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Artificial Intelligence and the Future of the Labour Economy: A Multi-Criteria Expert Evaluation of Institutional Models of Adaptation

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ABSTRACT

This study evaluates institutional models for adapting labour markets to the growing adoption of automation and artificial intelligence (AI). As AI continues to transform labour markets, identifying effective institutional responses has become increasingly important. Six institutional adjustment models were assessed against eight evaluation criteria using a hybrid fuzzy-rough decision-making framework that integrates the SiWeC (Simple Weight Calculation) and WASPAS (Weighted Aggregated Sum Product Assessment) methods based on expert judgments. The proposed approach explicitly incorporates uncertainty and imprecision into the evaluation process, thereby reducing subjectivity in decision-making. The results indicate that innovation and productivity incentives and institutional feasibility are the most influential evaluation criteria. A case study conducted in the Republic of Croatia further shows that the mass retraining and participatory AI capital models provide the most suitable institutional responses. The study contributes both methodologically, by proposing a robust fuzzy-rough evaluation framework, and practically, by supporting evidence-based policy decisions for labour market adaptation in the era of AI.

1. Introduction

The development of artificial intelligence (AI) represents one of the most significant technological transformations of the modern economy. Although the effects of automation and digitalization on the labour market are the subject of intensive research, the dominant part of the literature focuses on estimates of the exposure of individual occupations to automation and the short-term effects on employment and wages [1, 2]. Such an approach offers valuable microeconomic insights, but leaves open a key question: how should institutional systems adapt to the profound transformation of the labour economy in the long term?

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The theoretical framework of substitution and the creation of new tasks shows that technological progress alone does not determine the final outcomes in the labour market [3]. The effects depend on the balance between the replacement of labour with capital and the creation of new productive activities. However, the distributional and political-economic aspects of the AI transition further complicate the picture [4]. If gains are concentrated in equity holders, there may be an increase in inequality and a weakening of aggregate demand [5]. Macroeconomic debates about secular stagnation further warn that technological advances can simultaneously increase productivity and destabilize demand [6].

In this context, the issue of the sustainability of the labour economy supersedes the analysis of individual jobs. It is an institutional architecture that must at the same time ensure economic inclusion, preserve incentives for innovation, maintain fiscal stability and prevent political fragmentation. The political economy literature emphasizes that long-term growth depends on the quality and inclusiveness of institutions [7, 8]. However, existing research on AI transition rarely offers a systematic and comparative evaluation of alternative institutional models of adaptation.

Debates on universal guaranteed income [9], automation rent taxation [10), participatory capital [11], shortened working hours, mass retraining and industrial policy [12, 13] have mostly taken place in isolation, without an integrated analytical framework that would allow them to be juxtaposed according to clearly defined sustainability criteria. Still, there is a lack of a methodologically structured approach that would quantify the relative importance of economic, social and political dimensions and allow for the ranking of institutional alternatives.

The core of this paper's issue is precisely the research gap. The shift to AI produced a plethora of interrelated and frequently contradictory implications on employment, income distribution, the fiscal system, innovation incentives, and political stability. As a result, selecting an institutional model of adaptation is an inherent multi-criteria public policy issue. In the absence of a systematic examination, the discussion remains normative and fragmented.

The motivation for this research stems from the increasing application of AI technology and the need to investigate what is the limited institutional readiness of labour market systems. It is then necessary to investigate how AI adapts to the labour market in the long term and vice versa, because it is obvious that AI enters all aspects of life and thus automatic systems based on AI is offered to perform certain production or even the provision of services. Therefore, it is necessary to systematically evaluate the institutional adaptation model to address the consequences of the transformation in the labour market that is driven by AI systems.

This paper closes the observed gap by using multi-criteria decision-making methods (MCDM) as a methodological framework for systematic expert evaluation of alternative institutional models of labour economy adaption in the AI era. Additionally, this paper goes one step further in the research and uses a fuzzy-rough approach to determine the importance of the criteria applied and rank the alternatives. By applying this idea, the advantages of the fuzzy approach are utilized. Specifically, the use of imprecise facts conveyed by linguistic values is used to make decisions, and the rough method has the advantage of allowing uncertainty to be included in the process and reducing the subjective effect of experts on the final decision. This explicitly quantifies normative assumptions about priorities - for example, the importance of fiscal sustainability in relation to reducing inequalities - and makes them analytically transparent.

The aim of this paper is to assess institutional models of labour economy adaptation in the context of extensive artificial intelligence application using multiple criteria and to determine which model accomplishes the greatest potential for long-term social and economic sustainability. This shifts the discussion about the future of work from the level of automation risk assessment to the level of designing an institutional architecture capable of absorbing and directing technological transformation. The following research questions are posed in light of this goal:

RQ1: How can the fuzzy-rough SiWeC-WASPAS framework evaluate institutional models of labour market adjustment under conditions of uncertainty and expert judgment uncertainty?

RQ2: Which economic, social, fiscal, and institutional criteria are most important for evaluating labour market adjustment models in the context of AI diffusion?

RQ3: Which institutional models of adjustment provide the best balance between innovation incentives and institutional feasibility?

Several contributions to the theory and practice of research on the effects of AI on the future of the labour economy will be made by carrying out this study. Above all, this research contributes to the development of decision-making models to determine which models have the strongest impact on adaptation to market changes caused by the application of AI. Then, this research adds to the development of decision-making based on the application of fuzzy-rough approach and offers a theoretical foundation for adapting the labour economy in the context of intensified AI use.

2. Literature review

The development of artificial intelligence (AI) has triggered a new phase of discussions on the future of the labour economy, with a particular focus on the relationship between automation, employment, and income distribution [14, 15]. In contemporary literature, the dominant framework prevails according to which technological changes operate through two basic mechanisms: labour substitution and the creation of new tasks [16, 17]. The Autor [1] demonstrated that technological progress does not necessarily lead to a permanent decrease in employment because, in addition to automating routine work, new activities emerge that require complementary skills. A similar logic is developed by Acemoglu and Restrepo [3], who distinguished between the “displacement effect” - the replacement of labour with capital - and the “reinstatement effect” - the creation of new tasks and occupations. The final impact on employment and wages depends on the balance of these processes and on the institutional and regulatory context in which the technology is deployed.

Empirical evidence points to heterogeneity in the effects of automation. While Frey and Osborne [2] estimate a high proportion of occupations exposed to computing [18], later research shows that the risk is lower when analysed at the level of specific tasks rather than occupations as a whole. Graetz and Michaels [19] find that robotization can increase productivity, but with differentiated effects on employment. Goos *et al.,* [20] further highlight the phenomenon of labour polarization, where middle-skilled jobs disappear while the demand for high-skilled and low-skilled jobs grows. These findings suggest that AI transition is not just a technological issue, but a deep institutional and distributional dilemma. If the institutional framework does not allow for the adaptation of the workforce and the redistribution of profits, technological progress can exacerbate inequalities and destabilise social structures.

Despite optimistic expectations of productivity gains, Brynjolfsson *et al.,* [21] warn of the “modern productivity paradox”: namely, technological innovations are not immediately reflected in aggregate growth statistics. Reasons include the time lag between technology adoption and organisational adjustments, intangible investments, and measurement constraints. In this context, the AI transition requires complementary institutional changes - education, tax reform, regulatory adjustments, and industrial policy. According to Brynjolfsson *et al.,* [22], generative AI can greatly boost individual productivity in certain tasks, although the results vary depending on the worker’s starting level of expertise. Therefore, the question is not just how much AI increases output, but how the gains are distributed and what the long-term implications are for the labour market and aggregate demand.

Macroeconomic literature on secular stagnation further warns that technological advances can simultaneously reduce labour demand and concentrate income, thereby weakening aggregate demand [6, 23]. Institutional models of adaptation also provide a stabilizing role in this situation. The distribution of income between labour and capital is one of the central themes of AI's political economy. Pata and Kartal [24] demonstrates that there is a concentration of wealth when the rate of return on capital exceeds the pace of economic expansion. As capital-intensive assets, AI technologies may contribute to this tendency. Korinek and Stiglitz [5] argue that AI may raise inequality and reduce labour's negotiating strength, especially if labour markets are rigid and technology ownership remains concentrated.

Atkinson [25] highlights that distribution outcomes are not technologically determined, but institutionally shaped. The distribution of growth gains is determined by the tax system, ownership structure, and social policy. Acemoglu and Robinson [7] and Rodrik [8] further emphasize that political stability and inclusive institutions are a prerequisite for long-term growth. Otherwise, the raise of inequality can generate political polarization and institutional erosion. The AI transition raises the question of the sustainability of the tax base. Traditional labour taxation systems may become financially unsustainable if the labour income share declines and capital income rises. The necessity of modifying the tax system to accommodate the new production structure gives rise to discussions about the taxation of robots or automation rents [10, 26].

Blanchard [27] points out that in conditions of low interest rates, the fiscal flexibility may be greater than traditionally assumed, although the long-term sustainability still depends on the structure of incomes and expenditures. The OECD [28] highlights the necessity of striking a balance between redistributive goals and innovation incentives since excessive capital taxation can impede technological progress. Numerous institutional reactions to the AI transition are presented in the literature. The aim of Universal Guaranteed Income is to maintain economic inclusion in conditions of an unstable labour market [9, 29]. According to empirical assessments, work incentives and fiscal sustainability are significantly impacted by transfer design [30]. While current debates on public investment funds and social co-ownership [31] provide an alternative to traditional transfer politics, the participatory capital model expands on Al Mamun and Ehsanullah [11] notion of a broader distribution of ownership.

Mass retraining and industrial policy rely on the theory of endogenous growth [12] and on the idea that the state can actively shape technological transformation [13]. Goldin and Katz [32] show that historically, the race between education and technology has determined distribution outcomes. Although the human-in-the-loop regulation and the shortened workweek pose concerns about incentives for productivity and creativity, they still maintain employment and social legitimacy. The New Institutional Economy emphasizes that administrative competence and enforceability are key components of policy efficacy [33, 34]. Unless the institutional models are made compatible with the existing political and legal systems, normative constructions remain ineffective.

The impact of AI on changes in the labour economy, i.e., in employees, was also examined using MCDM techniques. Some of these studies will be discussed in the text that follows. Agarwal [35] established priorities for enhancing the interaction between people and technology by optimizing employee responsibilities in the implementation of AI systems using the AHP (Analytic Hierarchy Process) method. Nouib *et al.,* [36] attempted to forecast the employment of graduates through the ranking of necessary skills by combining AHP and TOPSIS (Technique for Order of Preference by

Similarity to Ideal Solution) methods with a machine learning algorithm. Istudor *et al.,* [37] examined the suitability of employee skills in the adoption of AI applications in Central and Eastern European countries using the ENTROPY, EDAS (Evaluation Based on Distance from Average Solution), and MOORA (Multi-Objective Optimization on the basis of Ratio Analysis) methods.

In the conducted research, Bhatt [38] focused on the hiring process using AHP and fuzzy TOPSIS to analyse the criteria that affect the adoption of AI applications in companies. Lin and Wang [39] investigated how to improve talent retention in the Work 4.0 era using fuzzy AHP and DEMATEL (Decision-Making Trial and Evaluation Laboratory) methods. Barragán Moreno *et al.,* [40] developed a framework for assessing the risk of automating individual tasks using the AHP method, applying it to the accounting profession. Entezami *et al.,* [41] applied the Hesitant fuzzy BWM (Best Worst Method) method to rank AI criteria in the development of the digital economy, highlighting the process of process automation. In order to prioritize strategies for overcoming obstacles in the implementation of Industry 4.0, which includes AI in the implementation of specific processes, Kumar *et al.,* [42] proposed a hybrid MCDM approach using modified SWARA (Stepwise Weight Assessment Ratio Analysis) and WASPAS (Weighted Aggregated Sum Product Assessment) methods.

Analyses of the automation of certain professions and the micro-effects of AI are widely available in the literature, but systematic, comparative, and quantitative assessments of institutional models of adaptation are scarce. Therefore, this paper makes a contribution by combining distributional, fiscal, and political-economic criteria into a unified multi-criteria framework, which makes it possible to rationalize the institutional response selection in the face of significant technological change.

With the increasing application of AI, various studies are being conducted that deal with the topics of automation, AI, labour market transformation, and more. However, this research seeks to cover certain areas that have not been sufficiently researched. First, existing studies focus on the microeconomic effects of automation and study how automation affects changes in the workforce and the occupations of employees. Therefore, it is necessary to conduct a systematic evaluation of the institutional adaptation model that is caused by the change in the labour market affected by the introduction of AI systems. Second, previous studies rarely integrate various dimensions into a single framework, which is why it is necessary to evaluate AI application models from different aspects in order to obtain results that consider all these aspects. Third, the application of an integrated approach using the fuzzy-rough approach has been used in many studies, but this approach needs to be promoted even more, especially in evaluations in studies where AI is included. The reason is that it cannot be assumed with certainty how AI will affect changes in the labour market in the future, so it is necessary to strengthen these assumptions with this approach that integrates uncertainty and insecurity when conducting evaluations.

3. Research methodology

The research will be carried out through four related phases of research (Figure 1).

The preparatory phase is the first phase of the study, during which the research objectives will be established, which will help specify the essential components and select the respondents, leading to application of the criteria and scrutiny of the alternatives in this research. The respondents in this research consist of experts from the Republic of Croatia in the field of labour economics, macroeconomics and public finance. The research includes experts who have at least five years of relevant experience in research and analysis of the labour market and institutional economic systems. Most of the experts are employed in the higher education system and participate in scientific research related to economic policies and the labour market. The selection of experts is based on the criterion of expertise and research experience in areas relevant to the evaluation of institutional models of labour market adaptation. Given the nature of the research, emphasis is placed on the economic evaluation of institutional models in the context of the transformation of the labour market caused by the development of artificial intelligence. After the selection of experts, alternatives and research criteria will be determined.

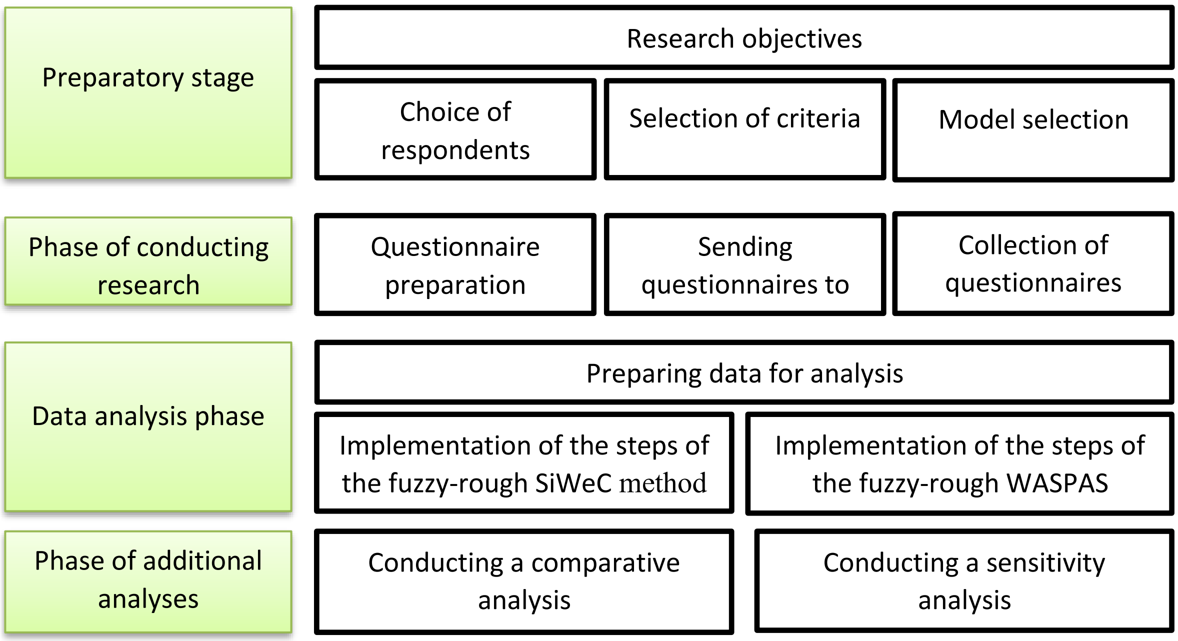

Fig. 1. The fuzzy-rough SiWeC-WASPAS model

The selected respondents are tasked with first assessing the importance of the criteria and then the alternatives related to models of institutional adaptation to changes in the labour market caused by the use of AI. The application of AI will result in significant changes since it will automate institutional or business procedures and minimize the amount of time and number of employees required to complete a given task [43]. Because of this, it is essential to determine the standards that will enable all of these models to be assessed fairly, consistently, and impartially. A total of eight criteria were selected to achieve the results (Table 1).

Table 1
Criteria for the assessment of institutional adjustment models

Id	Criterion	Description
C1	Preservation of economic inclusion	Ability of models to prevent permanent marginalization of the workforce
C2	Preservation of vertical mobility	Encouraging skills development and long-term advancement
C3	Fiscal sustainability	Long-term financial sustainability without destabilising public finances
C4	Innovation and production incentive	Impact on motivation to work, entrepreneurship and investment
C5	Reduction of inequality	Impact on income distribution and wealth concentration
C6	Political and social stability	Reducing polarization and the risk of institutional erosion
C7	Macroeconomic stability	Impact on aggregate demand, employment and cycle stability
C8	Institutional feasibility	Regulatory, administrative and political feasibility

The models that will be employed in this study will be chosen when the criteria have been established. The following article will introduce these models.

Universal Basic Income (UBI) (Model 1) implies regular, unconditional cash transfers paid by the state to all citizens, regardless of their financial status or work engagement. In the context of the development of artificial intelligence, UBI is seen as a mechanism that would decouple income from labour and ensure economic security in conditions of mass automation [44]. Its implementation would allow individuals to devote themselves to creative work instead of routine tasks that will be taken over by robots [45]. The main challenges of this model relate to its funding and potential effects on social solidarity and work ethic [45].

Participatory AI Capital (Model 2) encourages societal co-ownership of AI by enabling all citizens to co-own technology and actively benefit from the capital returns it generates [46]. Participatory AI capital suggests that workers are co-owners of AI and take part in the distribution of surplus value generated by AI, as opposed to AI being developed only by private companies [47]. Collective ownership of AI guarantees a more equitable distribution of value and gives society more influence over technological advancement [48]. This aims to mitigate the growing concentration of capital and prevent further deepening of the economic disparities brought about by automation [46, 47].

A shortened working week with labour redistribution (Model 3) implies a reduction in standard working hours while maintaining the full income of employees [49]. Artificial intelligence and automation make this model feasible as they take over routine tasks and increase productivity, allowing output to be maintained with fewer operating hours. This mitigates the negative effects of automation on employment, improves the quality of life of workers, and allows society to adapt to technological change without mass layoffs [49, 50].

Taxation of AI capital (Model 4) entails the introduction of additional taxes on the use of robots in various processes [51, 52]. The goal of this model is not to slow down technological progress, but to ensure a fairer distribution of profits from automation and mitigate the growing inequalities caused by the decline in the share of labour in gross national income [53]. In addition to preventing labour replacement and providing workers with time to adjust through retraining, the automation tax also creates financial flexibility for social transfers [52]. In order to avoid endangering long-term growth, the robot tax must be effectively designed to safeguard the generations of workers impacted by automation [51, 52].

In order to prepare the workforce for the jobs of the future, mass retraining (Model 5) entails investments in educational programs from both the public and private sectors [54, 55]. These retrainings place a strong emphasis on lifelong learning and the growth of digital, creative, and socioemotional competency skills that complement AI systems [55]. To provide a framework for retraining in accordance with the demands of the labour market, an active industrial policy requires coordinated action by the government, academic institutions and companies [56]. This aims to empower employees to harness the potentials brought by AI technologies [57].

According to the regulated “human-in-the-loop” model (Model 6), human responsibility must be incorporated into automated systems, particularly in their decision-making processes [58]. This paradigm is based on the understanding that algorithms frequently need human supervision due to concerns of accountability, transparency, and the potential ethical ramifications of automated decision-making [58]. Studies warn us that human presence alone is insufficient since organizational dynamics and the way AI is incorporated into work processes can diminish the effectiveness of human decision-making [59]. For this reason, effective regulation must provide the conditions in which people can make informed and independent decisions [59, 60].

After the subjects, criteria and models have been selected, the second phase of the research is carried out, which is the phase of conducting the research. At this stage, a questionnaire is first formed. When forming the questionnaire, selected criteria and models are used, and the questionnaire itself is divided in two parts. The respondents evaluate the significance of the criteria they have selected in the first section of the questionnaire, and the degree to which each model satisfies the established criteria is evaluated in the second section. The respondents utilize a seven-level linguistic scale of values (Table 2) to evaluate criteria and models which was modified for this purpose.

Table 2
Score Values Scale

Assessment of the criteria	Model rating	Function of affiliation
Very Insignificant (VI)	Very bad (UK)	(1, 1, 2)
Insignificant (IN)	Bad (BA)	(2, 3, 4)
Moderately Insignificant (MI)	Moderate Poor (MB)	(3, 4, 5)
Intermediate (ME)	Intermediate (ME)	(4, 5, 6)
Moderately significant (MS)	Medium Good (MG)	(5, 6, 7)
Significant (SI)	Good (GO)	(6, 7, 8)
Very Significant (VS)	Very Good (VG)	(8, 9, 9)

Once the respondents have completed the questionnaire, they return the completed questionnaire for processing. With this step, the third phase of the research begins, namely the data analysis phase. First, data is collected for analysis. Due to the fact that the fuzzy-rough procedure is used in this study, it is necessary to adjust the collected data in the form of linguistic values for this research. This process involves transforming linguistic values into fuzzy numbers and then applying a rough procedure to those fuzzy numbers. In this process, the lower and upper limits of individual fuzzy numbers are determined. The determination of limits in the fuzzy-rough approach is based on the application of fuzzy number values, where the lower and upper approximation limits for these numbers are determined on the basis of the uncertainty approximation principle. The lower approximation represents the minimum degree of confidence associated with a particular expert assessment, while the upper approximation reflects the maximum degree of assessment taking into account the assessments of other experts. The lower limit is calculated from expert assessments that are equal to or lower, while the upper limit is determined from assessments that are equal to or higher than the assessments of the observed expert. Fuzzy-rough numbers provide a more robust representation of uncertainty compared to fuzzy numbers, because they include the boundary intervals of expert disagreement. The procedure is as follows: the individual assessments of all experts are examined. The average value is calculated by taking all expert scores that are higher and equal to the individual expert score in order to determine the lower limit. When determining the upper limit, scores that are equal to or greater than the individual expert score are identified. An average score is then created from these scores, which serves as the upper limit. In this way, the lower and upper limits for fuzzy numbers are formed and fuzzy-rough numbers are formed ($FR(\alpha) = ([\alpha^{lL}, \alpha^{lU}], [\alpha^{mL}, \alpha^{mU}], [\alpha^{uL}, \alpha^{uU}])$). Thus, the conditions for the implementation of MCDM methods are set in determining the importance of criteria and ranking models by converting linguistic values to fuzzy-rough numbers.

The fuzzy-rough SiWeC (Simple Weight Calculation) method will be used to determine the significance of the criteria. This method was chosen due to its simplicity; respondents only need to provide an evaluation based on linguistic value and they are not required to rank or compare the criteria. The grades of specific respondents can subsequently be prioritized using this method, namely if the respondents provided dispersed responses, their importance will be greater. This approach also requires fewer steps and is very simple to utilize. The steps of this method were explained by Puška *et al.,* [61] and for the purposes of this study they were corrected so that fuzzy-rough numbers could be used. Based on this, the steps of this method are as follows:

Step 1. Normalization of fuzzy-rough numbers.

$$\bar{\bar{n}}_{ij} = \left(\left[\frac{x_{ij}^{lL}}{max\, x_{ij}^{uU}}, \frac{x_{ij}^{lU}}{max\, x_{ij}^{uU}}\right], \left[\frac{x_{ij}^{mL}}{max\, x_{ij}^{uU}}, \frac{x_{ij}^{mU}}{max\, x_{ij}^{uU}}\right], \left[\frac{x_{ij}^{uL}}{max\, x_{ij}^{uU}}, \frac{x_{ij}^{uU}}{max\, x_{ij}^{uU}}\right]\right) \tag{1}$$

whereby $max\, x_{ij}^{uU}$ is the greatest fuzzy-rough number in all fuzzy-rough numbers.

Step 2. Determination of the standard deviation ($\mathrm{st.dev_j}$) of normalized fuzzy-rough numbers for each respondent.

Step 3. Aggravating normalized fuzzy-rough numbers with standard deviation values.

$$\bar{\bar{v}}_{ij} = \bar{\bar{n}}_{ij} \times st.dev_j \tag{2}$$

Step 6. Determining the value of the sum of the weights of individual criteria. This step is obtained by adding the weighted fuzzy-rough numbers for each individual criterion.

$$\bar{\bar{s}}_j = \sum_{j=1}^{n} \bar{\bar{v}}_j \tag{3}$$

Step 7. Calculate the weight of the criterion. In this step, the individual aggregate weights are divided by the total aggregate weight for all criteria.

$$\bar{\bar{w}}_j = \frac{\bar{\bar{s}}_{ij}}{\sum_{j=1}^{n} \bar{\bar{s}}_{ij}} \tag{4}$$

After determining the importance of the criteria, the model is ranked using the fuzzy-rough WASPAS method. The specificity of the WASPAS method is that the ranking of alternatives is performed on the basis of a compromise between the two methods WSM (Weighted Sum Model) and WPM (Weighted Product Model). In this way, this method uses these two simple methods to form a compromise ranking of alternatives. By applying the WSM method, the ranking order is formed by weighing normalized data, and in the WPM method, normalized data are graded with weights. Zavadskas *et al.,* [62] employed this approach for the first time and described its phases. This approach has been corrected to employ these phases in fuzzy-rough numbers. Based on this, the steps of this method are:

Step 1. Normalization of fuzzy-rough numbers:

$$\bar{\bar{n}}_{ij} = \left(\left[\frac{x_{ij}^{lL}}{max\, x_{j}^{uU}}, \frac{x_{ij}^{lU}}{max\, x_{j}^{uU}}\right], \left[\frac{x_{ij}^{mL}}{max\, x_{j}^{uU}}, \frac{x_{ij}^{mU}}{max\, x_{j}^{uU}}\right], \left[\frac{x_{ij}^{uL}}{max\, x_{j}^{uU}}, \frac{x_{ij}^{uU}}{max\, x_{j}^{uU}}\right]\right) \tag{5}$$

Step 2. Calculation of the WSM method fuzzy-rough value:

$$\bar{\bar{Q}}_i = \sum_{i=1}^{n} \bar{\bar{n}}_{ij} \cdot \bar{\bar{w}}_j \tag{6}$$

Step 3. Calculation of the WPM method fuzzy-rough value:

$$\bar{\bar{P}}_i = \prod_{j=1}^{n} (\bar{\bar{n}}_{ij})^{\bar{\bar{w}}_j} \tag{7}$$

Step 4. The final value of the WASPAS method. This value is obtained as a compromise of the WSM and WPM methods.

$$\bar{\bar{K}}_i = \lambda \cdot \bar{\bar{Q}}_i + (1-\lambda) \cdot \bar{\bar{P}}_i \tag{8}$$

Both of these approaches are given equal weight in this study, and the values will be 0.5. λ.

Step 5. Transformation of the fuzzy-rough value of the WASPAS method into a crisp value. This is done by calculating the average value of fuzzy-rough numbers.

$$K_i = \frac{K{i_1^L} + K{i_1^U} + K{i_2^L} + K{i_2^U} + K{i_3^L} + K{i_3^U}}{6} \tag{9}$$

The model is ranked using the fuzzy-rough WASPAS method, and the model that best meets these criteria is selected. Nevertheless, additional analyses, specifically sensitivity and comparative analyses, will be performed to validate this ranking. These two analyses are part of the fourth phase of this study, known as the phase of additional analyses.

Conducting a comparative analysis is designed to use the same data for models and the same weights for criteria, while ranking is done using different MCDM methods [63]. In addition to the WASPAS method, seven other methods will be used in this study. The WSM and WPM methods were selected because the WASPAS method essentially performs a ranking of alternatives based on the trade-offs of these methods [64]. Therefore, a comparison is made using these approaches to ascertain whether the ranking of these individual methods differs from the ranking of the WASPAS method [65]. While CoCoSo (Combined Compromise Solution) and MABAC (Multi-Attributive Border Approximation Area Comparison) methods use similar normalization [66], ARAS (Additive Ratio Assessment) method employs a different normalization from the WASPAS method. The application of these methods is carried out to determine whether the normalization used affects the change in the ranking of the model. Since CRADIS (Compromise Ranking of Alternatives from Distance to Ideal Solution) and MARCOS (Measurement of Alternatives and Ranking according to COmpromise Solution) use the same normalization, these methods are used to determine whether different steps of the methods affect the final ranking. Consequently, these methods are used to compare the ranking provided by the WASPAS approach with other MCDM methods.

Unlike the comparative method, sensitivity analysis changes the weight of the criteria and observes how this change affects the final ranking of alternatives. The WASPAS method will be used in this analysis, but the ranking will be based on different weights of the criteria. The determination of these new weights can be done in several ways, and in this study the initial weights of the criteria will be used. These weights will be then lowered for individual criteria by 30, 60 and 90%, while the weights of other criteria will rise in proportion to this change in the weight of the individual criterion. Due to the fact that there are eight different criteria in this research, 24 different scenarios will be created depending on which these weights will be altered.

4. Results

Phases three and four of the research process are included in the research results; that is, the results are computed using the conducted research. Since the weight of the criteria is required in order to rank the models, the weights of the criteria will be calculated first in order to determine their importance. This calculation is performed using the fuzzy-rough SiWeC method. First of all, with this method, it is necessary to systematize the collected data and present them through tables that indicate the initial decision matrix (Table 3). To use this method, the acquired data must be converted into fuzzy-rough numbers. The process will be described for calculating the weights of the criteria, not for ranking the model, because it is carried out in the same way.

Table 3
Evaluation of the importance of criteria for institutional adjustment to labour market changes

Expert	C1	C2	C3	C4	C5	C6	C7	C8
Expert 1	MS	ME	ME	SI	MS	MI	MI	MS
Expert 2	VS	VS	VS	VS	VS	VS	VS	VS
Expert 3	SI	SI	SI	SI	SI	SI	SI	SI
Expert 4	ME	MS	SI	VS	ME	MS	VS	VS
Expert 5	SI	SI	MS	SI	VS	ME	SI	SI
Expert 6	SI	MS	MS	VS	MS	SI	SI	VS
Expert 7	SI	MS	MS	VS	VS	SI	SI	SI
Expert 8	SI	MS	MS	SI	SI	SI	SI	SI
Expert 9	SI	SI	VS	VS	MS	MS	MS	SI

After the data in linguistic values are collected, the formation of fuzzy numbers is performed based on the defined affiliation function (Table 2). In this way, for example, the linguistic value of Mean Significant (MS) is converted into a fuzzy number (5, 6, 7). By applying the defined affiliation function, all linguistic values are transformed into corresponding fuzzy numbers. The next step is to determine the lower and upper limits of the rough numbers based on fuzzy numbers. As an example of the presentation of this procedure, an expert score of 1 for criterion C1 will be taken. At the lower limit, the same or lower scores for criterion C1 by other experts are detected, and at the upper limit, the same or higher scores of other experts for criterion C1 are detected, and the average values of individual fuzzy numbers are detected as these limits. In this example, this is done as follows:

$$C_{11}^{lL} = \frac{5+4}{2} = 4.50; C_{11}^{lU} = \frac{5+8+6+6+6+6+6+6}{8} = 6.13;$$

$$C_{11}^{mL} = \frac{6+5}{2} = 5.50;\ C_{11}^{mU} = \frac{6+9+7+7+7+7+7+7}{8} = 7.13;$$

$$C_{11}^{uL} = \frac{7+6}{2} = 6.50; C_{11}^{uU} = \frac{7+10+8+8+8+8+8+8}{8} = 8.13.$$

Using this procedure, fuzzy-rough numbers are calculated for all respondents' scores and a fuzzy-rough decision matrix is formed, which is the basis for calculating the values of the fuzzy-rough SiWeC method. The defined steps of the fuzzy-rough SiWeC method are then applied to this matrix. The first step is to normalize these numbers. All of these numbers are divided by the fuzzy-rough number, which has a maximum value of 10. In the same example, this is calculated as follows:

$$\bar{\bar{n}}_{11} = \left(\left[\frac{4.50}{10.00} = 0.45, \frac{6.13}{10.00} = 0.61\right], \left[\frac{5.50}{10.00} = 0.55, \frac{7.13}{10.00} = 0.71\right], \quad \left[\frac{6.50}{10.00} = 0.65, \frac{8.13}{10.00} = 0.81\right]\right)$$

Once the normalization has been set, the next step is to calculate the standard deviation values for each respondent, taking the values of the normalized fuzzy-rough numbers separately. Expert 4 had the largest value of dispersed scores, according to the standard deviation value. As a result, this expert has the highest standard deviation value, and when weighing his or her scores, the score will be the highest. This implies that rather than being the decisive factor in establishing the weight of the criteria, his or her scores will have a somewhat larger impact on the final result. Other experts' scores also affect the final weights of the criteria because their standard deviation values are marginally lower. The next step is weighing of the normalized values, where they are multiplied by the values of the standard deviation. Using the same expert and criterion, this is done in the following way:

$$\bar{\bar{v}}_{11} = ([0.45 \times 0.146 = 0.07, 0.61 \times 0.146 = 0.09], [0.55 \times 0.146 = 0.08, 0.71 \times 0.146 = 0.10], [0.65 \times 0.146 = 0.10, 0.81 \times 0.146 = 0.12])$$

After the values of the fuzzy-rough numbers are weighed, the values of the aggregate weights are calculated. This is done by adding the weighed values for each criterion separately (Table 4). Finally, based on the aggregate weights of the criteria, the individual weights of the criteria are also calculated. This step is done by dividing the individual aggregate weights of the criteria by the total aggregate weights of the criteria (Table 4). Care should be taken to ensure that the lower limit of the fuzzy-rough number is not higher than the upper limit of that number. Using the example of criterion C1, this is calculated as follows:

$$\bar{\bar{w}}_1 = \left(\left[\frac{0.63}{8.29} = 0.08, \frac{0.76}{6.93} = 0.11\right], \left[\frac{0.74}{7.35} = 0.10, \frac{0.88}{5.98} = 0.15\right], \left[\frac{0.86}{6.40} = 0.13, \frac{0.99}{5.04} = 0.20\right]\right)$$

In this way, the weight of the criteria is calculated for the other criteria as well. The results of this analysis (Table 4) show that criterion C4 - Innovation and productive incentive was given the greatest importance, followed by criterion C8 - Institutional feasibility. The lowest weight of the criterion was given to criterion C6 - Political and social stability. When we look at the results in detail, it can be concluded that none of the criteria significantly deviates from the other criteria, and based on this, it can be concluded that all criteria affect the final selection of the model.

Table 4
Results of the fuzzy-rough SiWeC method

Crit.	$\bar{\bar{s}}_j$	$\bar{\bar{w}}_j$	Rank
C1	([0.63, 0.76], [0.74, 0.88], [0.86, 0.99])	([0.08, 0.11], [0.10, 0.15], [0.13, 0.20])	6
C2	([0.58, 0.73], [0.70, 0.85], [0.82, 0.97])	([0.07, 0.11], [0.10, 0.14], [0.13, 0.19])	7
C3	([0.59, 0.79], [0.71, 0.90], [0.83, 1.02])	([0.07, 0.11], [0.10, 0.15], [0.13, 0.20])	5
C4	([0.78, 0.90], [0.90, 1.02], [1.02, 1.14])	([0.09, 0.13], [0.12, 0.17], [0.16, 0.23])	1
C5	([0.61, 0.83], [0.73, 0.95], [0.85, 1.07])	([0.07, 0.12], [0.10, 0.16], [0.13, 0.21])	3
C6	([0.53, 0.74], [0.65, 0.86], [0.77, 0.98])	([0.06, 0.11], [0.09, 0.14], [0.12, 0.19])	8
C7	([0.60, 0.81], [0.72, 0.92], [0.84, 1.04])	([0.07, 0.12], [0.10, 0.15], [0.13, 0.21])	4
C8	([0.71, 0.85], [0.83, 0.96], [0.94, 1.08])	([0.09, 0.12], [0.11, 0.16], [0.15, 0.22])	2
Sum	([5.04, 6.40], [5.98, 7.35], [6.93, 8.29])		

Once the importance of the criteria has been determined, the rankings of the selected models are performed. Before performing the steps of the fuzzy-rough WASPAS method, the linguistic values are transformed into fuzzy-rough numbers. The procedure is the same as in the fuzzy-rough SiWeC method, i.e. first, the linguistic values (Table 5) are transformed into fuzzy numbers using the affiliation functions, and then the lower and upper limits of the fuzzy-rough numbers are calculated. The specificity of this transformation is that it will be done according to the models and the average value of fuzzy-rough numbers for these models will be calculated. After the aggregate fuzzy-rough decision matrix is formed, the steps of the fuzzy-rough WASPAS method are performed.

Table 5
Evaluation of the Institutional Adaptation Model to AI-Induced Labour Market Changes

Model 1	C1	C2	C3	C4	C5	C6	C7	C8
Expert 1	MG	ME	ME	ME	MG	ME	MG	ME
Expert 2	VG	VG	VG	VG	VG	VG	VG	VG
Expert 3	GO	GO	GO	VG	GO	GO	VG	VG
Expert 4	GO	BA	ME	MB	MG	MG	GO	GO
Expert 5	GO	ME	ME	ME	GO	VG	VG	MG
Expert 6	GO	MB	MB	MB	GO	GO	MG	MG
Expert 7	GO	BA	GO	MB	VG	VG	MG	GO
Expert 8	GO	MG	ME	MB	MG	GO	MG	MG
Expert 9	GO	MG	ME	GO	GO	MG	MG	GO
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Model 6	C1	C2	C3	C4	C5	C6	C7	C8
Expert 1	MG	GO	GO	MG	MG	GO	GO	MG
Expert 2	VG	VG	VG	VG	VG	VG	VG	VG
Expert 3	VG	GO	VG	VG	GO	VG	VG	GO
Expert 4	GO	GO	MG	ME	ME	MG	MB	ME
Expert 5	GO	GO	MG	VG	GO	GO	GO	GO
Expert 6	MB	MB	BA	ME	MB	MB	MB	ME
Expert 7	MG	ME	BA	MG	ME	ME	MB	ME
Expert 8	ME	MB	BA	BA	BA	BA	ME	ME
Expert 9	MG	MG	GO	GO	VG	MG	GO	ME

The first step of the fuzzy-rough method is normalization. In contrast to the normalization applied in the fuzzy-rough SiWeC method, the fuzzy-rough number for an individual criterion is here divided by its largest value. After that, the steps of the fuzzy-rough WSM and WPM methods are performed. The example of model 1 and criterion C1 will explain the computation for the purposes of these two methods:

$$\bar{\bar{Q}}_{11} = ([0.62 \cdot 0.08 = 0.05, 0.68 \cdot 0.11 = 0.07], [0.72 \cdot 0.10 = 0.07, 0.79 \cdot 0.15 = 0.12], [0.83 \cdot 0.13 = 0.11, 0.89 \cdot 0.20 = 0.18])$$

$$\bar{\bar{P}}_{11} = ([0.62^{0.08} = 0.96, 0.68^{0.11} = 0.96], [0.72^{0.10} = 0.97, 0.79^{0.15} = 0.97], [0.83^{0.13} = 0.98, 0.89^{0.20} = 0.98])$$

In order to obtain the values of these methods, the fuzzy-rough WSM method sums the individual criteria values for the observed models, while the fuzzy-rough WPM method multiplies the individual criteria values (Table 6). When the values of these methods are obtained, a compromise is made, and the average value is calculated, which represents the values of the fuzzy-rough WASPAS method. By defuzzification these values, the final value of this method is obtained. The results of this approach (Table 6) show that model 5 - Mass retraining received the best scores according to expert assessments, followed by model 2 - Participatory AI capital, while model 3 - Shortened working week with work redistribution received the worst scores from the experts.

The obtained results of the application of the fuzzy-rough WASPAS method will be compared with the results of selected fuzzy-rough methods through comparative analysis. The results of the comparative analysis show that the ranking of alternatives differs in the three models that are ranked from fourth to sixth place. The fuzzy-rough WSM and WPM methods and the fuzzy-rough CoCoSo method (Figure 2) have an identical rank with the fuzzy-rough WASPAS method. It is logical that the same rank is the order of the WASPAS method and the WSM and WPM methods because the values of the WASPAS method are made based on the compromise of the results of these two methods [67, 68]. It is specific for the fuzzy-rough CoCoSo method that a compromise of several different parameters is made, and based on this, it can be concluded that when performing a compromise of several methods, the ranking remains the same. Other methods do not compromise, which is why there is a difference in the ranking of these models. When looking at the values of the fuzzy-rough WASPAS method, it can be seen that in these three models there were the least differences in results, so due to the application of some other normalization and other steps of the method, a different result will be certainly obtained. It should be said that these three models are ranked from fourth to sixth place, and on this basis, they are not the first choices for institutional adaptation to changes in the labour market. The discrepancy in the ranking of lower-ranked models can be explained by the values of the results of the WASPAS method, where these models had a small difference between them. Therefore, changing the steps when implementing certain methods affected the change in the ranking these models. This was influenced by small differences between them because experts gave them similar ratings. Models with a higher ranking, on the other hand, had a larger difference between them, and certain models dominated over others. Therefore, the application of other steps when implementing these methods did not affect the change in the ranking of these models, and the ranking was more stable.

Table 6
Results of the fuzzy-rough WASPAS method for models of institutional adaptation

Models	$\bar{\bar{Q}}_i$	$\bar{\bar{P}}_i$
Model 1	([0.31, 0.66],[0.51, 1.01],[0.80, 1.54])	([0.66, 0.73],[0.68, 0.79],[0.72, 0.89])
Model 2	([0.31, 0.69],[0.51, 1.05],[0.85, 1.59])	([0.67, 0.76],[0.68, 0.82],[0.77, 0.95])
Model 3	([0.26, 0.65],[0.44, 1.01],[0.71, 1.54])	([0.59, 0.73],[0.60, 0.78],[0.63, 0.89])
Model 4	([0.28, 0.69],[0.50, 0.99],[0.75, 1.52])	([0.62, 0.76],[0.67, 0.77],[0.66, 0.87])
Model 5	([0.34, 0.73],[0.66, 1.05],[0.84, 1.59])	([0.70, 0.80],[0.85, 0.82],[0.76, 0.94])
Model 6	([0.27, 0.66],[0.45, 1.02],[0.72, 1.55])	([0.60, 0.73],[0.61, 0.79],[0.64, 0.90])

Models	$\bar{\bar{K}}_i$	K_i	Rank
Model 1	([0.49, 0.69],[0.60, 0.90],[0.76, 1.22])	0.776	3
Model 2	([0.49, 0.72],[0.60, 0.94],[0.81, 1.27])	0.804	2
Model 3	([0.42, 0.69],[0.52, 0.90],[0.67, 1.21])	0.736	6
Model 4	([0.45, 0.72],[0.58, 0.88],[0.70, 1.20])	0.756	4
Model 5	([0.52, 0.76],[0.76, 0.93],[0.80, 1.27])	0.840	1
Model 6	([0.43, 0.70],[0.53, 0.90],[0.68, 1.23])	0.745	5

In order to further analyse the results of the fuzzy-rough WASPAS method, a sensitivity analysis was performed. This analysis showed that there was a change in the ranking of models that were ranked from fourth to sixth place (Figure 3). In this way, it has been confirmed that their rankings are sensitive and that they are influenced by several factors. The comparative method proved that the normalization of the steps of the method is affected, while the sensitivity analysis showed that the ranking of these four models is affected by the change in the weights of the criteria. The changes in the ranking of model 4 occurred due to the decrease in the importance of criterion C3 - Fiscal sustainability. Based on this change, it can be concluded that the model 4 had better scores than the model 6 in this criterion, and by reducing the importance of this criterion, there was a change in the ranking of the model. The same situation occurred with criterion C5 - Reduction of inequality, where the reduction in the importance of this criterion has led to a change in the ranking order for model 6 and model 3. Based on the conducted analyses, it was determined that these three models that are best ranked have the best results, so they should be applied first, and then other models in order to make institutional adaptation to the changes in the labour market caused by the application of AI.

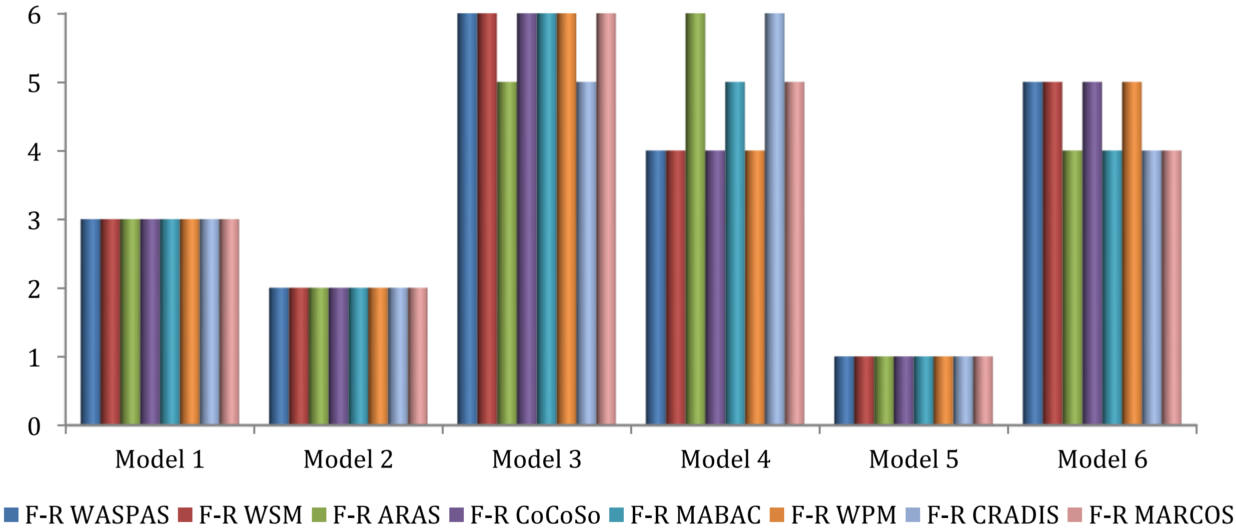

Fig. 2. The results of the comparative analysis

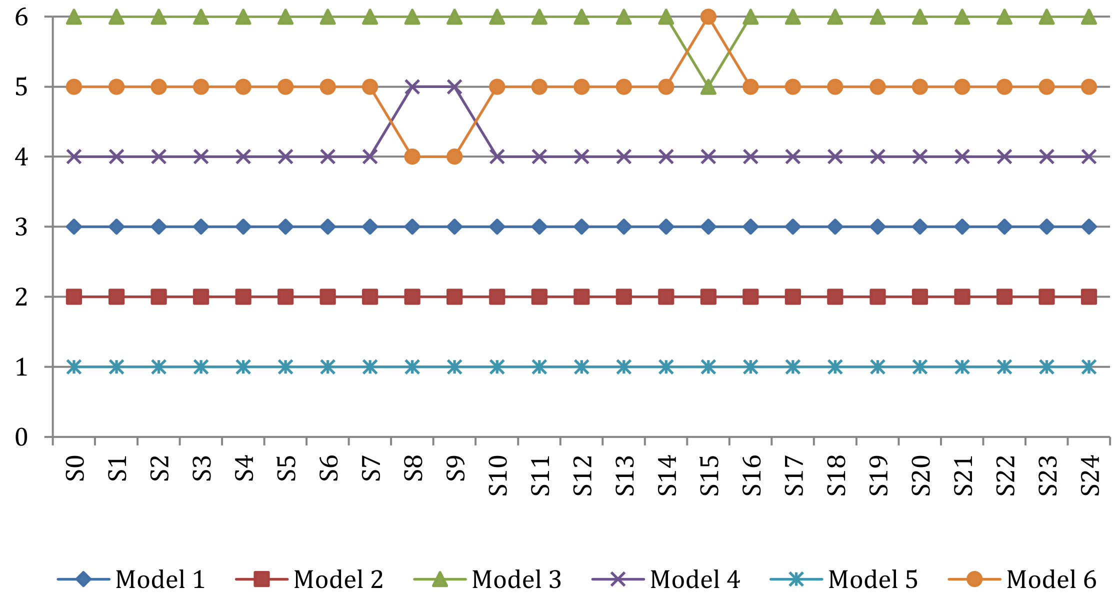

Fig. 3. Results of sensitivity analysis

5. Discussion

The results of the conducted research provide significant insight and provide a basis for the study of the field of labour economics and the ways of institutional models of adaptation to the challenges brought by the intensive use of AI. This research has provided a methodological approach to how the application of the fuzzy-rough approach enables not only the determination of the importance of individual criteria, but also the systematic analysis of the proposed models through their ranking. On this occasion the uncertainty and risk in decision-making that are inherent in such complex socio-economic evaluations that integrate labour economics and AI are incorporated. Expert opinion was used in this research, and experts who have at least five years of relevant experience in the field of labour market analysis and institutional economic systems were considered experts. A total of nine experts were used, most of whom work in the higher education system and participate in various scientific research papers related to this field. These experts first evaluated the importance of the criteria used, and then evaluated the selected models using these criteria.

To determine the importance of the criteria, the fuzzy-rough SiWeC method was used, which has shown great flexibility and simplicity in previous research [69, 70]. During the analysis of the selected eight criteria, the experts assigned the greatest importance to the criteria C4 - Innovation and Productivity Incentive. This research result indicates that the key to institutional response is to preserve employee motivation, develop entrepreneurship and invest in innovation. These results demonstrate that technological advancement should not be impeded and that the use of AI should be promoted in order to achieve the development objectives of a particular country. Acemoglu and Restrepo [3] also support this viewpoint, highlighting in their study how technology impacts the labour market, with the institutional framework playing a crucial role in maintaining the balance in the labour market. This leads to the conclusion that innovation and productive incentives are crucial and cannot be achieved without a suitable institutional framework that supports AI in order to boost productivity and accomplish economic growth and development. In addition to this criterion, criterion C8 - Institutional feasibility is of significant importance, which indicates that experts appreciate the realism and operationalization of policies. This means that the model must be feasible and can be implemented within existing regulatory, administrative and policy structures. Such results are confirmed by the authors of North [33], who emphasizes the need to effectively implement policies and take care of their implementation, while Neffati and Kaddachi [34] emphasizes that the institutional framework must be compatible with the capacities of institutions. In this way, it can be said that experts prefer those models that can be gradually introduced and adapted instead of those models that require radical solutions and a complete restructuring of government systems.

Criterion C5 - Reducing inequality ranked third in importance because experts are aware that the AI transition carries the risk of concentration of income and wealth, as indicated by Korinek and Stiglitz [5] and Pata and Kartal [24]. The fact that this criterion is so important does not mean that experts disagree with the idea that inequality will inevitably increase; rather, they think it will have an impact because every innovation requires a significant initial investment, which yields higher profits and leads to further stratification of the society. These findings lead experts to conclude that the institutional model needs to take proactive measures to distribute the benefits achieved by the application of technological progress. According to the experts' assessment, the criterion C6 - political and social stability was given the least importance. This does not, however, imply that experts believe that political and social stability is unimportant but that it is a consequence of well-implemented policies and the implementation of other, in the opinion of experts, more important criteria. For instance, political and social stability will arise if inequality is decreased, economic inclusion is maintained, and macroeconomic stability is attained. However, Korinek and Stiglitz [5] caution that under conditions of inequality, there is a risk of political fragmentation and institutional decay, therefore the low significance of this criterion may suggest that the market processes would resolve these issues on their own.

When ranking the models using the fuzzy-rough WASPAS method, results were obtained that showed that Model 5 - Mass Retraining was rated as the best by experts. In this way, they believe that this model provides the best institutional response to the changes in the labour market caused by the application of AI. This model is based on the idea that the workforce can adapt to technological changes and it is necessary to systematically invest in human capital in order to adapt to changes in the market. Education plays a big role in this because, as Goldin and Katz [32] claim, there is always a race between education and technology, and that education must adapt to technological changes. For this reason, Shengelia and Sichinava [54] and Bharati and Gosavi [55] emphasize that lifelong learning and the development of digital skills are key to preserving employment. In this way, it is necessary to continuously invest in education and improve skills and knowledge by applying lifelong learning. These results can be explained in such a way that each individual must actively face technological progress and thus must actively manage educational policies. According to experts, linking this model to the most crucial criteria means that the criterion of innovation incentives should be used through new technologies and contribute to productivity. It is also linked to the criterion of institutional feasibility because, although education systems are inherent, they must be gradually reformed to adapt to the changes in the labour market.

The second ranked model was Model 2 - Participatory AI Capital. This model advocates extending ownership of technology to workers or citizens in order to prevent the concentration of capital and ensure a fairer distribution of profits. These results are also supported by Lowitzsch and Magalhães [46], who argue that without the intervention of the ownership structure, the application of AI will only reinforce existing inequalities. In addition, Makridis [47] shows that models such as worker co-ownership and tokenization can significantly alter the distribution of gains. The high score of this model can be considered as a response to the criterion of reducing inequality. Moreover, it should be noted that this model does not necessarily reduce innovation incentives, as co-ownership can act as a motivating factor that can positively affect the strengthening of investments in digital technologies.

The third ranked model, according to experts' score is Model 1 - Universal Basic Income. However, Van Parijs and Vanderborght [9] and Lipianina-Honcharenko *et al.,* [29] interpret it as a response to the application of AI in automation. The third position of this model by experts suggests that there is still value in this model as a mechanism for separating income from labour and ensuring economic security in conditions of mass automation. In fourth place according to experts' assessments is Model 4 - Taxation of AI capital. This model, which involves additional taxation of the application of AI and robots on economic developments has a clear fiscal logic according to the opinions of Bastani and Waldenström [51] and Guerreiro *et al.,* [52]. The lower ranking of this model can be interpreted as that taxing AI could slow down technological progress. Thus, as Merola [53] points out, the quantity of taxes must be determined ideally to avoid endangering growth in the long run. The fact that experts view this model as both a primary and a secondary option for resolving this issue explains why it is ranked fourth.

Model 6 - Regulated "human-in-the-loop" is ranked at fifth place. This model emphasizes that special human supervision is exercised over automated processes, especially in cases where AI is used in decision-making with ethical implications [58]. This model may have received a low score because it emphasizes processual rather than structural adaptability to labour market changes. In this context, Wang and Pashmforoosh [60] note that it is essential to create an environment in which individuals can make well-informed and independent decisions. The lowest ranked model according to the results of this research is Model 3 - Shortened Work Week with Redistribution of Work, although there are many authors who advocate this model [49, 50]. This model may produce the lowest results in practice because productivity should rise while working hours are reduced, ensuring that the consequences of work remain the same. Experts are sceptical of this model since, instead of regulating working hours, other models propose active policies, such as investments in human capital (Model 5) and modifications to the ownership structure (Model 2). The scepticism of experts towards this model stems from the fact that other models offer active policies, such as investments in human capital (Model 5) and ownership structure modifications (Model 2), instead of regulating working hours.

In order to confirm the results obtained by applying the combination of fuzzy-rough SiWeC and WASPAS methods, two additional analyses were performed, namely comparative analysis and sensitivity analysis. Comparative analysis is an important methodological instrument in verifying the robustness of the results obtained by ranking [71, 72]. This is done by ranking alternatives with additional methods, so in this study a total of seven other fuzzy-rough methods were applied to rank the models. Here, the same decision matrix and weight of the criteria were used, and it was examined whether the application of other methods would provide a different ranking order. The results of the comparative analysis show that the result remained the same for the first three ranked models, while the ranking of the other models changed in relation to the method used. Thus, it has been demonstrated that these three models, which have demonstrated a high degree of consistency, should be employed in practice first, followed by models whose rankings in this study do not exhibit a high degree of consistency. The ranking of model 3, which was the lowest ranked model in other methods and placed in the penultimate position, and model 4, which had the lowest results in these methods but was ranked fourth in other methods, demonstrated that the ARAS and CRADIS methods exhibit the greatest difference when compared to other methods. This is because the ARAS method uses a percentage normalization that affects the change in the ranking of alternatives, whereas the CRADIS method focuses on calculating deviations from ideal solutions. The CRADIS method is somewhat more complex compared to other methods, so by applying these steps, there was a deviation in the results compared to other methods.

Sensitivity analysis in this study was conducted to examine the impact of changing the weights of the criteria on the ranking of the models [73, 74, 75]. Due to the specificity of this analysis that each individual criterion was reduced by 30%, 60% and 90%, 24 scenarios were formed in this analysis. The purpose of the sensitivity analysis was to examine how much each individual criterion affected the model ranking [76]. Similar to the comparison study, when weights were changed, the ranking and order of the first three ranked models remained unchanged, but the remaining models underwent modifications, albeit only in three scenarios [77]. In this way, the stability of these top three ranked models has been confirmed, as they have shown the best results according to experts' assessments. When changing two criteria, a change in the ranking of the model occurred, namely the change in the criteria of fiscal sustainability and the reduction of inequality. Thus, model 6 showed better results when the importance of fiscal sustainability criteria was reduced compared to model 4. This indicates that Model 4 has better indicators in terms of fiscal sustainability compared to Model 6. On the other hand, when the impact of the inequality reduction criteria was reduced, Model 3 showed better results compared to Model 6, and thus showed that Model 6 had better indicators in reducing inequality. The results obtained by altering the fuzzy-rough SiWeC and WASPAS methods were validated because these two additional analyses demonstrate a very consistent and rough ranking of the three best-ranked models.

6. Implications of the research

The conducted research has implications for the further development of the theory and practice of public policy making, as well as for the methodological development of the application of MCDM methods and approaches to measuring the impact of the application of AI on changes in the labour market. The application of potential models for institutional adaptation to these applications is significant because this research offers a theoretical foundation for investigating how AI would affect changes in the labour market. In this way, several possible models and their possible application in practice were processed. The results of this research show that it is necessary to develop new knowledge and skills in order to respond to new tasks and professions that arise from the use of AI. In order to boost competitiveness, it is therefore essential to concentrate on staff retraining and the development of new professions that, in conjunction with AI, will develop and improve processes. For this reason, it is necessary to develop theoretical directions and formulate practical guidelines for the retraining of workers in order to respond to the increasing application of AI in business processes, which will affect the reduction of the number of employees, as they will be replaced by AI and robots. Accordingly, the key to taking advantage of the complementarity between work and technology should be human capital. Additionally, in order to establish a more equitable distribution of wealth through ownership, a share of the ownership of AI in automation must be formed. As a result, new strategies must be developed, such as the joint investment of owners and employees in the automation processes, which would include employees in the revenue distribution. Instead of investing in capital through shares, in this way it is invested in technology that will generate additional capital. The findings of this study give policymakers precise direction on which institutional models should be employed in order to prepare for the AI transition, which is already certain and is starting to be applied in practice.

On the basis of theoretical new postulates, which include institutional support in adapting, changing the way of production and providing services, it is necessary to develop practical guidelines in order for these theoretical foundations to gain practical application. Because of this, widespread retraining must be implemented in practice. This includes investing in lifelong learning, the development of digital skills, as well as the strengthening of socio-emotional competencies. All of this should have an impact on how people apply their skills, so they can adjust to the changes caused by the introduction of AI and automation in business, rather than waiting to be replaced before retraining. Institutions must ensure that these programs are widely available to all age groups, especially taking into account vulnerable groups such as older employees, employees with certain needs, and the like. In addition to retraining, it is necessary to provide the opportunity for employees to participate in co-ownership of technology that would allow them to distribute revenue. Certain tax incentives are offered with these co-ownership models if employees are co-owners of technologies, as it is important to incorporate some other models that are discussed here. These models would be therefore easier to apply and benefit employees more.

The application of fuzzy-rough approach has enabled the practical evaluation of these models, including uncertainty and risk in subjective decision-making, while reducing the subjective influence of an individual expert on the final results of the research. In this way, this combination of the two methods has proven to be suitable for these and related decision-making problems, and this approach should be further developed in future research that will analyse the impact of AI and automation on the labour market. Further analyses have shown that the results can be examined in a robust way. Therefore, in order to improve the conclusions of these studies, these additional analyses must be included in future research employing MCDM methods.

7. Limitations and guidelines for future research

This research has certain limits in addition to its contributions to the advancement of theory and practice, as well as management implications on how to behave in practice to lessen the adverse effects that the deployment of automation and AI would produce on the labour market. The first limitation of this research is the geographical scope of the implementation as it is limited to the Republic of Croatia. In this sense, the results cannot be observed at the global level, but only at the local government level. Therefore, in order to obtain results that involve more countries, future research must extend to other countries in the region. In this manner, it would be possible to compare the outcomes of different nations and draw broader conclusions about some of them. In addition, the limitations of this research also apply to the coverage of the experts involved in this research. Because of their modest number and geographic location within the Republic of Croatia, this study might be regarded as a preliminary methodological investigation. Because of this, a greater number of experts as well as experts from other countries must be included in future studies modifying nevertheless the methodological framework of that study. In addition, it is necessary to include other experts who operate in the real sector and originate from different institutions that study the impact of AI on the labour market, thus providing different scores from the university professors. Such a wide range of experts may also provide new guidelines on how to preserve employment levels while facilitating a more seamless transition to automation and the use of AI with institutional models of adaptation. Increasing the number of experts would also address the limitation regarding the risk of certain expert's subjectivity. When there are fewer experts, each expert has more individual impact; when there are more experts, each expert's own influence decreases and more objective research is produced.

To further address this problem of subjectivity, this study used a rough approach that allows for a reduction in subjectivity that affects the final results. However, the application of the fuzzy-rough approach imposes additional limits on the boundary levels of fuzzy-rough numbers. The problem is that this study used linguistic values with seven levels of agreement or disagreement. Furthermore, due to the difference in scores, the upper limits of the first fuzzy-rough number are higher than the lower limit of the second fuzzy-rough number, while the upper limit of the second fuzzy-rough number is higher than the lower limit of the third fuzzy-rough number. To fix this, the affiliation function must be adjusted and scores with five levels of agreement or discrepancy must be used. The boundaries of fuzzy numbers must be taken into consideration so that the discrepancy does not occur within the boundaries of fuzzy-rough numbers. Therefore, in future studies, if a large number of respondents were to be included, it is necessary to predefine fuzzy numbers that would solve this research limit. The limit of the research is that the focus of this research is at the national level, so it is necessary to reduce it to the level of the company, sector or region of the country. This is because individual sectors have their own peculiarities and the same basics cannot be applied to all sectors. In order to enable reciprocal comparison of various sectors and improve institutional adjustment through the implementation of these models, future research on this premise should concentrate on the micro-levels of a certain nation and encompass several sectors. Additionally, since six models were used in this study, other models that might aid in resolving this issue must be included. These additional models must be included in future studies as some of them might yield positive results and could be applied in practice. Moreover, combined models should be considered in future research, as the application of multiple models in practice may have greater effects on institutional adjustment. Future research must also take the time dimension into account because AI is being used more and more in practice. As a result, it may be possible to choose models for a specific period of time when implementing automation and AI, since different models may be needed at different stages of implementation. This allows for the inclusion of many criteria, which can then be adapted for purpose of future researches.

8. Conclusion

This research provided a systemic and methodologically based evaluation of institutional models of labour market adaptation to the challenges posed by the development of AI and process automation. To achieve this, a hybrid approach based on fuzzy-rough SiWeC and WASPAS methods has been developed. Applying this fuzzy-rough number approach has enabled the inclusion of uncertainty and risk in decision-making and the reduction of subjectivity in decision-making. The fuzzy-rough SiWeC method was used to evaluate eight selected criteria for the evaluation of the model of institutional adaptation to the labour market. Based on the results of this method, the experts assigned the greatest importance to institutional and productive incentives and institutional feasibility. On this basis, the selection of the model was adapted to institutional achievement and feasibility. The evaluation of the model was done using the fuzzy-rough WASPAS method, which is actually a compromise between the results of the WSM and WPM methods. The results of this approach showed that Model 5 - Mass Retraining shows the best results in expert evaluation. This is followed by Model 2 - Participatory AI Capital and Model 1 - Universal Basic Income. The lowest results, according to experts, would be provided by model 3 - Shortened Working Week. Comparative analysis and sensitivity analysis confirmed these results, especially in the ranking of the three best models.

The contribution of this research is reflected in the integration of various factors that affect the institutional adjustment of the labour market, which is demonstrated through the use of selected criteria. Furthermore, this study offers some guidelines on how it should adjust to the applications produced by the use of automation and artificial intelligence. Different forms of lifelong learning systems should be offered by institutions to help employees prepare for potential changes in the labour market. In this way, it is vital to develop new knowledge and vocations and thus be ready to welcome these changes. Naturally, it is necessary to implement other measures identified by other models in order to support the initiatives and reduce the detrimental effects that the use of AI has on the labour market. Additionally, the use of the fuzzy-rough methodology, the understanding of risk and uncertainty in subjective evaluation, and the execution of supplementary studies that strengthen the robustness of results constitute the methodological contribution of this study. Another contribution of this research is the integration of these two approaches with other approaches.

Despite its shortcomings, this study lays the groundwork for future research on this key topic, where expert evaluations will be used to address the issues that will arise from deployment of automation and AI in the labour market. Therefore, while keeping in mind the limits of current research, new research must be developed to provide potential solutions in a complete manner. Concurrently, new hybrid solutions that combine various models must be developed and evaluated at all economic levels, from micro to macro. This study has demonstrated the necessity of adapting to the market's constant changes, particularly in the era of AI expansion. The risks that automation and artificial intelligence (AI) pose must be addressed in order to prevent the workforce from becoming marginalized in processes, which would increase unemployment and exacerbate social inequality brought on by wealth dispersion. In order to effectively address this issue, all spheres of political, economic, and social life must be involved. This study revealed that the two best-rated approaches, according to experts, are mass retraining and participatory capital.

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Conflicts of Interest
The authors declare no conflicts of interest.

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