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Implementing AI Collaborative Robots in Manufacturing – Modeling Enterprise Challenges in Industry 5.0 with Fuzzy Logic

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ABSTRACT

The purpose of this article is to propose a fuzzy logic system as a tool for automated risk identification of potential technical challenges and social barriers during the implementation of artificial intelligence-based co-bots on workstations in manufacturing enterprises. On the basis of an extensive literature review, as well as industry reports and expert consultations, the basic challenges and enterprise barriers occurring during the implementation of changes in enterprises, especially during the implementation of the latest technologies, were selected. A fuzzy logic model was then developed that, based on the values of the input factors, generates an answer as to whether there is a risk of technical or social challenges in an enterprise when implementing the latest technologies. The results generated by the developed model, when confronted with expert knowledge, experience and subjective assessments, showed that the model works as expected. The results of the study suggest that the use of fuzzy logic can effectively support companies in detecting challenges and obstacles, thereby facilitating decision-making in reducing the risk of their occurrence. Adaptation to the conditions currently prevailing in the company allows for dynamic adjustment of co-bot deployment strategies, which in turn can lead to more effective management of technological changes and minimization of potential operational disruptions.

Keywords: co-bot, AI, Fuzzy Logic, model, enterprise.

INTRODUCTION

Industry 5.0 is a vision representing the fifth industrial revolution, following Industry 4.0, which focused on automation, the use of the Internet of Things and digitization in manufacturing. The fifth industrial revolution emphasizes the combination of advanced technologies with human creativity and experience. It is characterized by three main pillars: resilience, sustainability and human-centeredness [1].

Resilience is understood here as the ability of production systems to adapt to unforeseen events and possible disruptions. Sustainability as the activities of companies, using the latest technologies to, among other things, optimize energy and resource consumption, minimize waste, and reduce pollutant emissions [2]. Human-centricity, on the other hand, means putting people's well-being at the center of industry, so as to combine the speed and efficiency of modern technologies with the talent, ingenuity and experience of people. Thus, creating workplaces in such a way that technology and machines support the worker's ability to perform tasks more efficiently, rather than performing them for him or her [3]. Human-centered industry puts human needs and interests at the center of the production process. Instead of asking what workers can do with new technology, Industry 5.0 asks what technology can do for workers. While robots are tireless and precise, they are literal and lack the ability to think critically and creatively about their human partners [4].

One of the technologies that is part of the vision of the fifth industrial revolution and represents one of the latest and most exciting trends in the field of industrial automation is collaborative robots (co-bots). This is a type of robots designed to work safely alongside humans [5]. Unlike traditional industrial robots, which are typically isolated from humans for safety purposes, co-bots are designed to safely collaborate with humans in the same work environment [6].

In the industrial sector, collaborative robots have been used to automate simple and repetitive tasks while retaining humans for more complex tasks. These robots have the potential to improve productivity and safety in a variety of industries [6]. Through the use of state-of-the-art technology and advanced algorithms, co-bots can work with humans to perform tasks that require a high degree of precision, strength or repetition, while additionally allowing the worker to focus on more complex aspects of production [7]. Tasks performed "alongside" or "face-to-face" an operator with a co-bot will be the future of the manufacturing industry. Adaptive co-bots combined with "intelligent cognitive support" for the operator may be one solution to increase human-robot interaction. Adaptive co-bots will be able to dynamically adapt to a human's pace, stress level and experience. This results in increased flexibility, slightly reduced ergonomics, but increased quality (e.g. 100% complete and accurate assembly tasks) [8]. With the development of co-bot technology, we can expect to see more and more integration of these devices in a variety of industries. Advances in areas such as artificial intelligence, machine learning and sensorics will continue to enhance the capabilities of co-bots, making them even more versatile and safer [9].

Despite their many advantages, co-bots also pose some challenges for the company. They require ongoing research and development in terms of improving human-machine interaction, preparing the worker for the new environment, safety, and integration with existing production systems. It is also important to train staff in the operation and programming of co-bots[10]. The ability of collaborative robots to work with humans opens up new opportunities for sustainable manufacturing and increased productivity in various sectors of the economy. On the other hand, it can generate new technical, social and organizational challenges.

Artificial Intelligence technology is another key element of Industry 5.0 – as it plays a key role in supporting this concept, especially in the context of digital business transformation. Allowing rapid analysis of large amounts of data, it allows optimizing processes and responding to unexpected changes, such as market changes. The integration of artificial intelligence and big data in Industry 4.0 has paved the way for the development of sustainable and human-centered services in Industry 5.0. However, to ensure human-centeredness, an artificial intelligence architecture is proposed that prioritizes security, reliability and synergy at the human-machine level [11]. The rapid development of AI technology is significantly influencing the implementation of AI in collaborative robots (co-bots). Artificial intelligence in industrial applications has great potential to improve the user experience of the workstation, as well as reduce the cost of process implementation [7]. In addition, there are many productivity benefits of human collaboration with artificial intelligence in knowledge-based work [12]. With the current pace of AI technology development, it is only a matter of time to create workplaces equipped with collaborative robots with an implemented artificial intelligence model tailored to the job.

Any change in an enterprise goes hand in hand with challenges and barriers, hindering the process of implementing new technologies or work methods, among others. The literature identifies a number of barriers to implementing change in enterprises. Significant obstacles are industry and organizational barriers. These obstacles are deeply rooted in the structures and organizational culture of enterprises. They can include resistance to change among management, lack of adequate resources and infrastructure, and limited flexibility of internal processes. Many enterprises, may find it difficult to adapt modern technologies due to entrenched practices and procedures that are difficult to modify [13]. The market can also be a barrier, especially for small businesses. Competition, demand volatility and limited financial resources can greatly complicate the implementation of new technologies, of which co-bots are a component. In addition, small businesses often struggle with a lack of economic scale, which can make investments in cutting-edge technologies too costly and risky. Additionally, the rapid pace of technological change in the market can create uncertainty and put investment decisions on hold [14]. Negative attitudes, including reluctance and lack of productivity among employees can also hinder change. Aversion to new technologies, fear of losing their jobs and lack of motivation can lead to low productivity and resistance to change. Employees may fear that new technologies such as AI and co-bots will replace their jobs, which creates fear and uncertainty. In addition, a lack of adequate training, information transfer and support from management can exacerbate these negative attitudes, making it difficult to successfully implement new solutions in the company [15].

Implementing modern technology in an enterprise is a complex process that is affected by a number of factors. It is important to make careful and thoughtful decisions, taking into account factors such as investment costs, maintenance and safety [16]. A systematic approach to change is also important, especially in the context of complex systems such as artificial intelligence. Lack of systematicity when implementing new technologies can result in further unexpected challenges [17]. In turn, high initial costs can be a barrier, particularly for smaller companies [18]. Both internal and external factors can create obstacles and challenges [19]. The literature on the subject emphasizes the multifaceted nature of the challenges of implementing modern technologies in enterprises and the need for a strategic and systematic approach to solving them.

The social barriers that occur during the implementation of change in an enterprise can be a significant problem in the functioning of the enterprise and can be detrimental to the changes themselves. Understanding and overcoming these barriers is key to maintaining the proper health and growth of the enterprise. Developing strategies that take into account the specifics of the industry, the market and the needs of employees can help mitigate resistance and increase acceptance of new technologies. Thoughtful communication, investment in training and involvement of all levels of the organization are essential to effectively manage the implementation of change and maximize the benefits of modern technology [20].

The process of implementing change in an enterprise is also technically complex. A dynamic and uncertain business environment further complicates the process [21]. The narrow frame of reference of the company's current situation vis-à-vis the changes being implemented, inadequate quality standards, the ability to maintain the new infrastructure and the cost of implementation are other factors rooted in the business paradigm [22]. Technical challenges often arise during the implementation of new technologies, for example, when there is a digitization of operations in production, requiring changes in processes as well as work methods [23]. Social barriers as well as technical barriers have been identified in the literature as important in terms of impediments during the implementation of change in companies [24].

In the context of implementing AI-based cobots in a manufacturing enterprise, effective management, strategic planning and flexibility towards the problems encountered is crucial to ensure a smooth implementation process. To this end, the use of advanced analytical methods can significantly facilitate the identification of potential challenges and the planning of appropriate countermeasures. The decision to implement changes in the company's processes belongs to executives, who make it based on their experience, relevant indicators or the current situation of the company. As decision-making processes are implemented by people, they contain a subjective component.

The literature indicates that fuzzy logic systems, among others, can be used to support such decision-making activities [25]. Fuzzy sets were introduced by Zadeh in 1965, and their use allows working with data where we are dealing with imprecise boundaries [26]. One definition says that fuzzy logic is a tool that is user-friendly and allows flexibility in decision-making processes [27]. In addition, the tool is able to work with complex data and solve complex problems without mathematical modeling if there is not a lot of data to process. In fuzzy logic systems, a set of membership functions and decision rules is necessary, which is obtained, among other things, from experts in the field [28].

The fuzzy logic system is used in many fields and areas. In energy companies, it has been used to evaluate production rates and support real-time decision-making [29]. The financial sector has used fuzzy logic to predict financial indicators, demonstrating high performance in various geographic regions [30]. In addition, fuzzy sets have been used to improve decision-making processes by creating summaries of production states [31].

Due to the wide range of possibilities for the application of fuzzy logic, as evidenced by the mentioned examples from various fields, it was also decided to apply it to the ongoing research.

The purpose of this article is to propose a fuzzy logic system solution as a tool for automated risk identification of potential technical challenges and social barriers during the implementation of

AI-based co-bots into workstations in manufacturing enterprises. Taking into account the fundamental challenges and barriers of enterprises, occurring during the implementation of changes in enterprises, especially during the implementation of the latest technologies.

The use of the fuzzy logic model in this area will be a novelty, as well as an important contribution to the scientific discussion of the complexity and dynamics of modern technology integration processes in the industrial context.

RESEARCH METHODOLOGY

Selection of input parameters for fuzzy logic model

The input parameters of the fuzzy logic model were carefully selected based on a literature review, analysis of industry reports and consultation with experts and business practitioners. The literature review identified key factors affecting the introduction of new technologies into the manufacturing environment. Table 1 shows the formulated factors that may predict the occurrence of impediments and technical and social challenges associated with the implementation of co-bots with artificial intelligence into the enterprise, along with the literature sources described in the introduction. Industry reports provided up-to-date data and trends on the challenges of adapting modern technological solutions, while consultations with experts provided practical insights into problems encountered in real business scenarios [32, 33, 34]. In addition, one of the reports analyzed is based on an online questionnaire conducted in early 2024, with 1.363 respondents representing a wide range of industries, business sizes and specializations. Of which, some 980 said their companies had deployed artificial intelligence to perform at least one function [35]. Thus, the fuzzy logic model is well grounded in the practical and theoretical context, which increases its effectiveness and reliability in predicting potential challenges in the implementation of the latest technologies in enterprises, including AI-based co-bots.

Characteristics of the fuzzy logic model

To carry out the study, the authors proposed using fuzzy logic, implemented in Matlab - Simulink, version 2023a, using the Fuzzy Logic Designer toolbox. The scheme of the conducted research is shown in Figure 1.

Based on the previous analysis, nine key criteria were selected (Table 1) as input variables for this study. Each input variable can take values from 1 to 5 (five-point Likert scale). The output variable, defined as the Risk of barriers to implementation of AI-based co-bots, determines whether such a risk exists or not. A Mamdani-type controller was chosen. The fuzzy logic-based model illustrating this concept is shown in Figure 2.

With expert judgment, knowledge, and experience, fuzziness was applied to both input and output variables. For the input data, a Gaussian function was used, while for the output data, a triangular function was used. The Gaussian function was chosen for the input data to provide a smooth, gradual transition between different membership levels. Often, data from CRM systems can show dispersion without clear category boundaries. The Gaussian function provides flexibility, resulting in a more accurate representation of real-world data. The mathematical form of the Gaussian function is:

$$f(x) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{1}$$

where: c represents the center of the function, and σ denotes.

Table 1. Summary of factors with confirmation in the literature

No.	Factors	Literature position
1	Adequacy of quality indicators (for a specific production system)	[22], [36]
2	Fear and uncertainty about replacing humans with robots on the job site	[17], [21]
3	Ability to maintain co-bot infrastructure	[15], [22]
4	Level of research on enterprise production systems	[13], [21]
5	Compatibility with existing systems	[13], [23]
6	Experience from previous implementations/changes in the enterprisec	[19], [24]
7	Level of understanding of the technology (Clarity and comprehensibility)	[19], [20]
8	Cost of implementation	[18], [22]
9	The level of training and support for employees during and after the changes are implemented	[15], [24]

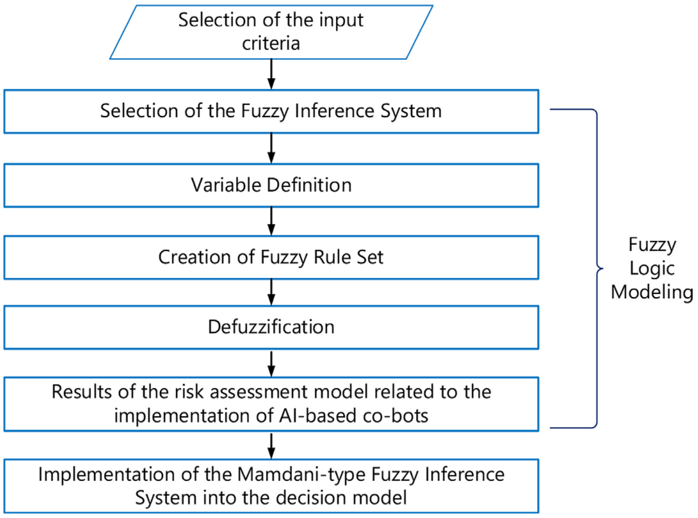

Figure 1. Research scheme

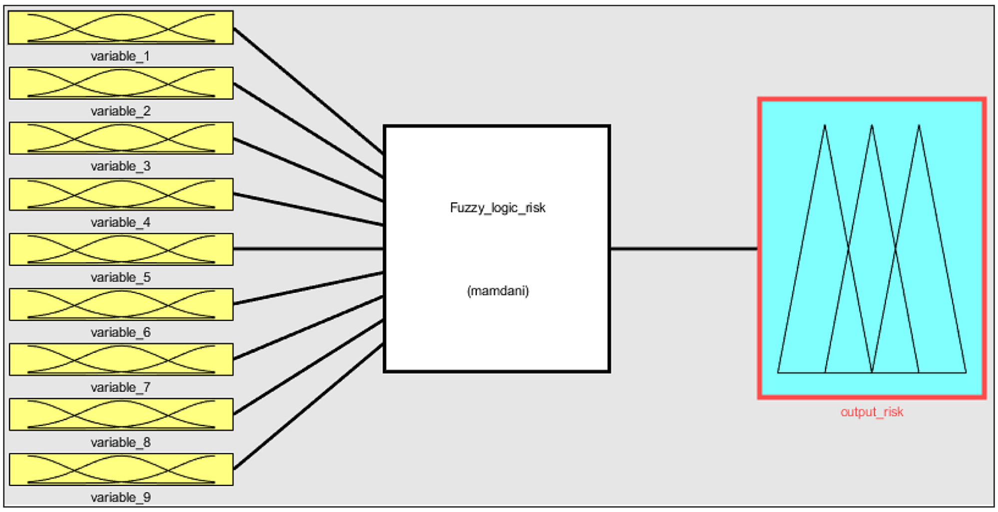

Figure 2. Fuzzy logic model – risk of barriers to implementation of AI-based co-bots

The scale used has three categories. The criteria used for the input variable are as follows:
1. Adequacy of quality indicators (for a specific production system) – scale: low (1–2), medium (3), high (4–5),
2. Fear and uncertainty about replacing humans with robots on the job site – scale: small (1–2), medium (3), large (4–5),
3. Ability to maintain co-bot infrastructure – scale: low (1–2), medium (3), high (4–5),
4. Level of research on enterprise production systems – scale: low (1–2), medium (3), high (4–5),
5. Compatibility with existing systems – scale: weak (1–2), medium (3), strong (4–5),
6. Experience from previous implementations/changes in the enterprise – scale: negative (1–2), neutral (3), positive (4–5),
7. Level of understanding of the technology (clarity and comprehensibility) – scale: low (1–2), medium (3), high (4–5),
8. Cost of implementation – scale: low (1–2), medium (3), high (4–5),
9. The level of training and support for employees during and after the changes are implemented – scale: low (1–2), medium (3), high (4–5).

The triangular function was selected for its straightforward nature and ease of understanding. When evaluating the risk of barriers to implementation of AI-based co-bots, the primary focus is on categorizing the risk into two distinct groups: exist or not exist. The triangular function offers clear demarcations between these groups and is user-friendly for individuals without a background in fuzzy logic. The mathematical formula for the triangular function is provided as follows:

$$f(x;a,b,c) = \begin{cases} 0 \; for \; x \leq a \\ \frac{x-a}{b-a} \; for \; a \leq x \leq b \\ \frac{c-x}{c-b} \; for \; b \leq x \leq c \\ 0 \; for \; x \geq c \end{cases} \quad (2)$$

where: a, b, and c respectively represent the left, middle, and right vertices of the triangular function.

An example membership function for the variable_4 " Level of research on enterprise production systems " is shown in Figure 3. The centroid-centre of gravity method was chosen for defuzzification, which converts the fuzzy results obtained from the fuzzy logic system back into precise scalar values.

By compiling sets of fuzzy rules, the risk of barriers to implementation of AI-based co-bots is evaluated. The impact of specific criteria on this risk is analyzed using a series of fuzzy IF-THEN rules. These rules are based on the subjective judgment, knowledge, and expertise of specialists. They are designed to consider significant interdependencies among the input criteria. A total of 39 fuzzy rules have been established. Below are four examples of these fuzzy rules along with their corresponding weights from the knowledge base:

1. IF "Fear and uncertainty about replacing humans with robots on the job site" is large AND "Level of research on enterprise production systems " is high AND "Experience from previous implementations/changes in the enterprise" is neutral AND "Level of understanding of the technology (Clarity and comprehensibility)" is low THEN "Risk of barriers to implementation of AI-based co-bots" is exist; weight: 1;
2. IF "Fear and uncertainty about replacing humans with robots on the job site" is small AND "Ability to maintain co-bot infrastructure" is high AND "Level of research on enterprise production systems" is high AND "Cost of implementation" is low AND "The level of training and support for employees during and after the changes are implemented" is medium THEN "Risk of barriers to implementation of AI-based co-bots" is not exist; weight: 0.7;
3. IF "Fear and uncertainty about replacing humans with robots on the job site" is medium AND "Compatibility with existing systems" is weak AND "Cost of implementation" is high THEN "Risk of barriers to implementation of AI-based co-bots" is not exist; weight: 0.9;
4. IF "Adequacy of quality indicators (for a specific production system)" is high AND "Fear and uncertainty about replacing humans with robots on the job site" is small AND "Ability to maintain co-bot infrastructure" is high AND "Experience from previous implementations/changes in the enterprise" is neutral AND "Level of understanding of the technology (Clarity and comprehensibility)" is high AND "Cost of implementation" is low THEN "Risk of barriers to implementation of AI-based co-bots" is not exist; weight: 0.5.

RESULTS AND DISCUSSION

Figure 4 illustrates the operation of a fuzzy logic controller for a selected enterprise. The figure

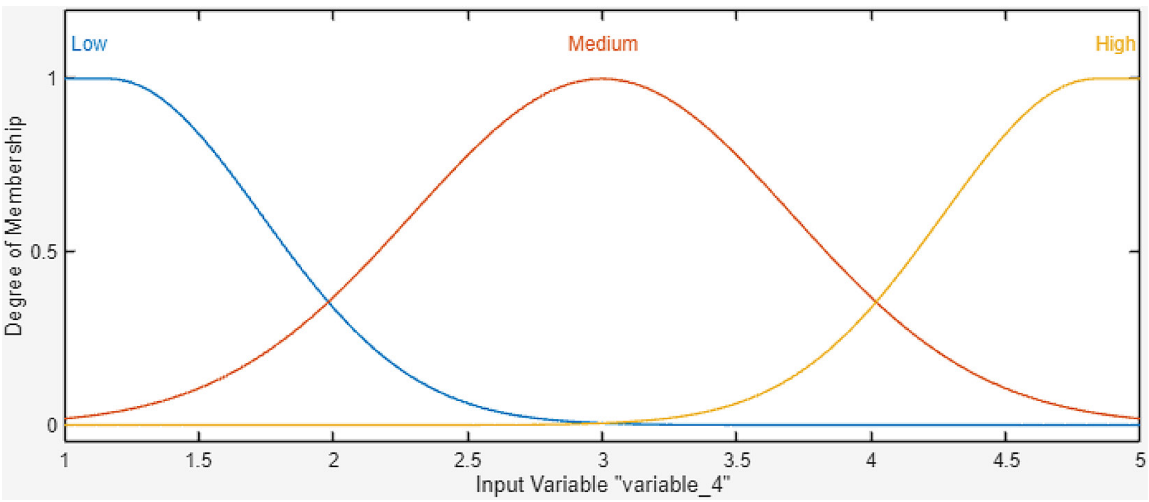

Figure 3. Membership function example for variable Level of research on enterprise production systems

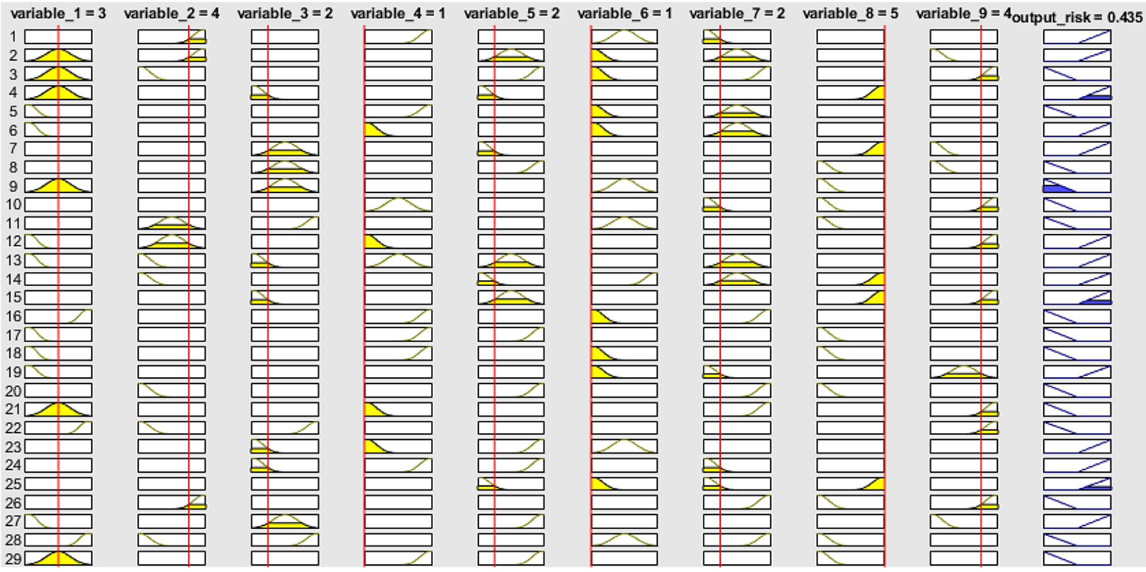

Figure 4. Sample window fragment from the program on how the rules work

organizes inference rules in rows and model variables in columns. The first nine columns represent the input variables, and the last column represents the output variable. Due to the limitations of displaying long names in the toolbox in the figure, the variables have been renamed as – Variable_1, Variable_2, and so on. Only the first 16 of the 56 rules fit in the figure due to the limitations of the rule viewer. The overall estimated result is shown in the upper right corner. This interface allows users to visualize and analyze the performance of individual fuzzy logic rules by interacting with the membership functions based on the input parameters. In this particular case, the output value was determined to be 0.435. Experts, based on their knowledge, experience, and subjective evaluation, have concluded that a value above 0.5 indicates a risk of barriers to implementation of AI-based co-bots, while a value below 0.5 indicates no such risk. Therefore, for the company shown in Figure 4, the conclusion is that there is no risk.

Developed and implemented in the Simulink environment, the Mamdani fuzzy inference system is designed to help enterprises decide whether there are barriers to deploying AI-based co-bots. The model generates a binary decision: "1" indicates the presence of risk, while "0" indicates no risk. A key component of the model is the function fcn, which processes the output data from the Mamdani system. If the output value is greater than or equal to 0.5, the function returns "1"; for values below 0.5, it returns "0". The input to the model is a vector of data characterizing each firm. The schematic representation of the model is shown in Figure 5, and its performance is detailed in Table 2. Table 2 shows sample responses for seven selected enterprises in the study.

Based on subjective assessments, expert knowledge, and experience, when compared with the outcomes produced by the developed model, it can be concluded that the model operates correctly.

The implementation of advanced technologies such as artificial intelligence and collaborative robots (co-bots) in intelligent manufacturing systems is increasingly prevalent. However, this process encounters numerous barriers, particularly social and technical, that can significantly affect the success of these technologies' integration. Understanding and identifying these barriers is crucial for the effective adoption of technologies

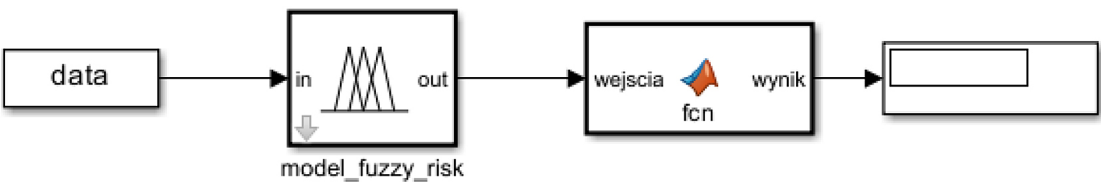

Figure 5. Decision model with implemented fuzzy logic model

Table 2. Model performance based on selected responses

No.	Variable	Enterprises						
		#1	#2	#3	#4	#5	#6	#7
1	Adequacy of quality indicators (for a specific production system)	3	2	1	1	4	3	3
2	Fear and uncertainty about replacing humans with robots on the job site	4	5	4	3	3	2	2
3	Ability to maintain co-bot infrastructure	2	1	1	1	3	3	4
4	Level of research on enterprise production systems	1	1	1	1	4	3	4
5	Compatibility with existing systems	2	2	2	2	4	4	4
6	Experience from previous implementations/changes in the enterprisec	1	1	1	1	5	5	5
7	Level of understanding of the technology (clarity and comprehensibility)	2	3	3	2	2	2	2
8	Cost of implementation	5	5	4	3	3	3	1
9	The level of training and support for employees during and after the changes are implemented	4	3	0	2	2	5	5
Results of the fuzzy logic driver		0.4351	0.5519	0.8132	0.7644	0.1996	0.1988	0.1918
Output – Is there a risk that there are barriers to the implementation of AI-based co-bots? (1- risk exists, 0 - risk not exists)		0	1	1	1	0	0	0

Note: Own elaboration.

that can enhance the efficiency and competitiveness of enterprises. Despite extensive research on the technical aspects of AI and co-bots, there is a limited focus on the social and technical challenges associated with their implementation.

Fuzzy logic has proven to be a valuable tool in implementing advanced technologies in enterprises, particularly for decision-making under uncertainty. It has been applied to assess organizational readiness for technological changes in industrial enterprises and to analyze cause-and-effect relationships in enterprise architecture [37, 38]. Fuzzy logic techniques have also been utilized to evaluate the efficiency of IT usage in industrial environments and to forecast financial indicators for various types of enterprises [30, 39]. These applications demonstrate the capability of fuzzy logic to handle imprecise and ambiguous data, making it well-suited for complex business environments.

The study opens the prospect of practical application of the model in a real business environment. The possibility of using the solution to support management decisions in enterprise processes can contribute to more effective adaptation of enterprises to changing conditions.

CONCLUSIONS

In conclusion, the study on the application of fuzzy logic in the process of identifying the risk of impediments to enterprises during the deployment of co-bots in production positions has yielded promising results. The results indicate that the use of the model, implemented in Matlab - Simulink, can effectively support enterprises in identifying and managing risks associated with technical and social challenges during the integration of new technologies. Thanks to the model's ability to dynamically analyze and adapt to changing operational conditions, companies can proactively respond to potential problems, minimizing disruptions to the production process and increasing the efficiency of co-bot deployment.

The approach used in the article, by relating it to past scientific developments, has the potential for further development and adaptation in various management contexts. The model represents a novel approach that contributes to the scientific debate on the complexity and dynamics of integrating modern technologies into the industrial environment, highlighting its practical utility and potential for broad application in various sectors of the economy. This could include not only manufacturing, but also other sectors such as logistics, healthcare or services, where the integration of advanced technologies requires effective change management. Further research could focus on extending the model to include new variables and parameters, as well as on its practical application to different types of enterprises, allowing for even more precise and effective management of technological and social risks.

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