Journal of System Management (JSM)
Online ISSN: 2538-1571
Print ISSN: 2322-2301
7(1), Winter 2021, pp. 155-190
Research Paper

Open Banking Innovation Model by Digital Transformations, Based on Adaptive Neuro-Fuzzy Inference System (ANFIS)

Mohammadali Mirfallah Lialestani [1] **Abbas khamseh** [2]

Abstract

Given the emergence of digital transformation from Industry 4 and the rapid dissemination of technological innovations as well as their impact as a strong driving force in new banking businesses, efforts should be made to identify the dimensions of this core factor as rapidly as possible. Providing a comprehensive overview of all aspects of the model. The purpose of this article is to provide insights into the state of the art of digital transformation in the banking industry and suggest ways for future research. Existing literature, especially research for 2019 and 2020, has enhanced our understanding of the specific aspects of digital transformation in future banking, and we are now grasping a clearer picture of nature, how, and the consequences of these in the years ahead. However, all its dimensions are not yet clear. In this article, by review of 218 articles in the WOS database, and the analysis has utilized the data-driven tools,165 questionnaire and 90 specialized interviews with experts, extracted factors of the research, and using SMART PLS statistical software, ANFIS and MATLAB software for analysis. The paper, therefore, tends to understand Open Banking Innovation based on the digital transformation area and its dimensions in its previously known domains.

Received: 10/12/2020 Accepted: 19/04/2021

[1] Department of Technology Management, Roodehen Branch, Islamic Azad University, Roodehen, Iran

[2] Department of Industrial Management, Karaj Branch, Islamic Azad University, Karaj, Iran, Correspond Author : abbas.khamseh@kiau.ac.ir

Keywords *Digital Transformation, Open Banking, Banking Innovation, Business Strategy, Business Model*

Introduction

Today, the world is realizing a big change, a change centered on evolving innovations and technologies that will have a profound impact on people's lives, the structure and thinking of organizations, and even the interactions of countries. Understanding this change and timely accompanying this change seems to be essential for all organizations of all sizes. The advent of new and powerful digital technologies, digital platforms and digital infrastructure has transformed innovation and entrepreneurship in significant ways. Beyond opening up new opportunities for innovators and entrepreneurs, digital technologies have wider implications for value creation and development (Nambisan, et al., 2019 OCT). But digital transformation (DT) is a process by which people can adapt themselves to modern technology. As digital technology becomes more prevalent (automation, cameras, sensors, touch screens, artificial intelligence, etc.), there will be more pressure on companies to make more profit (Young & Rogers, 2019). Digital transformation in the field of industry (also known as industry 4.0 or smart manufacturing) at both the professional and academic levels has increased interest in and interest in production, but is still in its infancy and in-depth research Needs more and more. Even with the current and potential benefits of digital production that are very significant, in terms of improved productivity, sustainability, customization and flexibility, only a limited number of companies have been able to adopt interim strategies to achieve superior performance and utilize this and formulate their position (Savastano, et al., 9 February 2019). We know that research to understand digital transformation requires combining

multiple themes and cross-level analysis, embracing ideas and concepts from multiple contexts and disciplines (Nambisan, et al., 2019 OCT). The main purpose of this study is to identify the dimensions of digital transformation and to examine the different domains of its impact and ultimately to prepare a Grounded theory model to provide an appropriate analysis of the digital transformation process for future studies. Innovation in this paper has been the combined use of library research including the volume of previous research and the use of Grounded theory method in their content analysis, as well as the complementation of experts' views in developing a model for digital transformation.

Literature Review

We know that the disruption caused by digital conditions is transforming all industries, leading to new business models based on new technologies. Industry 4.0 is therefore a model for understanding and using digital disruption and interference. Industry 4.0 offers include vertical and horizontal integration of value chain, digital services, digital transformation of products, digital transformation of production equipment, digital transformation of factories, and digital transformation of supply chains (Cozmiuc & Petrisor, 2018 APR-JUN). Also, special attention to the relative advantages of the economy is the best way toward economic development. In the absence of a systematic perspective, all the planning and costs in this field will fail. (Doulabi, khamseh, & Torabi, 2020). The "Industry 4.0" factories have machines that are powered by wireless connectivity and sensors, connected to a smart system that can visualize and decide on the entire production line. In essence, industry 4.0 is a trend towards automation and data exchange in technologies and production processes that include physical and cyber systems, IoT, IIoT, cloud computing, cognitive

computing and artificial intelligence (Wikipedia, 2016). Systematic risks are also essential to be able to execute Industry 4.0 comprehensively. The economic, environmental and social risks posed by the implementation of Industry 4.0 in the field of SMEs need to be addressed. In addition, the technical, IT and political or legal risks arising from the concept are very important (Birkel, et al., 2019). Digital transformation includes new elements that deserve sufficient attention and interesting challenges for future research. Specifically, when managers need to adapt their business strategy to digital realities by integrating new technologies into their business models (Reis, et al., 2018). The understanding of digital transformation can be distinguished by focusing on the following: technology first, strategy second, technology and strategy third. Organizations in the third group will understand the importance of integrating the different aspects of digital transformation, so that new technology is implemented and associated organizational change is complemented by a separate digital strategy through transformation strategy (Bosilj Vuksic, et al., 2018). On the other hand, the digital transformation and innovation of the resulting business model fundamentally alters consumer expectations and behaviors and disrupts the performance of many small markets (Verhoefa, Broekhuizena, & Bartb, 2019). In addition, the intellectual property system, along with the immense potentials available as digital tools, includes data and knowledge on complementary capital, labor, natural resources and other processes that are constantly changing, leading to restructuring of supply chains (Scholz, et al., 2018). In the business models sector, digital transformation is an ongoing process of applying new digital technologies to the everyday life of an organization that is agile as a key mechanism for strategic reshaping of business models in parts of (1) the organization, (2) a collaborative approach, and finally (3) will bring culture

(Warner & Waeger, 2019 JUN). In recent years, companies in almost all industries have undertaken a number of initiatives to discover the benefits of digital and to use technologies and exploit their benefits. These changes have often affected the evolution of key business functions, products, processes, and organizational changes. Corporate governance structures and concepts need new management approaches to manage these collections. Transformations are an important approach to formulating digital transformation strategies. The potential benefits of digitization are enormous and include increased sales or productivity, innovation in value creation and other forms of customer interaction. As a result of this change, entire business models can be transformed or replaced (Downes & Nunes , 2013). Digital transformation is described as a new business model or as a transformation. A digital transformation project involves implementing digital capabilities to support the business model. The changes resulting from this change affect the entire organization, especially the operational processes, resources, and internal operations, which are in fact coordinated and based on the intensive cooperation and interaction of external users in optimizing work habits and methods (Henriette, et al., 2015). And in order to digitize the product, you need to analyze the size of the company or its core size. Similarly, it is interesting that the patterns of B2C companies are quite different from those of B2B models for success (Matt, et al., 2015). The four main tasks that the industry faces are: enhancing customer experience, improving business processes, delivering new products, and preparing to compete with other industries (Eling & Lehmann, 2017). Digital transmission is accelerating by two key drivers in the industry: cloud services and resource virtualization, as key building blocks in cyber systems that integrate IT-OT principles, models, platforms and integration requirements Digitally produced, they focus on the concept of Industry 4.0,

with a focus on the "future industry" (Borangiu, et al., 2019 JUN). One of the important factors in the failure of the technology application to gain a competitive advantage in firms is the lack of awareness and knowledge of the level of technological capabilities of the firm and their use for comparative advantages. The high importance of technology development has led the company's senior managers to identify and evaluate the technological capabilities of their firm and in parallel to identify technological developments in the world and monitor the efforts of competitors to achieve new technologies and to improve the technology capability of the firm. On the other hand, evaluating technological capability is one of the key tools in the field of technology management that uses this tool to identify strengths and improvements to measure the technological gap. (khamseh & Marei, 2020). The institutional perspective is also a very applicable lens for the study of digital innovation and transformation. In digital transformation, we mean the effects of a combination of several digital innovations that make new actors, structures, practices, values and beliefs that change, replace or complement the existing rules of play in organizations and contexts. From this perspective, three types of new formalities for digital transformation have been identified that include: digital organizational forms, digital institutional infrastructures, and digital building blocks (Hinings, et al., 2018 MAR) . Despite the increasing importance of digital transformation and the concept of malicious innovation, strategy literature still lacks a more complete picture of how organizations committed to their business models after this disruption (Cozzolino, et al., November 2018). However, scientific research and innovation management practices have emphasized the important role of individual competencies in addressing the challenges of digital transformation. However, this sector still lacks sufficient empirical studies,

and preliminary results show that individuals' high growth in cognitive and metacognitive skills enhances a company's digital transformation processes. But surprisingly, social competences have only a small effect (Butschan, et al., 2019 MAY). Organizations are using digital technologies to change the paths of value creation and change the conditions of competition. To this end, they must implement structural change and overcome the obstacles that hinder their efforts to evolve. Because they have more information with digital technologies, their computing, communication and connectivity creates new forms of collaboration between actors and distributed networks. In doing so, they also create dependencies among actors whose interests may not be fully aligned. Digital technologies influence the strategic implications of digital transformation and the dynamic interaction that occurs between companies and their environments (Vial, 2019). Digital transformation can also come from the integration of end-to-end systems that are separate from one another in the traditional value chain or in the digital ecosystem of the larger IT industry and through IoT. Digital transformation will potentially affect the workforce. It is challenging to build the skill and pay gap between skilled digital workers and workers in their more traditional role in industry, especially in emerging economies (Accenture, January 2017). Changing the industrial production paradigm, digitizing business processes, reconfigures every aspect of the organizational and operational activities throughout the value chain, and manufacturing companies need to take a systematic approach by mapping digital roadmaps to address job opportunities throughout the value chain (Savastano, et al., 9 February 2019). However, the application of technology alone is not enough, but to gain the benefits of digitalization, it requires business model innovation such as making changes to advanced jobs and service models. Specifically, the challenges of creating value, delivering value and the components of a business innovation value

capture model need to be understood more fully as well as how to align these components in creating a sustainable industry (Parida, et al., 2019). Successful implementation of innovation practices that ensure effective value creation throughout the supply chain includes: (1) changing the mind and developing an innovation strategy and communicating it to all members of the supply chain; (2) seeing evolution as a long-term process and evolutionary innovation as a cycle, which will be implemented after several tests (3). Functional and inter-organizational (Sabria, et al., 2018). Process improvement is the most added value in the Business Process Management (BPM) cycle. With the mature knowledge, many approaches have failed due to lack of guidance on how to make the process better. Given the diversity of emerging digital technologies, organizations are not only facing the black box of process improvement, but there is also uncertainty about digital technologies (Denner , et al., 2017). Many customers are also facing a digital transformation process that will lead to partial or fully virtual processes, compliant enterprise structures and digital business models. Virtualization promises innovative opportunities for optimum performance and service delivery, thereby strengthening the competitive position (Nissen, 2018). Digital transformation calls for a redefinition of economics, labor, and democracy for humanity. AI-based devices may take over key areas of human work, reorganize supply chains, induce platform economics, and alter the participation of economic actors in the value chain. Digital transformation defines knowledge and data as the main variables of economic, capital, labor and natural resources. Digital data and technologies will produce a major capital and fuel in the subsequent profitability process, and traditional democratic processes can be (intentionally or unintentionally) replaced by digital technologies (Scholz, et al., 2018). Also, business Intelligence (BI) covers the tasks of collecting, processing, and analyzing

large volumes of data. The main purpose of BI is to help companies improve their performance in the turbulent environment of business and enhance their competitive advantage in this immense data age. (Ahmadi & Zare, 2021). Digitalization promises to change tax management faster than the tax law itself will change. These changes include systems analysis, big data, and ongoing process automation. Although digital transformation will be challenging for taxpayers, the benefits are also significant. In this way, examining legal, ethical issues is important together. With the development of big data technology, automation, artificial intelligence, security and blockchain, all of these changes will affect tax management (Bentley, Duncan, 2019) . In reporting from traditional business to government (B2G), can use the conceptual lens of the institutional function of examining how traditional business reporting to government and how digital reporting is to replace it and try to reduce it (Troshania, et al., 2018). The very dynamic success of the global expansion of digital multinationals is largely due to the widespread use of platform-based business models. Customer behavior patterns and expectations have become more sophisticated as the boundary between traditional industries fades in favor of digital leaders and consumers. In this environment, dynamic multinational activities are currently on the path to digital transformation (Alexey V, 2018 SEP). In the economic field, banks are still distant from digital banking because they still lack the key jobs and technical bases to implement digital banking. Likewise, digital culture is a lost asset in banking (Pourebrahimi , et al., 2018). We know that fintechs are a new segment of the financial market that is made up of a combination of technology and financial services. This section focuses on financial services and innovation. Innovations come under the heading of research, blockchain and security with a strong emphasis on this area, and represent the most sensitive aspects of the current

global issue of digital transformation (Milian, et al., 2019 MAR-APR). The digitalization of banking services based on new technology empowers banks to respond to new customer demands, and the banking sector has undergone major changes (Drasch, et al., 2018 NOV-DEC). With the growth of technology, organizations are also experiencing massive changes in the design and leadership of their work. Change in life - work and health, use of information and communication technology, performance and management of talent and organizational hierarchy. In addition, two dimensions of macro-level change have evolved with a focus on work structure and leadership (Schwarzmüller, et al., 2017). In the area of senior management, despite the importance of healthy partnerships between CEOs and CIOs in organizations for effective business and information technology alignment, we still have little information on how to compare aspects of mutual understanding between them and how they can collaborate and build a unique perspective (Benlian & Haffke, 2017). In the field of health in the healthcare ecosystem, the digital transformation of health services requires more advanced information technology competence that integrates directly with service users, residents, patients and their relatives in providing care services and creating value (Dugstad, et al., 2019). Collection, analysis and management of clinical data with electronic applications has already been widely used. But digitizing medical records along with the principles of electronic medical data management, in addition to enhancing efficiency and reducing treatment costs, ensures clinical effectiveness across all medical institutions and provides a good opportunity for structural transformation efforts in the field of health with digital transformation (Schoenermark, 2019 MAR). With the exchange of information, humans and intelligent objects are able to make common decisions on a broader, higher quality field (Zimmermann, et al., 2016). And smart, interconnected products are transforming the industry.

Live smart products must be (1) integrated at different levels of organizational strategy, including policy, intelligence, control, performance and communication channels, (2) modeled (3) integrated at different levels of organizational strategy. And digital transformation should not lead to separate investments in smart technologies (Barata & Rupino da Cunha, 2019). Future human scenarios and subsequent work and robotics life highlights the need for a robotic roadmap that covers key aspects of industrial and service robotics, including three important areas: the future of robotic technology, digitization and technology. Analyzes ICTs in the key economic, social and political challenges of digital transformation (Kaivo-oja, et al., March 2017). In the domain of identity, the virtual identity model is also presented as a multi-dimensional concept involving several levels. Virtual identity building is based on a variety of macro- or community-based factors, including narrative scripts, virtual intimacy, virtual community, and virtual instrument culture (Nagy & Koles, 2014). In the field of security, a growing synergy between IoT and social technologies is helping to advance the physical cyber-social systems. The integration of new technologies faces key challenges related to information security and privacy (Mendhurwar & Mishra, 2019). Most past studies of Open Innovation focus mainly on the firm level of large corporation. But now, the landscape of innovation has changed enormously. Enterprises can no longer afford to innovate on their own, due to the labor mobility, abundant venture capitals and widely dispersed knowledge across multiple public and private organization. (Khamseh, et al., 2012) Knowledge sharing in networks also seems to have not received much attention so far. Therefore, integrating the vision of key areas of knowledge, strategy, and innovation and information security management with the aim of identifying the requirements of knowledge protection in the era of digital transformation has been considered. In this

regard, both (1) the threat of leakage and exploitation by unauthorized persons, and (2) the threat of unavailability and destruction, are significant challenges for internal and external threats. What makes these threats more difficult to address is the digital transformation that constantly changes the operating landscape of organizations and stimulates the development of complex networks in which organizations participate (Ilvone, et al., 2018).

Method

Analysis of data and information in scientific research is one of the most important stages of research and includes classification, summarization, description and analysis of collected information. In the analysis process, first the statistical data are analyzed using descriptive indicators and to answer the research questions, data, statistical methods and appropriate measurement scales are used according to the purpose of the research. Raw data, as a mass of quantitative information, are first summarized and transformed into analyzable evidence, and finally analyzed. In this research, the above methods have been used to analyze the data and answer the research questions. In this way, using descriptive statistics, the collected data are summarized and described. Then, using the analysis of the conceptual model of the research, the statistical population is judged. Describing the research data and examining the required characteristics of the collected information such as the validity and reliability of the questionnaire and also analyzing the extracted factors of the research have been done using SMART PLS statistical software. ANFIS and MATLAB software.

Design of fuzzy inference system with adaptive neural approach and General model information: The main component of the research (final output of the system) Table 1. shows the factors and indicators related

to them (primary and intermediate input of the system). Accordingly, the relevant mathematical model in this study includes a main ANFIS in the field of open banking innovation with digital transformation approach and eight Sub-ANFIS belonging to the aggregation of the effects of each of the indicators on the relevant factors. Also Figure 1. the show conceptual model of research in one view.

Table 1.
Main Component of Research, Factors and Indicators

Index	source	indicators	factors	Main component
STR	Experts Nambisan et al, 2019 Ilvone, et al, 2018	Organizational strategy	**Organizational (ORG)**	Open Banking Innovation with Digital Transformation Approach (OBDT)
BIU	Experts Reis, et al, 2018 Matt, et al, 2015 Cozzolino, et al, 2018 Denner, et al, 2017	Business		
CHE	Experts Savastano, et al 2019 February Alexey, 2018 SEP Schwarzmüller, et al,2017 Hinings, et al , 2018 MAR	Organizational changes		
RES	Experts Henriette, et al, 2015 Savastano, et al,2019 Sabria, et al, 2018	Control of organizational resources		
COM	Experts Young & Rogers, 2019 Butschan, et al, 2019 MAR Vial, 2019 Benlian & Haffke, 2017	Alignment and adaptation to environmental changes		
INN	Experts Verhoefa, et al, 2019	Innovation approaches		

Index	source	indicators	factors	Main component
	Eling & Lehmann, 2017 Parida et al, 2019 Nissen, 2018			
NBA	Experts Warner & Waeger, 2019	New approaches to banking		
DTC	Pourebrahimi, et al, 2018 JUN Experts Nagy & Koles, 2014	The pervasiveness of digital culture	**Cultural** (**CUL**)	
ITA	Schoenermark, 2019 MAR Experts	Approach to innovation and technology in society		
ECR	Scholz, et al, 2018 Milian, et al, 2019 MAR-APR	Economic requirements of digital	Economic (**ECO**)	
ESD	Experts Pourebrahimi, et al, 2018	Economic dimensions of digital development		
ECA	Experts Scholz, et al, 2018 Drasch, et al, 2018 NOV-DEC	The level of attention to the digital economy		
EES	Bosilj Vuksic, et al, 2018 Dugstad, et al,2019	Social effects	**Social** (**SOU**)	
EER	Experts	Social requirements		
POL	Kaivo-oja, et al, March 2017	Political factors	**Political and** (**PIE**) **legal**	
LES	Scholz et al, 2018 Troshania, et al, 2018	Legal structuring		
LED	Bentley, Duncan, 2019	Dimensions of legal protection		
SYB	Mendhurwar & Mishra, 2019	Digital space security issues	**security** (**SEC**)	

Index	source	indicators	factors	Main component
SYP	Experts	Security policies		
FCH	Experts	The evolution of the financial industry	**Financial (FIN)**	
FSR	Experts	New approaches to banks' financial services		
TET	Experts Barata, et al, 2019 Downes & Nunes, 2013	Transformational technologies	**Technology (TEC)**	
TCH	Experts Birkel, et al, 2019	Technological developments		
DAT	Experts Borangiu, et al, 2019 JUN Zimmermann, et al, 2016	Data field		
DTA	Experts Cozmiuc, et al, 2018 APR-JUN Accenture, January 2017	Digital approach		

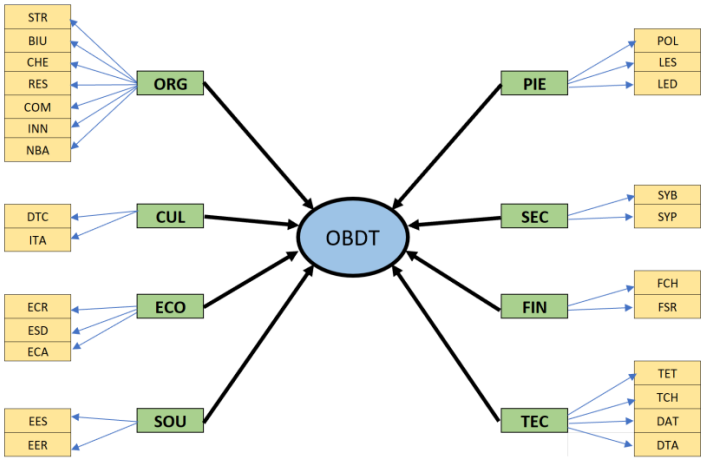

Figure 1. The conceptual model

Define the primary membership function for input and output variables: ANFIS systems require the function to be derivative. Due to the application of Gaussian functions (as a membership function in adaptive network-based fuzzy inference systems) in the vast majority of similar studies, the Gaussian function category has been used for this purpose. These functions, with the ability to open and close (due to changes in the parameter σ (standard deviation)), can also cover most values.

$$\text{gussian}(x,\sigma,c) = e \times p\left(-\left(\frac{x-c}{\sigma}\right)^2\right)$$

In the above relation, c denotes the center of symmetry and σ denotes the opening of the function. The Gaussian function has a smooth curve and its parameters can be adjusted with linguistic variables. The change range for input and output variables is also defined between 0 and 10. The Figure 2. shows the initial membership function for the input and output language

variables of the adaptive fuzzy neural inference system of open banking innovation with digital transformation approach and its subsystems.

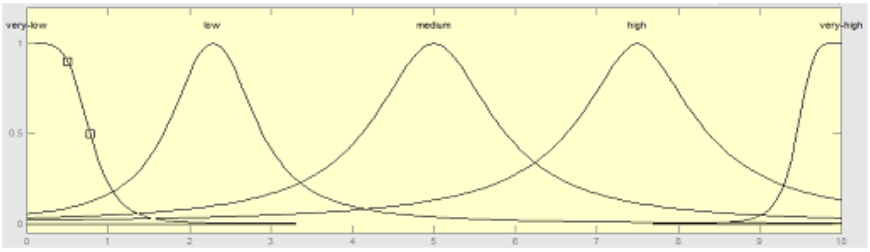

Figure 2. Initial membership function to evaluate OBDT

Structuring inference rules: The most important part of a fuzzy system is its rule base. This set of rules is a set of logical "if-then" rules that lead to the mapping of input variables to output variables, and various methods such as direct use of expert knowledge are used for this purpose. In this research, in order to design inferential rules, the powerful ANFIS tool (in other words, relying on the combination of neural network learning power and logical operation of fuzzy systems) and the knowledge of experts in the field of digital banking and open banking have been used. For this purpose, to extract the knowledge of experts, oral questionnaires (a kind of interview) containing a combination of different values for input variables (randomly) have been prepared and experts have been asked to consider these values for input variables and according to experiences. Judge the output variable by themselves or their scientific knowledge. Fuzzy inference rules actually relate the inputs of a fuzzy inference system to the output. In other words, the inferential laws express the different combinations of input on output. For this purpose, by defining the input and output variables in the range of 0 to 10 and the effect of the results obtained from the ranking of research factors (by FANP method), has led to a more structured way to

extract expert knowledge. The main ANFIS has eight inputs of organizational, cultural, economic, social, political-legal, security, financial and technological factors and its output is open banking innovation with digital transformation approach. Here, experts are asked to consider different values for the eight input components and according to their experimental (or specialized) knowledge, the amount of output variable or in fact the performance of open banking innovation with digital transformation approach. Estimate the effects of these factors. The information extracted from the knowledge of experts and their judgment about the output variable of the designed model (under different values of its inputs), is divided into three categories: training data, test and review. Training data is used in modeling the target system and test and review data is used to validate the model (designed). Table 2 shows how the information and values obtained for designing the aforementioned ANFIS inferential rules are collected (meaning Ei Certified i th).

Table 2.
Model Data Collection

	Random values generated for expert presentation								Expert opinion
E_i	Organizational	Cultural	Economic	social	Political-legal	security	Financial	Technology	OBDT
E_1	3	7	0	7	2	4	9	10	5
E_2	2	6	3	6	3	10	7	1	4
E_3	5	6	7	0	7	3	10	9	6
...	...	...	...	...	...	...	...	...	...

	Random values generated for expert presentation								Expert opinion
E_i	Organizational	Cultural	Economic	social	Political-legal	security	Financial	Technology	OBDT
...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...
E_{88}	3	9	9	3	5	8	6	0	5
E_{89}	2	4	5	7	2	9	6	1	4
E_{90}	7	9	1	3	٠	4	5	2	4

After collecting information from experts, we have to categorize the numerical data used to model the inference system. The purpose of categorization is to identify natural data sets from a large set of data to form the overall shape of system behavior. Fuzzy classification models the data behavior best and with the least number of rules, and the C-mean fuzzy classification method is commonly used for classification. But this algorithm is only useful when the centers of the clusters can be defined. Another disadvantage is the determination of parameter C as input, which must be specified by the user first, and there is no specific way for it. Also, this algorithm is not suitable for detecting clusters with complex shapes. Subtractive clustering is an enhanced method of clustering that has overcome the limitations of the previous method, and in the absence of any clear idea that the given set should be multi-part, this clustering method can be used. In this research, to form the structure of inferential rules, this method has been used, which has a fast and one-pass algorithm for estimating the number of categories and data centers in a data set, and in the

clustering process by Subtractive clustering values Impact coefficients, approval ratio and rejection ratio are 1.25, 0.5 and 0.15, respectively.

ANFIS training: To achieve the parameters of the membership function in the training routine, two methods are available: Back Propa and Hybrid. In the Back Propa method, after calculating the error and returning backwards, the error value is spread to the inputs (on the parameters) and finally, using the downward slope algorithm, the value of the parameters is corrected (just like the after-method Propagation of error used in neural networks). Therefore, by combining the two methods, we achieve a hybrid and optimal training method (Hybrid) that has been used in this research.

Error Tolerance is also directly related to the magnitude of the error and is used to determine a criterion for stopping training. Designed ANFIS with 40 training courses (EPOCH) achieved an acceptable error rate and Table 3. shows the amount of this error in the main ANFIS and Sub-ANFIS after 40 training courses.

Table 3.
Error Rate Designed in ANFIS

ANFIS	Error	ANFIS	Error
ORG	9.9622×10^{-8}	PIE	4.98914×10^{-5}
CUL	0.104058	SEC	0.0131556
ECO	2.86812×10^{-5}	FIN	0.0515827
SOU	0.129132	TEC	7.35834×10^{-7}
OBDT	8.17775×10^{-7}		

The designed model, which has eight inputs (eight factors) and the output of open banking innovation with a digital transformation approach, has 50 inferential rules. Figure 3.

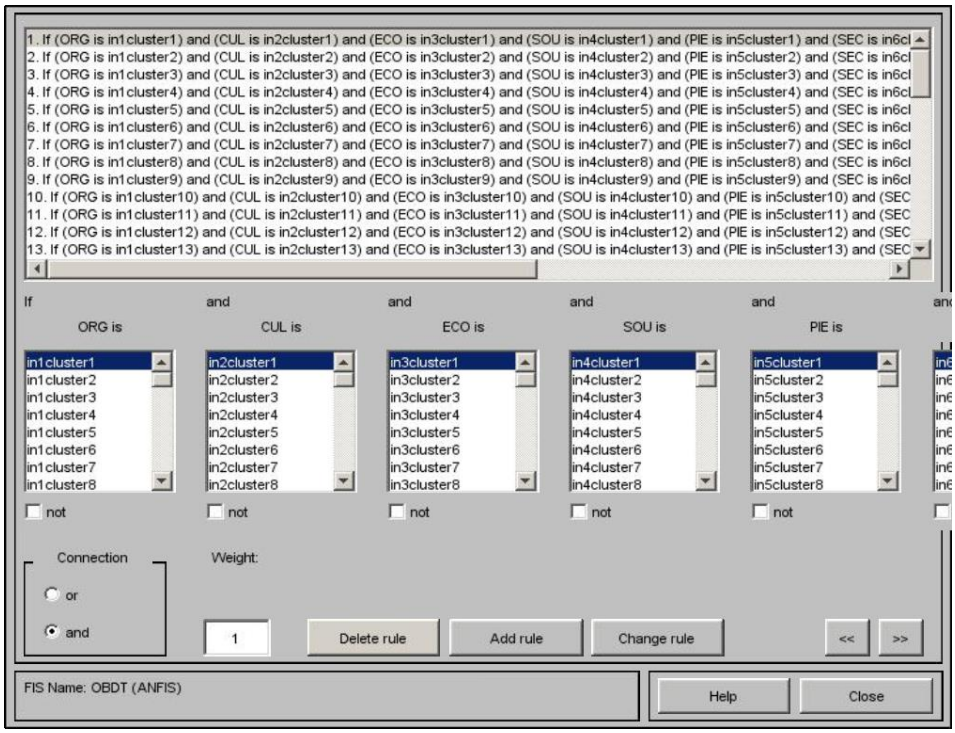

Figure 3. Rules of fuzzy inference of research

ANFIS architecture: In order to evaluate the factors affecting open banking innovation with the digital transformation approach, we first design a main ANFIS, which is shown in Figure 4. Its structure consists of 50 rules and has 5 layers and the first layer is dedicated to 8 inputs (Sub-ANFIS) which are the following factors: 1. Organizational (ORG), 2. Cultural (CUL), 3. Economic (ECO), 4. Social (SOU), 5. Political and Legal (PIE), 6. Security (SEC), 7. Financial (FIN), 8. Technology (TEC). And the fifth layer also includes the output of the model.

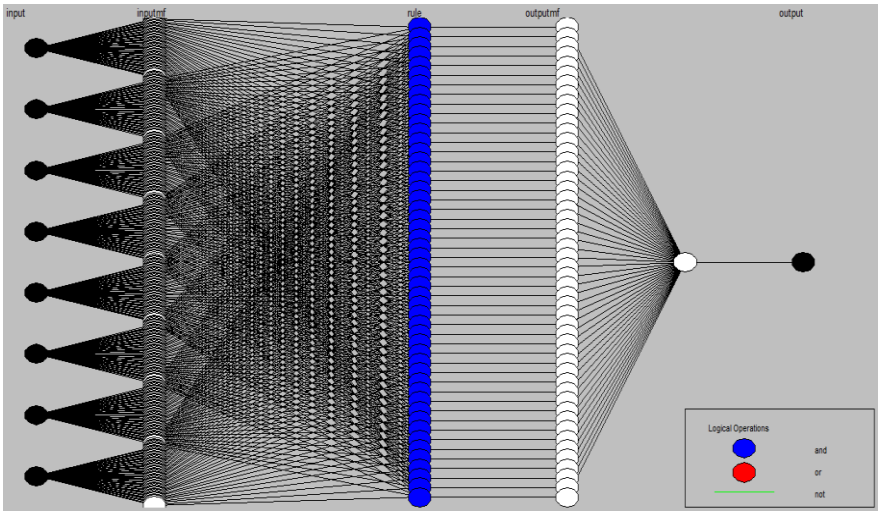

Figure 4. ANFIS structure to evaluate OBDT

As can be seen in the Figure 5 the main ANFIS inputs (eight factors) are each a Sub-ANFIS, which in the following figures are adaptive fuzzy neural systems (Sub-ANFIS) designed for each component. The main ANFIS system inputs are shown.

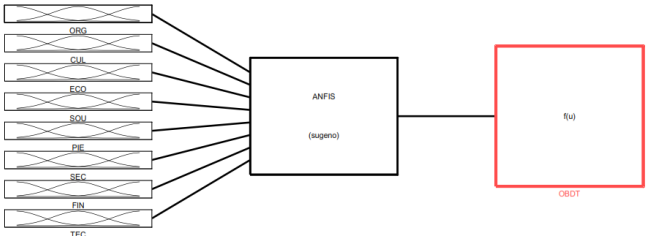

Figure 5. Main ANFIS inputs (eight Sub-ANFIS factors)

- ANFIS 1- Organizational Factors (ORG) Inputs (components): Organizational Strategy (STR), Business (BIU), Organizational change (CHE), Enterprise Resource Control (RES), Adaptation and adaptation to

environmental changes (COM), Innovation Approaches (INN), New Approaches to Banking (NBA) Figure 6.

- ANFIS 2- Cultural factor (CUL) Inputs (components): The prevalence of digital culture (DTC), Approach to Innovation and Technology in Society (ITA)
- ANFIS 3- - Economic factor (ECO) Inputs (components): Economic requirements from digital (ECR), Economic Dimensions of Digital Development (ESD), Attention to Digital Economy (ECA)
- ANFIS 4- Social Factors (SOU) Inputs (components): Social Impacts (EES), Social Requirements (EER)
- ANFIS 5- Political and Legal Factor (PIE) Inputs (components): Political factors (POL), Legal Structuring (LES), Dimensions of legal protection (LED)
- ANFIS 6- Security Agent (SEC) Inputs (components): Digital Space Security (SYB) Topics, Security Policies (SYP)
- ANFIS 7- Financial Agent (FIN) Inputs (components): Financial Industry Transformation (FCH), New Approaches to Banking Financial Services (FSR)
- ANFIS 8- Technology Agent (TEC) Inputs (components): Transformational Technologies (TET), Technological Developments (TCH), Data field (DAT), Digital Approach (DTA) Figure 7.

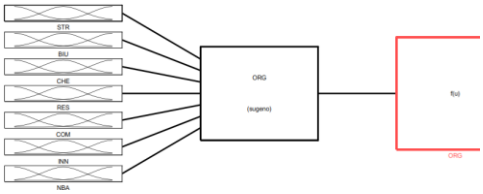

Figure 6. ANFIS 1- Organizational Factors (ORG)

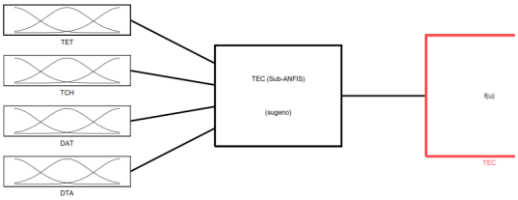

Figure 7. ANFIS 8 -Technology Factors (TEC)

Findings

According to the database of rules extracted for this research, the combination of different modes of factors will lead to different outputs of the designed system. Figures 8 to 11 present the curves of the factors affecting the issue of open banking innovation with a digital transformation approach. Each of these factors has been compared with each other either independently or in pairs and their effect on the main component of the research has been shown. In Figures 8 and 9, increasing the amount of organizational, political and legal factors in the range of zero to five, compared to values greater than five, has had a lesser effect on increasing open banking innovation with the digital transformation approach. In other words, for values greater than four, they increase the output variable almost several times (except that the increasing trend of the organizational factor ends with an increasing rate compared to the initial interval and with a decreasing rate for the political and legal factor). That is, the influence of the eight factors makes sense over time. However, they may have less effect on system output at initial values.

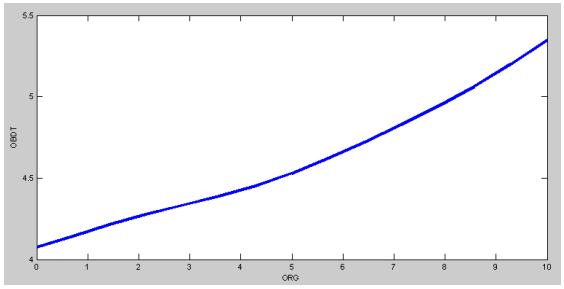

Figure 8. Diagram of the Impact of Changes in Organizational Factors on Open Banking Innovation with Digital Delivery Approach

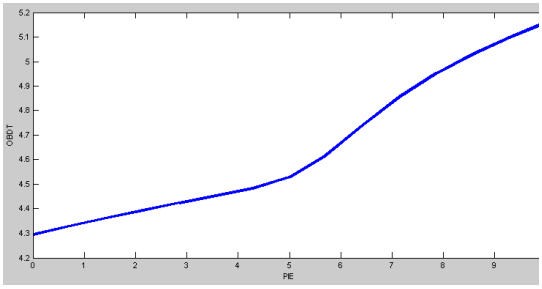

Figure 9. Chart of the Impact of Changes in Political and Legal Factors on Open Banking Innovation with a Digital Delivery Approach

The Figures 10 and 11 are three-dimensional diagrams whose decision level is created by ANFIS (designed). The structure of these curves is such that it shows the effect of binary values of input components on the output variable of the research subject.

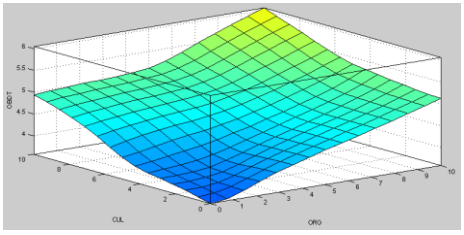

Figure 10. Comparison curve of the effect of two organizational (cultural) factors (input) on the output variable

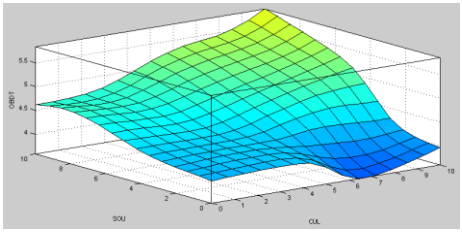

Figure 11. Comparison curve of the effect of two cultural (social) factors (input) on the output variable

Implementation of mathematical model: In order to evaluate the factors affecting the improvement of open banking innovation with a digital transformation approach, a questionnaire was designed and experts in this

field (number of 90 people) were asked to announce their views on the four factors of banks' performance level. The survey was identified by marking the relevant continuum containing values from 0 to 10. Tables 4, A, B, C, D, E, F, G, and H, input and output values under organizational subsystems (ORG), cultural (CUL), economic (ECO), social (SOU), Political and Legal (PIE), Security (SEC), Financial (FIN) and Technology (TEC). Also, the figures below each table represent the rules base of the mentioned subsystems.

Table 4-A.
Organizational Sub-ANFIS Input and Output Vvalues

STR	BIU	CHE	RES	COM	INN	NBA	ORG
8.65	7.62	7.2	1.65	10	5.47	8.55	6.27

Table 4-B.
Cultural Sub-ANFIS input and output values

DTC	ITA	CUL
2.9	4.14	3.84

Table 4-C.
Economic Sub-ANFIS input and output values

ECR	ESD	ECA	ECO
1.03	8.28	8.85	5.13

Table 4-D.
Social Sub-ANFIS input and output values

EES	EER	SOU
2.49	1.85	3.02

Table 4-E.
Political and Legal Sub-ANFIS Input and Output Values

POL	LES	LED	PIE
0.16	2.67	5.14	6.89

Table 4-F.
Security Sub-ANFIS input and output values

Table 4-G.
Input and Output Amounts of Financial Sub-ANFIS

SYB	SYP	SEC
4.67	0.89	4.66

FCH	FSR	FIN
4.78	3.94	4.86

Table 4-H.

Input and output values of Sub-ANFIS technology

TET	TCH	DAT	DTA	TEC
4.61	9.98	4.6	2.53	3.16

After the implementation of Sub-ANFIS, their output is used as the main ANFIS input to evaluate the factors affecting open banking innovation with a digital transformation approach (OBDT). Table 5. shows the values of these inputs and outputs in the main model as well as Figure 12 of the main ANFIS rule database.

Table 5.

ANFIS Input and Output Values of OBDT

ORG	CUL	ECO	SOU	PIE	SEC	FIN	TEC	OBDT
6.27	3.84	5.13	3.02	6.89	4.66	4.86	3.16	4.25

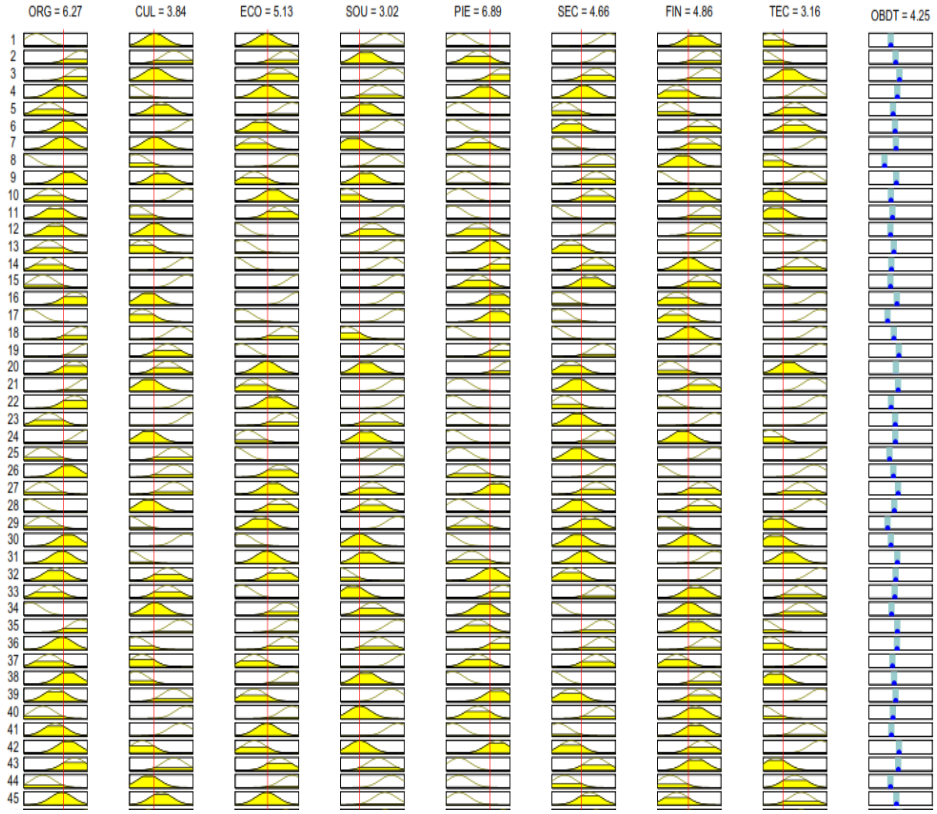

Figure 12. Open Banking Innovation Rules with Digital Transformation Approach Database

As can be seen, the level of open banking innovation with the digital transformation approach is estimated at 4.25, which is in the average range.

Mathematical model validation: Before implementing and executing the system designed in the case study, the validity of the mathematical model was assessed. Model testing and its validity increase the reliability of the model and its applicability. For this purpose, two methods of "testing and

examining the data set" and "limit condition test" have been used to validate the mathematical model.

Test and review datasets: Validation was performed with the help of test data to test the ability to generalize the obtained fuzzy inference system, and we used the latest data set (review data) to control the problem of overfitting. For this purpose, in the present study, the designed ANFIS error trend was investigated and Figures 13 and 14 clearly show the consistency between the training data and the test and review data.

In the diagram above, the * sign (star) indicates the ANFIS output and the circle symbol indicates the test data with the mean error calculated at 8/17775. In Figure 14, the asterisk indicates the system output and the plus sign indicates the survey data, which is almost identical, indicating a lack of Over Fitting in the designed ANFIS.



Figure 13.
Comparison diagram between ANFIS output and test data

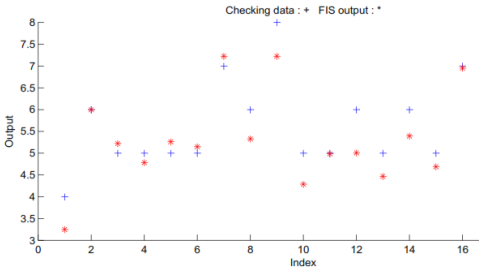

Figure 14.
Comparison diagram between ANFIS output and survey data

Limit condition test: In this test, the value of the main ANFIS input variables is changed in different limit states (very high and very low) and the output of the model against these changes is investigated. In other words, the purpose of this test is to validate the appropriate behavior (reliability) of the

obtained mathematical model with respect to changes in the values of input data.

Table 6.
The Effect of Simultaneous Changes in Inputs on Output

ANFIS Outputs	ANFIS Inputs							
OBDT	TEC	FIN	SEC	PIE	SOU	ECO	CUL	ORG
0/02	0	0	0	0	0	0	0	0
4/53	5	5	5	5	5	5	5	5
9/36	10	10	10	10	10	10	10	10

As shown in the Table 6, the model behaves quite logically against changes in input variables from very low (zero) to very high (10). This test was performed for all eight Sub-ANFIS and all of them showed a logical behavior towards the limit values of the inputs, which indicates the validity of the designed model.

Model sensitivity analysis: To investigate the amount of output changes versus input changes, two inputs with maximum effect on output and minimum effect on output can be selected and the effect of their changes on output can be examined. For this purpose, we select the ORG input as the most effective factor on the output and increase its value by one unit. The result of this change is shown in Table 7 and Figure 15.

Table 7.
Output Rate Change in Exchange for ORG Change

ORG	CUL	ECO	SOU	PIE	SEC	FIN	TEC	OBDT
7.27	3.84	5.13	3.02	6.89	4.66	4.86	3.16	4.38

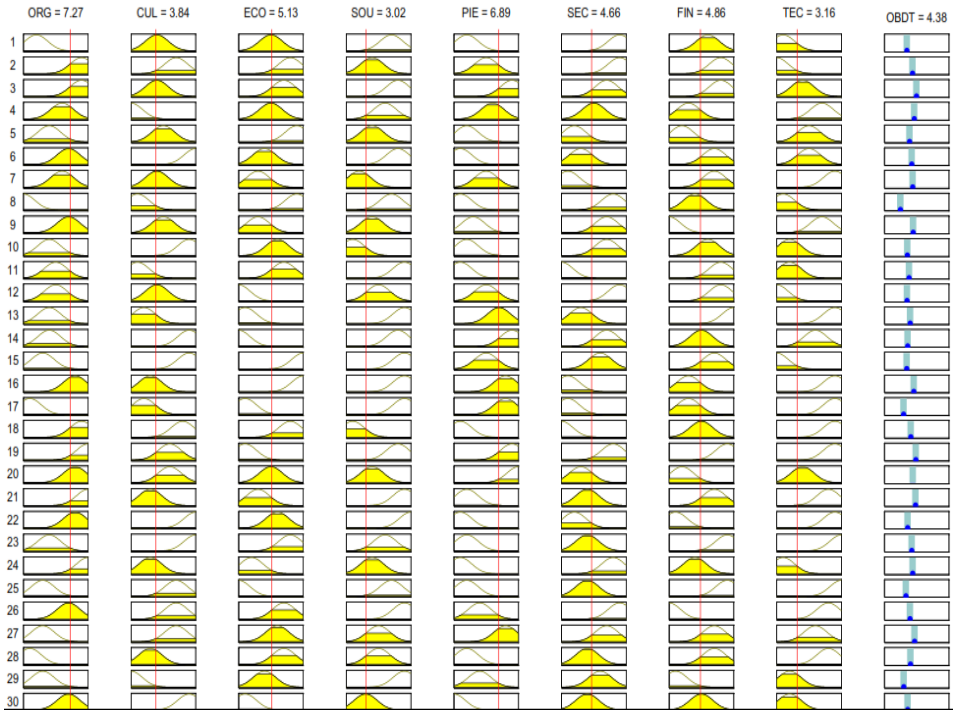

Figure 15. Rate of output change in exchange for ORG change

Also, by keeping all the factors constant, we examine the politico-legal input as a unit of reduction and the output changes. The results of this change are shown in Table 8 and Figure 16.

Table 8.

Rate of Output Change in Exchange for PIE Change

ORG	CUL	ECO	SOU	PIE	SEC	FIN	TEC	OBDT
6.27	3.84	5.13	3.02	5.89	4.66	4.86	3.16	4.25

As can be seen, the output changes by 0.06 in response to a change in the PIE component. In contrast, the same amount of change in the ORG component changes only 0.13. That is, the effect of ORG on output is greater than the effect of PIE on output.

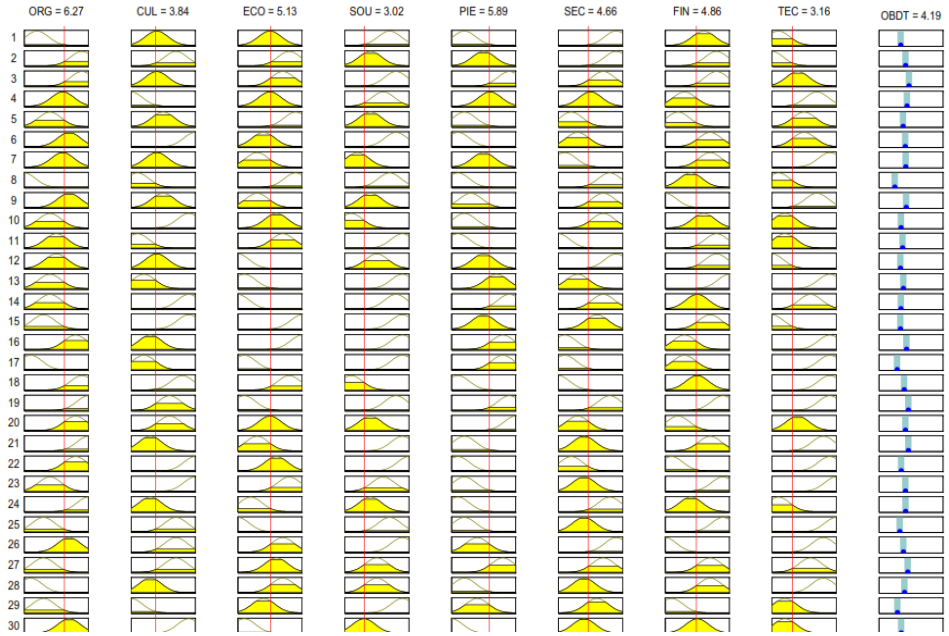

Figure 16. Output rate change in exchange for PIE change

Conclusions

As can be seen from the results, the organizational factor with the first rank and weight criterion of 24.24% is the most important variable among the factors affecting open banking innovations with digital transformation approach and can be the main decision criterion in the field under study. Be. And the political-legal factor with a weight criterion of 4.80% is in the last rank and can be expected to have the least influence in the relevant decision.

Technology factor with a weight of 18.36% Financial factor with a weight of 14.68% Economic factor with a weight of 11.90% Security factor with a weight of 10.30% Social factor with a weight of 8.88% Cultural factor with a weight of 6.79% In the next categories of factors affecting open banking innovations with The approach to digital transformation in Iran. As a result, Iranian banks in the development of open banking innovation with digital transformation approach, must first create organizational changes such as changing organizational strategy, changing business models and processes, replacing innovation-oriented business model instead of their current business. Organize changes related to digital transformation, align and adapt to environmental change, and develop a business network for their digital ecosystems with an innovative approach. In this direction, important issues such as complexity management, development of knowledge within the organization, decision-making agility and service production, readiness for open innovation along with enterprise resource planning and digital maturity development have an important effect on the development of open banking innovations. With the approach of digital transformation in Iran. On the other hand, attention to technological factors as the basis for new changes in banking, such as transformational technologies, attention to the importance of data and data mining and the use of digital approach in customer service processes in the second place in the development of open banking innovations with the approach to digital transformation.

References

Accenture, January 2017. Digital Transformation Initiative Mining and Metals Industry, Cologny/Geneva: In collaboration with Accenture.

Ahmadi , M. M. & Zare, S., 2021. Business Intelligence Technology in Research Organizations (Case Study of Academic Institutes in Tehran). Journal of System Management, Volume 6, pp. 69-101.

Alexey V, B., 2018 SEP. MULTINATIONAL BUSINESS IN THE ERA OF GLOBAL DIGITAL REVOLUTION. MIROVAYA EKONOMIKA I MEZHDUNARODNYE OTNOSHENIYA 62 (9), pp. 5-17.

Barata, J. & Rupino da Cunha, P., 2019. The Viable Smart Product Model: Designing Products that Undergo Disruptive Transformations. Cybernetics and Systems.

Benlian, A. & Haffke, I., 2017. Does mutuality matter? Examining the bilateral nature and effects of CEO–CIO mutual understanding. Journal of Strategic Information Systems, p. 104–126.

Bentley, Duncan, 2019. Timeless principles of taxpayer protection: how they adapt to digital disruption. EJOURNAL OF TAX RESEARCH 16 (3), pp. 679-713.

Birkel, H. S., Veile, J., Müller, J. M. & Hartmann, E., 2019. Development of a Risk Framework for Industry 4.0 in the Context of Sustainability for Established Manufacturers. Sustainability 2019, 11, 384.

Borangiu, T. Trentesauxb, D. Thomasc,A. Leitãod, P & Baratae, J. , 2019 JUN. Digital transformation of manufacturing through cloud services and resource virtualization. COMPUTERS IN INDUSTRY 108, pp. 150-162.

Bosilj Vuksic, V., Invancic, L. & Susa Vugec, D., 2018. A preliminary Litereture Review of Digital Transformation Case Studies. Rome Italy, s.n., p. 20 (9) Part VIII.

Butschan, . J., Heidenreich, . S., Weber, B. & Kraemer, . T., 2019 MAY. TACKLING HURDLES TO DIGITAL TRANSFORMATION - THE ROLE OF COMPETENCIES FOR SUCCESSFUL INDUSTRIAL INTERNET OF THINGS (IIoT) IMPLEMENTATION. INTERNATIONAL JOURNAL OF INNOVATION MANAGEMENT 23 (4): Art. No. UNSP 1950036.

Cozmiuc, D. & Petrisor, I., 2018 APR-JUN. Industrie 4.0 by Siemens: Steps Made Today. JOURNAL OF CASES ON INFORMATION TECHNOLOGY 20 (2): Art. No. UNSP 3.

Cozzolino, A., Verona, G. & Frank T. R, November 2018. Unpacking the Disruption Process: New Technology,Business Models, and Incumbent Adaptation. Journal of Management Studies 55:7.

Denner , M.-S., Pu¨schel, L. C. & Ro¨glinger, M., 2017. How to Exploit the Digitalization Potential of Business Processes. Springer Fachmedien Wiesbaden GmbH, part of Springer Nature .

Doulabi, H., khamseh, A. & Torabi, T., 2020. A System Dynamics Approach to Designing Technological Innovation Management Model in Downstream Petrochemical Industries. Journal of System management, Issue 1, pp. 113-148.

Downes, L. & Nunes, P., 2013. Big-bang disruption. Harv Bus Rev91(3), p. 44–56.

Drasch, B. J., Schweizer, A. & Urbach, N., 2018 NOV-DEC. Integrating the 'Troublemakers': A taxonomy for cooperation between banks and fintechs. JOURNAL OF ECONOMICS AND BUSINESS 100, pp. 26-42.

Dugstad, J., Eide, T., Nilsen, E. R. & Eide, H., 2019. Towards successful digital transformation through co-creation: a longitudinal study of a four-year

implementation of digital monitoring technology in residential care for persons with dementia. BMC Health Services Research.

Eling , M. & Lehmann, . M., 2017. The Impact of Digitalization on the Insurance Value Chain and the Insurability of Risks. The International Association for the Study of Insurance Economics.

Henriette, E., Feki, M. & Boughzala, I., 2015. The Shape of Digital Transformation: A Systematic Literature Review. s.l., AIS Electronic Library (AISeL).

Hinings, B., Gegenhuber, . T. & Greenwood, R., 2018 MAR. Digital innovation and transformation: An institutional perspective. INFORMATION AND ORGANIZATION 28 (1), pp. 52-61.

Ilvone, I., Thalmann, . S., Manhart , . M. & Sillaber, C., 2018. Reconciling digital transformation and knowledg protection: a research agenda. Knowledge Management Research & Practice.

Kaivo-oja, J., Roth, S. & Westerlund, L., March 2017. Futures of Robotics. Human Work in Digital Transformation. International Journal of Technology Management.

khamseh, A., & Marei, P., 2020. Designing a model development to assess the capabilities of technological innovation in Iranian constraints of power plant equipment industries. Jornal of Engineering, Design and Technology, Vol.18.

Khamseh, A., Radfar, R., Moeini, E. & Madani, H., Year: 2012, Volume: 5, Issue: 10, Pages. A survey of the success of open innovation model application in Iran`s knowledge base corporation (Case Study: Biotechnology Corporation). Indian Journal of Science and Technology, pp. 1-12.

Matt, C., Hess, T. & Benlian, A., 2015. Digital Transformation Strategies. Bus Inf Syst Eng 57(5), p. 339–343.

Mendhurwar, S. & Mishra, R., 2019. Integration of social and IoT technologies:architectural framework for digital transformation and cyber security challenges. Enterprise Information Systems.

Milian, E. Z., Spinola, M. d. M. & de Carvalho, M. M., 2019 MAR-APR. Fintechs: A literature review and research agenda. ELECTRONIC COMMERCE RESEARCH AND APPLICATIONS 34: Art. No. 100833, pp. Milian EZ (Milian, Eduardo Z.); Spinola MD (Spinola, Mauro de M.); de Carvalho MM (de Carvalho, Marly M.).

Nagy, P. & Koles, B., 2014. The digital transformation of human identity: Towards a conceptual model of virtual identity in virtual worlds. The International Journal of Research into New Media Technologies Vol. 20(3), p. 276–292.

Nambisan, S., Wright, M. & Feldman, M., 2019 OCT. The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. RESEARCH POLICY 48 (8): Art. No. 103773.

Nissen, V., 2018. Digital Transformation of the Consulting Industry-Introduction and Overview. DIGITAL TRANSFORMATION OF THE CONSULTING INDUSTRY: EXTENDING THE TRADITIONAL DELIVERY MODEL , pp. 1-58.

Parida, Vinit., Sjödin, David., Reim, Wiebke., 2019. Reviewing Literature on Digitalization, Business Model Innovation, and Sustainable Industry: Reviewing Literature on Digitalization, Business. Licensee MDPI, Basel, Switzerland.

Pourebrahimi , N., Kordnaeij, A., Hamid , K. H. & Azar, A., 2018. Developing A Digital Banking Framework in the Iranian Banks: Prerequisites and Facilitators. International Journal of E-Business Research (IJEBR) 14(4), pp. 65-77.

Reis, J., Amorim, M., Melão, N. & Matos, P., 2018. Digital Transformation: A Literature Review and Guidelines for Future Research. Springer International Publishing AG, part of Springer Nature , p. 411–421.

Sabria, Y., Michelia, G. J. & Nuurb, . C., 2018. Exploring the impact of innovation implementation on supply chain configuration. Journal of Engineering and Technology Management.

Savastano, M., Amendola, C., Bellini, F. & D'Ascenzo, F., 9 February 2019. Contextual Impacts on Industrial Processes Brought by the Digital Transformation of Manufacturing: A Systematic Review. Sustainability 2019, 11, 891.

Schoenermark, M. P., 2019 MAR. Medical Data Management - Approach, Concepts, Strategic and Operative Implications. LARYNGO-RHINO-OTOLOGIE 98, pp. S220-S236.

Scholz, R. W., Bartelsman, E. J. & Diefenbach, S., 2018. Unintended Side Effects of the Digital Transition:European Scientists' Messages from a Proposition-Based Expert Round Table. Sustainability 2018, 10, 2001.

Schwarzmüller, T., Brosi, P., Duman, . D. & .Welpe, I. M., 2017. How Does the Digital Transformation Affect Organizations? Key Themes of Change in Work Design and Leadership. mrev, 29 (2), pp. 114-138.

Troshania, I., Janssenb, M., Lymerc, A. & Parkerd, L. D., 2018. Digital transformation of business-to-government reporting: An institutional work perspective. International Journal of Accounting Information Systems.

Verhoefa, P. C., Broekhuizena, T. & Bartb, Y., 2019. Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research.

Vial, G., 2019. Understanding digital transformation: A review and a research agenda. Journal of Strategic Information Systems.

Warner, K. S. R. & Waeger, M., 2019 JUN. Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. LONG RANGE PLANNING 52 (3), pp. 326-349.

Wikipedia, 2016. Industry_4.0. [Online]

Young, A. & Rogers, P., 2019. A Review of Digital Transformation in Mining. MINING METALLURGY & EXPLORATION 36, AUG, pp. 683-699.

Zimmermann, A., Schmidt, . R., Sandkuhl, . K. & Others, 2016. Leveraging Analytics for Digital Transformation of Enterprise Services and Architectures. Springer International Publishing Switzerland.

Copy protected with Online-PDF-No-Copy.com