create added value for businesses. According to Hinchcliffe (2017), the enterprise’s digital transformation capacity includes 3 issues. Firstly, the transformation of operating processes; building and using an electronic data exchange system will help businesses save time and be much more efficient. Secondly, the transformation of the operating model, which means changing the way of operating to create value for the business. Finally, changing the customer’s experience, means the result of the interaction between customers and enterprises that customers can experience and feel.

2. Factors affecting the business’s digital transformation capacity

Swen Nadkarni and Reinhard Prug (2020), by synthesis of previous studies, show that internal factors affecting the ability to digitally transform businesses can be divided into 3 groups: 33% focus on technology, 34% focus on organizational issues, and 33% focus on both technological and organizational issues. In studies focusing on organizations, 4 factors are mentioned a lot and they have a direct impact on the expected results of the enterprise’s digital transformation: (1) leadership, (2) business digital technology strategy, (3) employee capacity, (4) corporate culture and (5) technology platform. For research focusing on technology, the use of technology platforms for business activities such as systematic data storing information, interacting with customers, internal communication and interaction, and other activities that affect the business's digital transformation ability.

3. The set of indicators to evaluate a business's digital transformation capacity

The set of indicators to evaluate the levels of the digital transformation capacity of ministries, ministerial-level agencies, government agencies, provinces, centrally controlled cities, and the whole country (Digital Business Indicators - DBI) has the function of monitoring and evaluating the essence, objective, and fairness of the results of annual levels of the digital transformation capacity of ministries, provinces, and cities during the implementation process include: National digital transformation program to 2025, orientation to 2030; E-Government Development Strategy (e-Government) towards digital Government for the period 2021-2025, with a vision to 2030; National strategy for digital economy and digital society development until 2025, with orientation to 2030.

DBI includes component indexes according to the nature and characteristics of state management of ministries, provinces, cities, and countries. Especially, indexes have been formed to compare between years and provide information for international organizations to evaluate and rank Vietnam globally on e-government (EGDI); IT (IDI); Network information security; Competitiveness (GCI); Creative Innovation (GII). At the same time, DBI also identified best practices, that are typical in the process of implementing digital transformation to replicate across the country; to allow entering report data online, to search the evaluation results of ministries, provinces/cities, and countries.

DBI can be applied to 03 levels: Province/city, ministry, and country. Specifically, the province/city level is structured according to 03 pillars (digital government, digital economy, and digital society), including general information (general information of the province/city is not used to evaluate); 09 main indexes include: digital awareness, digital institutions, digital infrastructure, digital human resources, network information security, smart cities; digital government activities, digital economic activities, digital social activities; and 98 component indices.

At the ministerial level, it will evaluate in general the level of the digital transformation of the ministry, in accordance with the characteristics of each ministry that oversees different fields, including general information (general information about the ministry is not used for assessment); 06 indexes; and 70 component indices.

At the national level: Includes 24 indexes, showing the achievement of goals and targets under the national digital transformation program to 2025, orientation to 2030; E-Government development strategy, with the references to internationally used and evaluated indicators, respectively.

4. Machine learning algorithm based on ontology language and fuzzy logic - application for assessing the business's digital transformation capacity

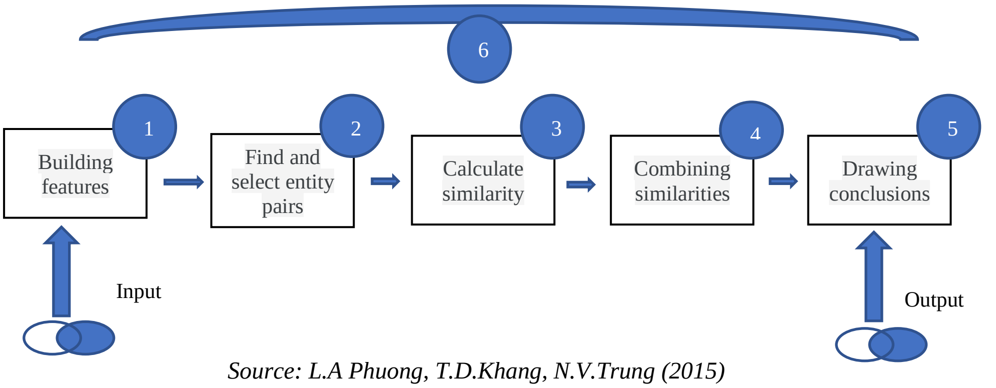
Machine learning is a data analysis method that automates the construction of analytical models, using iterative algorithms to learn from data. Machine learning allows computers to find hidden valuable information without being explicitly programmed where to look for it and to reason logically before making decisions.

This is one of the promising artificial intelligence applications that is proposed to support many fields in the future.

The term Ontology originates from philosophy, where it refers to a field that studies the nature of existence, focusing on identifying objects and describing them in nature, such as observing the real world, identifying objects, and then based on their common properties grouping them into abstract classes. In recent years, Ontology has become a well-known term in the field of computer science and has a different meaning than its original meaning. Ontology is considered the "soul" of building the Semantic Web, facilitating collaboration between humans and machines, helping machines "understand" and be able to deal with information effectively. An Ontology provides a common vocabulary used to describe a domain of meaning, a type of existing object or concept, along with properties and relationships between them and a specification for the meanings of words in the vocabulary *(L.A Phuong, et al., 2015).*

The components of Ontology include Individuals, which are the basic, foundational components of Ontology; Classes are groups and collections of abstract objects. They can contain instances, other classes, or a combination of both; Properties: Objects in Ontology can be described through the declaration of their properties, each property has a name and value of that property, and properties are used to store information that the object may have; Relationships: Represents a valuable attribute of a certain object. The OWL language which is like XML used to describe knowledge base systems, uses markup to publish and share data through data models called Ontologies, OWL represents the meaning of terms in words. vocabulary and relationships between these terms to ensure compatibility with the processing by the software.

The Ontology Matching (OM) process includes many steps and is an iterative process. For most current methods, this process is divided into basic steps, the order of steps may be different, or some steps in the process may be merged, but in general, the methods have the same basic components *(Irene Solaiman, et al., 2023).* The process can be divided into the following basic steps: (1) Building features: This is the initial step of the OM process using input values such as ontologies and alignment (if any), to select Input ontology, we will first rely on the set of concepts used to define the ontology. In addition, based on the common characteristics of the components of the input ontology, in this step, we will classify them. These attribute groups will be used during the matching process; (2) Find and select entity pairs: The input alignments (if any) will be used. Based on the attribute classification in step one and the candidate alignments, we will select entity pairs of the two ontologies to perform OM in the next step. Selecting suitable pairs and eliminating mismatching pairs makes the OM process faster and results more accurate, minimizing redundancy; (3) Calculating similarity: is a measure to determine the similarity between two entities that need OM. The value calculation is performed through a set of similarity, inference functions; (4) Combining similarities: Based on the input hypotheses, after calculating the similarity, we can produce the OM result between ontologies. However, there are many methods to calculate the similarities and they may give different results. Therefore, combining these results to come to the most accurate conclusion is very important; (5) Concluding: After combining the similarities and giving the result, it is necessary to draw conclusions based on that result. In other words, the results need to be interpreted to confirm whether two entities of two ontologies are similar or not. To do this, most systems today use a certain threshold value. If the result is greater than this threshold value, then the conclusion will be that the two entities are similar, otherwise not; (6) Iterative process: Helps to give more accurate results, avoid omissions, and eliminate inappropriate cases. However, to avoid infinite repetition, people often set loop-stopping conditions, which are the conditions that make the iteration process stop after a certain number of steps, and the iteration process stops after a certain time. The changed values still do not exceed the threshold, when the loop stops, we give the result.



Source: L.A Phuong, T.D.Khang, N.V.Trung (2015)

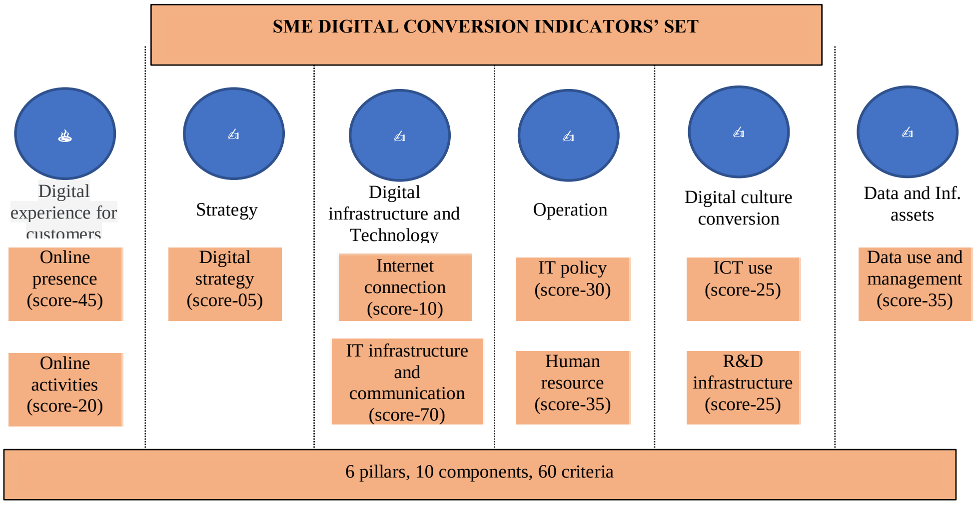
Fig 1. Ontology Matching Process

Fuzzy logic theory was first proposed by Zadeh, L.A. in 1965 *(L.A Phuong, et al., 2015)*. This theory solves problems very close to human thinking. Up to now, fuzzy logic theory has developed significantly and has been applied in many areas of life. According to traditional logic, a logical expression can only take one of two values: True or False. Different from traditional logic theory, a fuzzy logic expression can take on one of an infinite number of values in the real number range from 0 to 1. In other words, in traditional logic, an event can only be true (equivalent to True - 1) or false (equivalent to False - 0), and in fuzzy logic, the truth level of an event is evaluated by a real number with a value between 0 and 1, depending on the level of its “more” or “less” accuracy. The values of variables in fuzzy logic expressions are not the numbers but concepts, such as “fast”, “medium”, “slow” or “hot”, “medium”, “cold”. Therefore, the way to solve problems in fuzzy logic is closely resembles human thinking *(L.A Phuong, et al., 2015).*

5. Applied issue

Usually, people use natural language to describe phenomena, emotions, or knowledge. However, any language contains fuzzy concepts or words, or in other words, words whose semantics, although not expressed precisely and qualitatively, can still be evaluated quantitatively well by humans. The problem is how to model the knowledge representation and processing to build “smart” electronic computer systems with some human-like operating mechanisms. In this approach, each variable of linguistic value is represented within an algebraic structure, known as the Preposition Algebra *(Ministry of Planning and Investment, 2020).*

The specific problem is to evaluate the level of digital transformation for small and medium-sized enterprises (SMEs) using a structured set of indicators based on 6 pillars: (1) Digital experience for customers; (2) Strategy; (3) Digital infrastructure and technology; (4) Operation; (5) Digital transformation of corporate culture; and (6) Data and information assets. In each pillar there are component indicators, and in each component indicator there are criteria (10 component indicators and 60 criteria). The structure diagram of the indicators assessing the level of digital transformation of SMEs is described as follows:



Source: Ministry of Information and Communications (2023)

Fig 2. Index structure for SME digital transformation level evaluation

(1) The digital customer experience pillar includes 02 component indicators, and 13 criteria, specifically as follows: The Online presence index includes 09 criteria: Frequency of updating the business's website; Frequency of social network activities by the enterprise; Level of investment in digital marketing activities by the business; Frequency of using e-commerce platforms to sell the business products; Annual revenue rate of the enterprise's e-commerce segment; Revenue rate of the cross-border e-commerce segment of the enterprise annually; Frequency of updating product and service lists on the enterprise's digital environment; Percentage of businesses that communicate with customers through digital channels; Businesses provide digital tools/utilities for customers to choose products as desired. The online activity index includes 04 criteria: Frequency of professional interactions with other businesses in the digital environment; Frequency of professional interactions with state agencies in the digital environment; Frequency of using online banking services of businesses; The extent to which businesses shop for goods online; (2) The digital strategy pillar includes 01 component indicator and 01 criterion: The

enterprise has developed a digital transformation strategy/plan; *(3) The infrastructure and digital technology pillar* includes 02 component indicators and 16 criteria, specifically as follows: Network connection index includes 02 criteria: Connection to broadband Internet; Wireless internet connection. The information and communication technology infrastructure index includes 14 criteria: Basic digital technology (Intranet network; Electronic record storage solutions; Electronic invoices; Information and data sharing solutions number); Advanced digital technology (Cloud computing solutions; Integrated/specialized systems/tools for management and operations groups; Integrated/specialized systems/tools for customer and market groups; IoT devices and solutions; Blockchain technology); Digital technology for manufacturing (Robot or 3D printer; Automation processes; Automated/specialized product and brand recognition technologies in the supply chain; Supply chain management or partner support through digital solutions). Enterprises using database management software/applications; Businesses have their methods of collecting data through digital channels; The business has generated/enhanced revenue from exploiting its data; Enterprises using business intelligence support software, data analysis, and visualization tools; Knowledge management tools; Enterprise using decision support tools/utilities...; *(4) Operational pillar; (5) Corporate culture pillars; (6) Data and information assets pillar*.

The indicators of these pillars and evaluation parameters are built and linguisticized by using ontology terms and then the level value is determined through fuzzy logic algorithm.

Tab 1. Fuzzy logic value to evaluate SME digital transformation level

No	Indicators	Number of criteria	Max evaluation levels				
			Level 1	Level 2	Level 3	Level 4	Level 5
Overall evaluation		***60***	***64***	***128***	***192***	***256***	***320***
1	Customer's digital experience	13	13	26	39	52	65
2	Digital strategy	1	5	10	15	20	25
3	Digital infrastructure and technology	16	16	32	48	64	80
4	Operation	13	13	26	39	52	65
5	Corporate's culture	10	10	20	30	40	50
6	Data and information assets	7	7	14	21	28	35

Source: Ministry of Information and Communications (2023)

The parameters proposed in the study are a set of indicators for evaluating the digital transformation capacity of small and medium enterprises. In this study, we propose a set of fuzzy logic inferences to make level decisions based on sets of DBI indicators. Each fuzzy set will have values of low (L), medium (M) or high (H), all at a value between “0” or “1”. These values are fed into a correlation or inference engine for correlation and then a decision is made based on a set of fuzzy rules applied to determine the degree of digital transformation. An example of a fuzzy inference rule for digital transformation level decisions is as follows:

IF (TNSKH = Medium) AND (CLS = Low) AND (HTCN = Medium) AND (VH = Low) AND (VHDN = Low) AND (DLVTSTT = Low) THEN Threshold. IF (TNSKH = Medium) AND (CLS = Low) AND (HTCN = Medium) AND (VH = Hight) AND (VHDN = Hight) THEN Under threshold ELSE

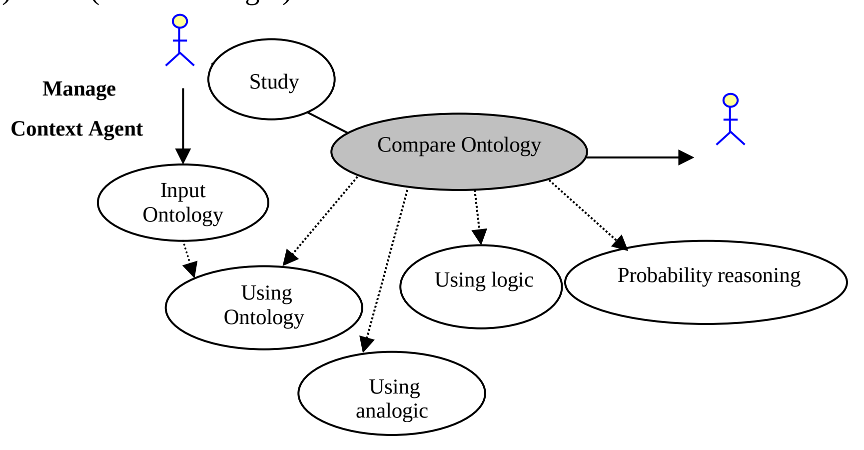


Fig 3. Matching linguistic principle

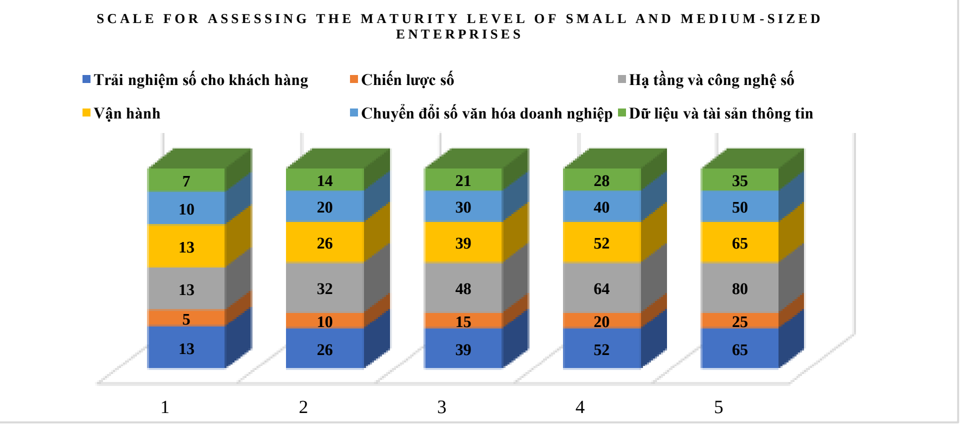
Examples of algorithms are shown as follows:

```
if (net.compareTo("TNS")==0){
                      result1 = HandCase.substring(9,11);
                        if ((result1.compareTo("VF")==0)||(result1.compareTo("FT")==0))
                            return 1;
                        else {
                            result2 = HandCase.substring(12,14);
                            if ((result1.compareTo("VF")==0)||(result1.compareTo("FT")==0))
                                return 2;
                            else
if ((result1.compareTo("FI")==0)||(result2.compareTo("FI")==0))
                                return 3;
                            else
                                return 0;
                        }
                    }
                    else if (net.compareTo("CLS")==0){
                         result1 = HandCase.substring(15,17);
```

```
            if ((result1.compareTo("VF")==0)||(result1.compareTo("FT")==0))
                        return 1;
                    else {
                        result2 = HandCase.substring(18,20);
        if ((result1.compareTo("VF")==0)||(result1.compareTo("FT")==0))
                            return 2;
                        else
```

6. Evaluation results

The chart represents the scale structure of the indicators used for assessing the level of digital transformation of small and medium-sized enterprises foreach pillar, calculated with the fuzzy logic algorithm and the overall evaluation score is shown in the following figure:



Source: Ministry of Information and Communications (2023)

Fig 4. Scales structure of SME digital transformation evaluation level

Depending on the evaluation results (overall score achieved for all criteria), businesses will be graded on the level of digital transformation according to the following principles: Based on the results of evaluating the overall score achieved for the criteria within the pillar, compare it with the evaluation scale in Table 1 to rate which level that Pillar is at in 5 levels: Level 1 - Start-up; Level 2 - Getting Started; Level 3 - Formation; Level 4 - Advanced; Level 5 Highly Advanced.

Table 2. Scale to evaluate the digital transformation level for each pillar

Level	Evaluation scale for each pillar	Level of digital transformation
0	Less than 10% of the highest score of each pillar	Not started yet
1	From 10% to 20% of the highest score of each pillar	Startup
2	From 20% to 40% of the highest score of each pillar	Getting Started

Level	Evaluation scale for each pillar	Level of digital transformation
3	From 40% to 60% of the highest score of each pillar	Formation
4	From 60% to 80% of the highest score of each pillar	Advanced
5	From 80% to 100% of the highest score of each pillar	Highly Advanced

Source: Ministry of Information and Communications (2023)

Enterprises with an overall score of 39 points for the Digital Customer Experience pillar will be assessed as: "The enterprise's Digital Customer Experience pillar reaches level 3 - formatted". In addition to these 5 levels of digital transformation, there will be another level, level 0 - the level where digital conversion has not yet started. This is the assessment level for businesses that have had almost no moves for digital transformation.

Overall rating: Level 0 - Digital transformation not yet started: Maximum total score is less than or equal to 20 points; Level 1 - Start-up: Maximum total score over 20 points, and at least 4 pillars reaching level 1 or higher but not meeting the requirements to be ranked higher than level 1; Level 2 - Getting started: Maximum total score over 64 points, with at least 4 pillars reaching level 2 or higher but not meeting the requirements to be ranked higher than level 2; Level 3 - Formation: Maximum score over 128 points, with at least 4 pillars reaching level 3 or higher but not meeting the requirements to be ranked higher than level 3; Level 4 - Advanced: Maximum score over 192 points, with at least 5 pillars reaching level 4 or higher but not meeting the requirements to be ranked higher than level 4; Level 5 - Leadership: Maximum score from above 256, all 6 pillars reach level 5.

7. Conclusion

With the ontologies' application base, data has been semanticized so that it can be "understood" by computers. This has helped a lot in the fields that need to retrieve and exchange information accurately and automatically. When each business builds the ontologies describing its digital transformation capability indicators, integration among businesses will be automated, smarter, and more accurate through the Ontology Matching process instead of having to do it manually as it had been done before. Research on integrating enterprise processes is now focusing on describing more information for input ontologies to find appropriate OM methods through combination with rule sets. This research can be applied to many fields during the digital transformation period for businesses and organizations. However, this model is not completely automated and requires human intervention in building metadata and rule sets.

Currently, there are about 899,000 operating businesses in Vietnam, with more than 98.7% of small and medium-sized businesses (As of August 2023) employing 70% of the country's workforce and contributing about 50% GDP of the total economy. The businesses' digital transformation activities have taken place strongly in recent years as a natural need of many businesses to meet the changes in customer consumption behavior as well as customer management needs. Assessing digital transformation capacity through AI tools aims to promote faster transformation, improve competitiveness among businesses, and help customers and organizations properly assess the health of businesses. /.

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